District Heat Networks: From Technical Feasibility to Socio-Economic Reality

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Declaration

I, the author, confirm that the Thesis is my own work. I am aware of the University's guidance on the Use of Unfair means (https://www.sheffield.ac.uk/ssid/unfair-means). This work has not been previously presented for an award at this, or any other, university. All this work is published or in review in the following papers:

1. T. Cowley, T. Hutty, and S. Brown, "Simulation of low-temperature district heat networks from mine water energy," *Comput. Aided Chem. Eng.*, vol. 52, pp. 1463–1468, 2023. [Online]. Available: https://doi.org/10.1016/B978-0-443-15274-0.50233-X
2. T. Cowley, T. Hutty, and S. Brown, "Agent-based modelling of policy interventions on district heating adoption," in *Proc. Int. Sustain. Energy Conf. (ISEC)*, Apr. 2024. [Online]. Available: https://doi.org/10.52825/isec.v1i.1161
3. T. Cowley, E. Morris, T. Hutty, and S. Brown, "Adoption dynamics of district heat networks: An agent-based commercial model," *Comput. Aided Chem. Eng.*, vol. 53, pp. 325–330, 2024. [Online]. Available: https://doi.org/10.1016/B978-0-443-28824-1.50055-7
4. T. Cowley, T. Hutty, J. Hammond, and S. Brown, "Achieving emission reduction through the utilisation of local low-grade heat sources in district heating networks," *Appl. Therm. Eng.*, vol. 242, Art. no. 122381, 2024. [Online]. Available: https://doi.org/10.1016/j.applthermaleng.2024.122381
5. T. Cowley, T. Hutty, J. Hammond, and S. Brown, "Accelerating residential decarbonisation: How stakeholder decision-making and socio-economic dynamics affect multi-decadal district heating network expansion," *Energy*, vol. 326, Art. no. 136304, 2025. [Online]. Available: https://doi.org/10.1016/j.energy.2025.136304
6. T. Cowley, T. Hutty, J. Hammond, and S. Brown, "Heat zoning aligns profit and equity in district heat networks," *One Earth*, submitted for publication, under review, 2025.

Abstract

The UK's heat transition lags electricity decarbonisation: residential heating remains dominated by fossil gas, and dense urban areas face electrical and spatial constraints that limit building-level solutions. District heat networks (DHNs) offer a scalable, collective pathway, yet rollout is hindered by the interplay of engineering limits, market design, and institutional coordination. Approaches are beginning to couple engineering simulation with socio-economic modelling, but they remain under-developed, particularly in representing stakeholder heterogeneity, social learning, environmental and spatial constraints, and path dependence. This limits planning-grade decision support for local authorities, operators and project developers, sustaining cost and delivery bottlenecks. This thesis develops and applies a sequential network dynamics and socio-technical modelling framework for planning and scaling DHNs in UK cities. A thermo-hydraulic model conceptually informs an agent-based model (ABM) of household connection decisions, developer strategies, and policy scenarios, so that behavioural diffusion shapes physical routing and deployment. Across the work, analysis indicates that slow DHN deployment arises less from technical limits than from market design, institutional coordination, and customer-side frictions. Technically, scale and connectedness suppress losses and unlock low-grade heat (for example, industrial waste heat, mine water); behaviourally, adoption is path-dependent and place-specific; strategically, purely commercial strategies can lead to systematic under-provision while purely social ones can create equity traps. The thesis identifies a policy-created 'performance plateau' in which zoning, balanced operator mandates, predictable support, and transparent tariffs align profitability with inclusive coverage. Methodologically, it advances a planning-grade approach that explains who connects and when and, once the bidirectional loop is implemented, what can be built and operated. The result is a decision-ready basis for equitable, financeable DHN expansion, with clear priorities for validation, local-authority planning, tariff design, and equity-aware optimisation.

Keywords: district heat networks; agent-based modelling; thermo-hydraulic simulation; socio-technical transitions; heat network zoning; industrial waste heat; mine water energy; adoption and diffusion; tariff design; equity-aware optimisation; urban energy systems; policy and market design.

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Preface (Thesis by Publication)

This thesis follows a thesis-by-publication format. Chapters 1–5 provide the integrative context: introduction, literature review, methodology, publication overviews and contribution statements, and overall conclusions and future work. Chapters 6–8 produce peer-reviewed publications that constitute the core research outputs.

1. **Relationship between objectives and publications.** The thesis addresses three objectives: O1 (dynamic thermo-hydraulic modelling), O2 (residential adoption dynamics), and O3 (operator strategy and policy evaluation). These map to the publications as follows: O1 → Paper 1 (Chapter 6); O2 → Paper 2 (Chapter 7); O3 → Paper 3 (Chapter 8). A summary table in Chapter 1 links objectives, papers, and usage.
2. **Formatting of published chapters.** Chapters 6–8 are produced as published. Formatting, figure/table caption styles, spelling conventions, and minor typographical errors are retained to preserve the published record. Citation formats within those chapters follow the journals' house styles; the rest of the thesis uses a consistent style.

Chapter 1 – Introduction

The decarbonisation of modern economies faces a critical bottleneck: the ‘heat transition gap’. In stark contrast to the rapid deployment of renewable electricity, heating systems remain stubbornly dependent on fossil fuels, representing a persistent barrier to meeting climate commitments [1]. This challenge is particularly acute in the United Kingdom, where net-zero targets for 2050 conflict with a reality where residential heating alone generates 78MtCO_2e annually [2] – a figure comparable to Belgium’s entire national CO_2 emissions in 2021 [3].

This impasse is rooted in systemic lock-in. In the UK, approximately 85% of homes are connected to a vast, ageing gas grid, whose physical and economic embeddedness actively discourages a transition to alternative heat sources [4] [5]. This problem is compounded by the UK's notoriously heterogeneous and inefficient housing stock, where the diversity of building ages and types complicates any standardised, cost-effective retrofit programme [6]. Unlike the electricity sector's visible transformation through wind farms and solar arrays, the heating revolution must occur discreetly inside millions of individual homes, making it both technically complex and socially disruptive.

Initial decarbonisation strategies have focused on building-level interventions, particularly the deployment of individual heat pumps. However, this approach faces significant barriers in dense urban areas, including insufficient electrical grid capacity to handle peak heating loads and spatial constraints restricting installation [7]. These limitations have directed attention towards District Heating Networks (DHNs) as a scalable, collective alternative that can overcome the infrastructure limitations of decentralised solutions [8].

While conceptually promising, deploying DHNs at a city scale is impeded by modelling challenges. Feasibility assessments require planners to test network layouts and policy scenarios, but existing tools present a trade-off between physical accuracy and computational demand. High-fidelity simulations provide detailed thermal-hydraulic data but are computationally prohibitive for networks spanning kilometres of pipework and thousands of buildings [9]. Conversely, reduced-order models gain speed by oversimplifying transient flows and thermal dynamics, sacrificing accuracy [10].

This trade-off, however, points to a deeper methodological problem. A successful DHN is not just an asset; it is a complex socio-technical system where network performance, stakeholder behaviour, and policy incentives interact dynamically. The central research challenge is therefore not to model the system's physics or its social dynamics in isolation, but to capture the crucial feedback loops between them. The following sections deconstruct this challenge, beginning with the limitations of current technical models.

1.1 The Technical Modelling Challenge

Current methods for modelling DHNs have three core weaknesses that undermine their assessment: inadequate temporal resolution [11], poor spatial scale integration [12], and the use of static network representations (fixed topology assessed in a single snapshot, no phased construction) instead of models that simulate expansion over time (pipes, connections, and capacity added sequentially under budget and uptake constraints) [13]. The most common limitation is poor temporal granularity. Simplified steady-state or reduced-order models often neglect critical demand fluctuations, thermal losses, and transport delays. Such oversimplifications can lead to an underestimation of peak thermal power requirements by up to 20% [10]. This directly translates into undersized infrastructure, compromised system reliability, and distorted economic and emissions calculations [14], invalidating the basis for a credible feasibility study and subsequent expansion modelling.

The second challenge is integrating spatial scales. Existing models typically operate at either the micro-scale (detailed building simulations) [9] or the macro-scale (simplified network-level tools) [15], but struggle to bridge the two. Building simulators become computationally prohibitive at the district level [11] [16], while network models run efficiently only by oversimplifying building dynamics and heat propagation in the pipework. This disconnect prevents an accurate representation of how local demand fluctuations affect overall network performance [15].

The third, and most critical, limitation is the failure to model dynamic network expansion. Real-world DHNs are not built instantaneously; they grow in phases over time. The technical and economic viability of each expansion phase is contingent on the outcomes of previous stages, creating strong path dependencies. While frameworks like Agent-Based Models (ABMs) are designed to capture this evolution by simulating how the decisions of interacting 'agents' collectively shape network growth, most current implementations largely overlook this reality. They tend to treat DHNs as static, pre-defined systems or simulate their expansion using coarse, often annual, time steps [11]. By failing to simulate the co-evolution of the physical network with its operational demands through staged development, these models cannot reproduce realistic growth trajectories or inform long-term investment planning [13].

1.2 The Socio-Technical Challenge

Beyond technical modelling, the viability of a DHN is governed by a range of socio-economic factors, as network expansion is ultimately predicated on on the collective decisions of diverse stakeholders, a reality that conventional frameworks ignore. Split incentives between landlords and tenants (where landlords prioritise upfront costs over long-term tenant savings) weaken the business case for DHN connections in high-rental areas [17] [18]. High connection fees can also exclude low-income households, creating energy poverty concerns that conflict with social equity objectives [19]. Furthermore, local authorities must navigate complex institutional tensions, balancing decarbonisation mandates with the risks and requirements of private-sector partnerships [13] [20].

Traditional deterministic models are ill-equipped for this reality. By assuming uniform adoption, they fail to capture the evolutionary nature of user behaviour or critical feedback loops where, for instance, poor service reported by early adopters stalls subsequent network growth [13] [21]. This oversight is damaging because social uncertainty directly compounds technical risk. A loss of stakeholder confidence can lower connection density, which in turn compromises the network's thermal-hydraulic efficiency and economic viability; both of which depend on achieving a critical mass of users [13] [22].

By persistently isolating technical performance from the dynamics of stakeholder decision-making, current approaches are fundamentally unable to evaluate the real-world deployment trajectory of a DHN. A new methodology is required. This thesis develops and applies an integrated framework that explicitly captures the feedback loops between physical network performance, human behaviour, and policy incentives to provide a more realistic assessment of how these systems evolve.

1.3 The Methodological Approach of This Thesis

The previous sections identified a systemic disconnect in DHN assessment: technical models optimise performance for predefined scenarios, while socio-economic analyses examine adoption barriers in isolation from the network's physical constraints. This fragmentation prevents the analysis of the feedback loop at the heart of DHN deployment: how the network's technical performance influences adoption decisions, which in turn reshapes the network's growth and technical requirements.

To bridge this divide, this thesis develops a technically informed socio-technical approach. Insights from detailed technical simulation are used to parameterise and bound an ABM of socio-economic dynamics. The framework is underpinned by socio-technical transitions theory, particularly insights from the Multi-Level Perspective (MLP) [23] and Strategic Niche Management (SNM) [24]. Accordingly, DHN rollout is treated not as a simple technology substitution but as a complex socio-technical transition. ABM is selected for its capacity to operationalise the interplay between the DHN niche, the incumbent energy regime, and wider landscape pressures.

ABM is particularly suited to this task due to its ability to represent heterogeneous agents (e.g., households, developers) and model the dynamic feedback loops between them [13] [25] [17]. This allows policy interventions or changing network performance to influence collective adoption behaviour over time, capturing both planned and emergent network growth patterns [25], thereby offering a means to investigate the persistent supply-demand coordination and timeline challenges in DHN development [14]. Most critically, ABM provides the potential for such integration. This work utilises this by first developing a high-fidelity dynamic thermal-hydraulic model (Paper 1) to establish a robust understanding of the system's physical and economic constraints. This technical understanding is then used to inform the ABM (Papers 2 & 3). This ensures that while the ABM focuses on socio-economic interactions, its core assumptions about performance, cost, and expansion logic are grounded in engineering reality. The approach allows the research to analyse the plausible interactions between network constraints and stakeholder behaviour without the prohibitive computational cost of a fully integrated simulation. This moves beyond correlation to explore causation: how technical issues impact adoption, and how adoption patterns alter a network's engineering and financial viability [26].

This approach, however, has known validation challenges. The ABM methodology literature advocates a 'realist' stance, prioritising mechanism exploration and scenario analysis over precise forecasting [8]. Hansen et al. [27] state that limited historical data and system complexity often prevent traditional time-series calibration. Thus, this thesis adopts a "realist" stance, using the model for mechanism exploration and scenario analysis rather than precise forecasting. Lacking sufficient historical data for traditional calibration, validation relies on pattern matching against observed behaviours, extensive sensitivity analysis of key parameters, and ensuring theoretical consistency.

Therefore, the framework developed in this thesis uses three layers: (1) a computationally efficient dynamic thermal-hydraulic model; (2) a spatially explicit ABM capturing the co-evolution of stakeholders and infrastructure; and (3) a policy evaluation layer to test interventions on this emergent system. By linking these layers in a sequential design, in which engineering validation preceding and informing social simulation, the framework supports a holistic assessment of path-dependent, feedback-driven dynamics in urban energy transitions. Section 1.4 sets out the research objectives that implement these layers.

1.4 Research Scope

Few existing frameworks attempt partial coupling of infrastructure design, user decisions and policy interventions. District-heating analyses often treat hydraulics, user behaviour and policy in separate silos, leaving planners without a clear view of how the three shape network roll-out. This thesis addresses this fragmentation by developing an integrated socio-technical framework delivered across three core research objectives:

1. Develop and validate a city-scale, hourly simulation for mine water DHNs, capturing the transient heat losses and staged spatial expansion for quick and reliable feasibility assessment.
2. Build an ABM of households and developers that responds to connection costs, peer influence, and heating-system replacement cycles to capture dynamic, path-dependent network growth.
3. Design and apply a policy evaluation layer to the integrated model, allowing for the stress-testing of different operator strategies and policy frameworks, including UK heat zoning legislation.

These objectives work together to address the overarching research question: *How can engineering-based socio-technical modelling frameworks bridge the disconnect between DHN technical feasibility assessments and real-world deployment outcomes?* The structure of this research, and how each objective is met in the subsequent chapters, is summarised in the Thesis roadmap (Figure 1).

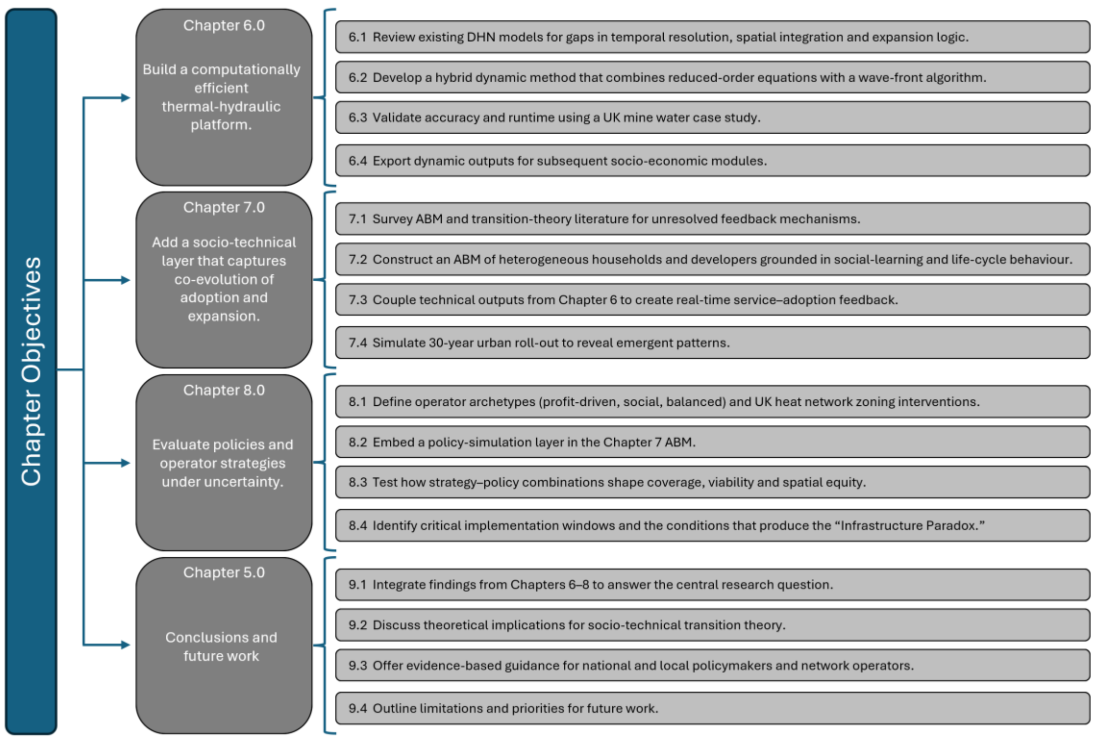

Figure 1 – Thesis roadmap and chapter objectives, showing the primary objectives of Chapters 6–8 (publications) and how they feed the synthesis in Chapter 5.

1.5 Publication Structure

Each research objective is addressed in a peer-reviewed (or in-review) publication that forms a core chapter of this thesis. Table 1 clarifies the relationship between the chapters and their corresponding papers and shows how outputs flow from the technical model to the behavioural model and finally to the policy testbed.

Table 1 - Relationship between chapters, papers and objectives.

Chapter	Paper	Objective	Stand-alone use	Combined use*
6	Paper 1 – Transient simulation for mine water DHNs	O1	Hourly hydraulics for feasibility or design studies	Supplies performance data and validated hydraulics to other models
7	Paper 2 – Agent-based adoption dynamics	O2	Behavioural uptake scenarios	Receives data from O1; passes adoption outputs to O3
8	Paper 3 – Adaptive policy evaluation	O3	Rapid policy/zoning testing	Runs end-to-end when linked with O1 + O2

**The codebase allows Paper 2 and Paper 3 to ingest detailed hydraulic outputs to validate each year, but the published versions use aggregated service-quality metrics to focus on socio-economic dynamics and policy.*

Finally, Chapter 5 synthesises the findings from all three papers, delivering a holistic analysis of the technical, behavioural, and policy implications for UK heat-network deployment.

Chapter 2 – Literature Review

This chapter is organised as follows. Section 2.1 sets the UK residential-heating decarbonisation challenge within its policy and emissions context. Section 2.2 explores why individual heat-pump deployment faces grid, economic, and spatial constraints, while Sections 2.2.1 – 2.2.3 unpack each barrier in turn. Section 2.3 introduces DHNs, tracing their technological evolution and contrasting successful international examples with the UK's fragmented landscape. Section 2.4 critiques current DHN simulation approaches, exposing spatial–temporal integration gaps that motivate the hybrid model in Paper 1. Section 2.5 evaluates mine-water as a low-carbon heat source. Section 2.6 examines socio-technical adoption dynamics and spatial equity. Section 2.7 argues that static techno-economic assessments overlook path-dependent development, and Section 2.8 reviews agent-based models to couple stakeholder behaviour with network evolution. Collectively, these sections justify the thesis's integrated socio-technical framework developed across Papers 1–3.

2.1 Background and Motivation

This literature review analyses the policy, technical, and market drivers that shape the UK's residential heating decarbonisation challenge, with particular emphasis on how policy complexity and institutional fragmentation necessitate integrated socio-technical modelling approaches. As illustrated in Figure 2, global energy-related CO_2 emissions have risen steadily from 1990 to 2024 [28], confirming the urgency of decarbonisation efforts. While the UK has made progress in decarbonising its electricity grid through renewable energy integration [29] and distribution efficiency enhancements [30], the residential heating sector remains a stubborn emissions source [31].

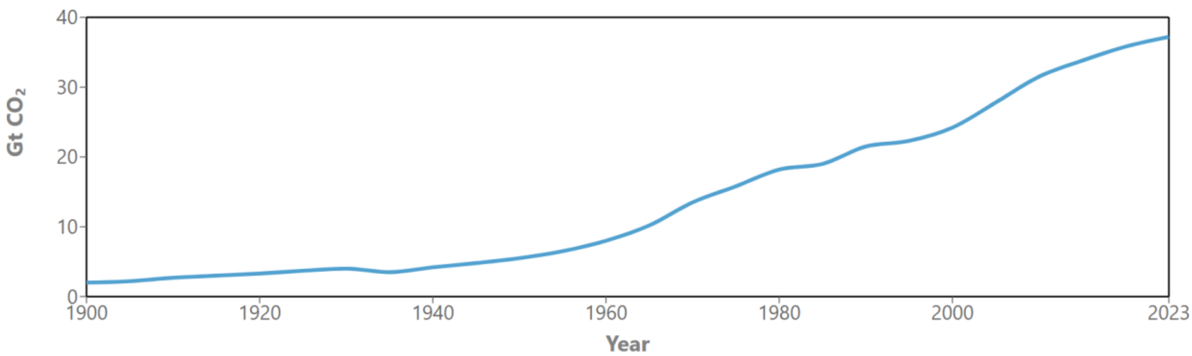

Figure 2: Global energy related CO2 emissions (Gt CO2) [28]

Domestic heating consumes 460 TWh of energy annually, accounting for 23% of the nation's greenhouse gas (GHG) emissions [32]. This is driven by heavy reliance on natural gas, which supplies roughly 75% of heating demand and contributes 14% of the nation's carbon emissions [33]. The extensive gas grid infrastructure, connecting 85% of UK households [4], has facilitated this dependency, with most remaining demand met through electrical resistive heating (6%) and fuel oil systems (4%) [34].

Despite a 17% reduction in residential building emissions between 1990 and 2020 [35], recent developments have complicated this progress. The COVID-19 pandemic increased household heating demand by approximately 15%, largely due to remote working arrangements [36]. This setback has intensified calls from both the Intergovernmental Panel on Climate Change (IPCC) and the Climate Change Committee (CCC) for accelerated decarbonisation measures to meet climate goals [1] [37].

The UK's decarbonisation targets are set in domestic law under the Climate Change Act 2008 [38], which predates the Paris Agreement. Subsequent amendments and carbon budgets align this framework with Paris-consistent ambition, including a 78% reduction by 2035 (vs. 1990) [39] and net-zero by 2050 [40]. Achieving these milestones requires a near-complete phase-out of unabated fossil fuel heating. The complexity of achieving these targets through coordinated policy intervention highlights the necessity for analytical tools capable of evaluating multiple, interacting policy instruments and their socio-technical feedback.

Key policy initiatives driving these targets include the Future Homes Standard, which is due to come into force on 24 March 2027, subject to transitional provisions, and is intended to ensure new homes are built with low-carbon heating and high levels of energy efficiency [41]. This measure aligns with broader housing ambitions, such as the Labour Party's commitment to construct 1.5 million new homes over five years, creating opportunities to embed low-carbon heating solutions at the design stage [42]. Concurrently, the Energy Act's Heat Network Zoning proposals establish zones where DHNs are the preferred heating solution [43], supported by the Green Heat Network Fund (GHNF) to finance local authority pilot projects [44].

However, aligning these policies in real projects is far from straightforward. The Future Homes Standard's introduction of low-carbon heating requirements from 24 March 2027 [41] will take effect before heat network zoning is fully implemented [43], leaving developers uncertain whether a new estate must connect to a DHN or install stand-alone low-carbon systems. At the same time, bids to the Green Heat Network Fund (GHNF) are judged against detailed techno-economic criteria, yet most local authorities lack the in-house modelling expertise and capacity to satisfy those templates [44]. These timing clashes and split institutional responsibilities expose the limits of conventional, single-policy appraisal tools and underscore the need for integrated, socio-technical assessment frameworks.

The Climate Change Committee projects that 52% of UK heating will be supplied by air source and ground source heat pumps, with 20% delivered through DHNs by 2050 [45]. However, this transition faces significant challenges, including volatile energy prices that create uncertainty for consumers, investors, and developers [45], complicating long-term planning and undermining the sustained commitment needed to reach these market shares [22]. This unpredictability particularly challenges the utility of static analyses for charting viable transition pathways under uncertain conditions [16].

International experience demonstrates both the promise of DHNs and the importance of context-specific socio-technical integration. Denmark reaches 64 % residential DHN penetration through municipal ownership, carbon taxation, and cultural acceptance of collective infrastructure [46], supported by heat planning under the Danish Heat Supply Act of 1979 [50]. Similarly, Sweden achieves 55% DHN penetration via biomass and waste heat integration [47], while Germany has developed 14% coverage through efficient combined heat and power (CHP) systems [48]. These successes contrast sharply with the UK's market-led approach [49].

The contrast between these coordinated institutional arrangements and the UK's liberalised energy market structure exposes deployment challenges that extend beyond engineering. Denmark's municipal heat planning framework, underpinned by the Danish Heat Supply Act of 1979, enables long-term planning [50], whereas the UK's fragmented ownership often favours short-term returns [51]. Responsibilities are split among planners, utilities, developers, suppliers, and customers, each operating under different (sometimes conflicting) incentives [52]. While the technical components of DHNs are comparable across nations, the institutional pathways to deployment are highly context-dependent. Assessment frameworks must therefore evaluate how policy configurations interact dynamically with local stakeholder behaviour and changing technical constraints [53].

The UK also faces distinct technical barriers. Heavy reliance on natural gas and deep infrastructure lock-in demand large capital outlays, sustained public engagement, and new business models to switch to low-carbon alternatives [5]. With less than 2% of UK heat demand currently met by DHNs [54], there is an urgent need for analytical approaches that can simultaneously assess technical feasibility, economic viability, and social acceptance within these challenging conditions.

The scale of this transition shows the danger of treating engineering, economics, or policy in isolation [8]. Interdependencies between regulation, technology choice, consumer behaviour, and place generate feedback loops that holistic models must capture [13].

Taken together, the evidence of market volatility, institutional fragmentation, persistent data gaps confirms that the UK's residential-heat targets cannot be met through siloed interventions. The remainder of this literature review therefore surveys DHN technical modelling, socio-economic dynamics, and policy research to pinpoint integration gaps and specify requirements for a new socio-technical modelling framework. It begins with the barriers to individual heat-pump deployment, illustrating why district-scale solutions demand fundamentally different assessment methods.

2.2 Heat Pumps: Potential and Limitations

Heat pumps are a pivotal technology for decarbonising residential heat, with theoretical Coefficients of Performance (COP) suggesting high efficiency [55]. However, a persistent gap between this potential and real-world performance undermines their standing. Recent UK evidence continues to show a substantial gap between theoretical and observed heat-pump performance. A recent analysis drawing on the Electrification of Heat trial reported an average seasonal performance factor (SPF) of 2.81, compared with 3.86 for high-performing monitored UK systems [57]. This discrepancy is attributed not to fundamental technological flaws, but to pervasive issues in practice, including incorrect sizing, poor installation quality, and improperly configured system controls [58].

The persistence of this underperformance, even after industry standards were updated in 2017 [59], indicates a systemic market failure rather than simple technical error. Current policy instruments, such as the Boiler Upgrade Scheme, focus primarily on upfront cost and fail to address this critical quality gap [60]. This consistent mismatch erodes stakeholder confidence and can create negative social feedback, where the poor experiences of early adopters deter subsequent households and perpetuate suboptimal installer practices, hindering wider uptake [61].

2.2.1 Infrastructure and Deployment Barriers

Beyond individual unit performance, scaling up heat pump deployment reveals system-level challenges. The electrification of heat is projected to increase UK electricity demand by 50% by 2035, requiring significant and costly grid reinforcement to manage coincident peak demand during cold periods [62] [7]. These constraints manifest differently across the country, creating high per-household upgrade costs in sparse rural networks and acute bottlenecks at overloaded urban substations [63]. Although deployment is growing, the scale-up challenge remains substantial: under the Warm Homes Plan, the government now aims for over 450,000 annual heat pump installations by 2030, while UK heat pump sales reached 125,037 units in 2025 [56]. This shortfall is rooted in deep institutional barriers, including a critical shortage of certified installers and fragmented supply chains that inhibit the coordinated planning necessary for mass deployment [64] [65].

2.2.2 Household-Level Economic and Spatial Constraints

For individual households, the most significant barriers remain economic and spatial. Upfront costs of £7,000–£13,000 are prohibitive when compared to a gas boiler (£1,500–£2,300) [66]. Even with a £7,500 government grant, the remaining cost is a major obstacle for the one-third of UK adults with less than £1,000 in savings [60] [67]. This cost barrier is unlikely to resolve naturally, with analyses suggesting only a 15–25% cost reduction by 2030; far short of price parity with conventional systems [58].

These financial hurdles are amplified by physical constraints in dense urban environments. Furthermore, installation costs are not spatially uniform; dense urban retrofits can incur significant additional expenses due to logistical complexity and limited site access. Space requirements for external units are often incompatible with terraced housing and flats, a problem historically exacerbated by restrictive planning rules, such as the 1-metre boundary requirement in England [58] [68]. Crucially, attempting to deploy at scale requires coordinating across multiple properties with differing tenure arrangements, a process often stalled by landlord-tenant split incentives and other collective action problems [55]. The combination of high costs, physical limitations, and coordination failures highlights the inherent difficulties of a strategy reliant on individualised solutions in the very urban areas where heat decarbonisation is most critical, pointing directly to the need for the district-scale alternatives this thesis explores.

2.3 The Emerging Role of District Heat Networks

2.3.1 DHNs as an Alternative to Individual Systems

The UK Climate Change Committee recognises that expanding low-carbon heat networks can be the most effective way to provide low-carbon heat "in heat-dense areas like cities, or around anchor loads such as schools and hospitals" [69]. DHNs offer a viable solution to the individual heating system limitations identified above, particularly in dense urban settings where space constraints, planning restrictions, and high upfront costs hinder heat pump deployment [70] [71].

By centralising heat production and distributing it through insulated pipes, DHNs can achieve economies of scale, reducing per-user costs and improving overall competitiveness relative to individual systems [72] [73]. This centralised approach proves especially effective in high-density areas where aggregated demand maximises infrastructure efficiency [54].

However, translating technical potential into deployment success faces significant implementation barriers in the UK context, particularly in mixed-tenure developments where diverse ownership structures and conflicting commercial interests create complex technical requirements. Conventional assessment methods often lack the socio-technical integration needed to navigate these heterogeneous stakeholder demands and their implications for technical design, and as a result project development frequently stalls [74].

The resilience benefits of DHNs become particularly evident during extreme weather events. During the "Beast from the East" in 2018, DHN load aggregation and diversified heat supply enabled more effective peak demand management compared to individual heating systems [75] [14]. This system-level flexibility, which integrates multiple heat sources and optimises supply across varied demand profiles, proves far more challenging to achieve with standalone heating systems [8].

2.3.2 Technical Evolution and System Characteristics

The development pathway has advanced through successive "generations," each designed to lower operating temperatures and improve efficiency, shown in Figure 3 [73].

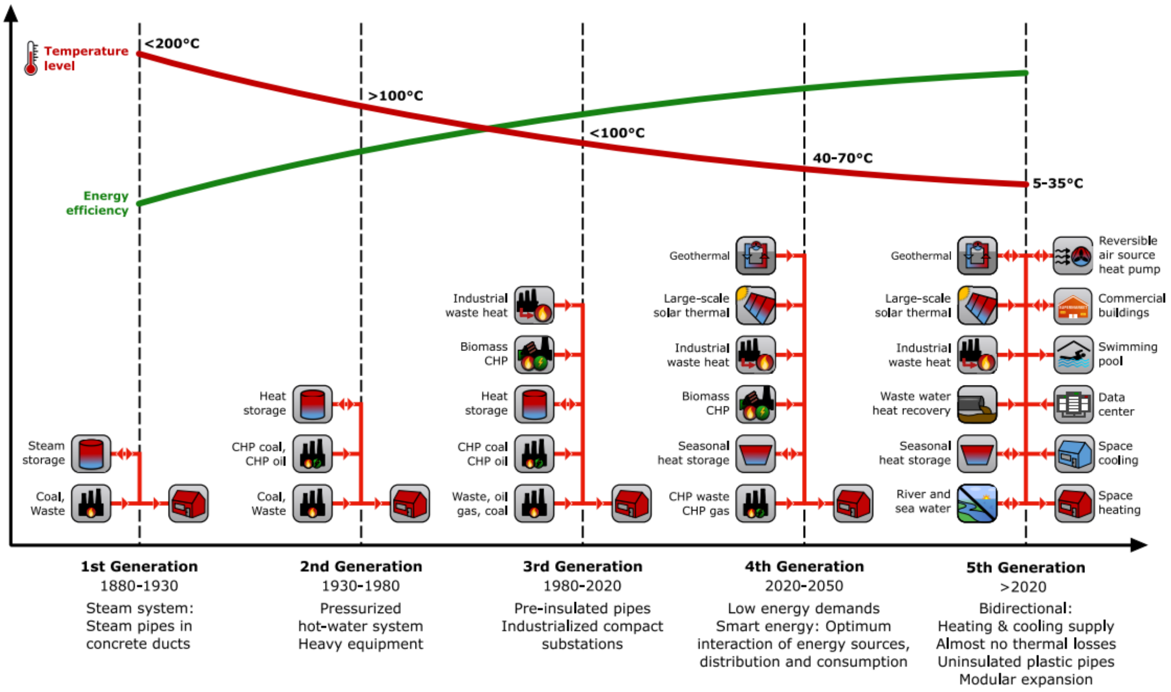

Figure 3 - 5th Generation District Heating and Cooling networks are the latest stage in the evolution of district heating. Illustration based on Lund et al. [73]

Early first and second-generation networks relied on high-temperature steam (<200°C), common in Soviet-era Eastern Europe [76], while third-generation systems standardised pressurised hot water operating at or below 100°C [77]. More recently, the transition fourth and fifth-generation designs (4GDH, 5GDH) has enabled operating temperatures between 45–70°C [73] [77]. These advanced networks achieve greater efficiency by incorporating features like decentralised heat pumps, bidirectional flow, and sophisticated demand-side controls [78]. Such low-temperature operation minimises thermal losses and, most critically, expands the portfolio of viable energy sources to include low-grade industrial waste heat, geothermal reservoirs, and flooded abandoned mines, thereby future-proofing networks against fuel-price volatility and strengthening local energy resilience [14] [16] [79].

Modern DHN designs increasingly incorporate renewable energy sources alongside smart electricity grid integration [73]. These configurations often pair Combined Heat and Power (CHP) or large-scale heat pumps with thermal storage to accommodate intermittent renewables [45]. Because peak gas and electricity usage in the UK often diverge in both timing and scale (see Figure 4) [80], thermal storage offers a strategic advantage by buffering seasonal heat-demand fluctuations without imposing additional stress on the power grid. By temporally decoupling heat generation from consumption, contemporary DHNs can coordinate across heat and electricity networks more effectively than isolated heating systems, taking a modern whole-system approach.

The reduction in operating temperatures is particularly significant for expanding heat source utilisation in Local Authorities. Lower-temperature operation directly facilitates integration of industrial waste heat, geothermal reservoirs, and mine water from abandoned coal workings, all of which can supply space heating and domestic hot water and strengthen local energy resilience [81] [14] [82]. However, leveraging these spatially distributed resources introduces complex planning challenges, as the availability and suitability, and spatially explicit aspect of each heat source varies significantly.

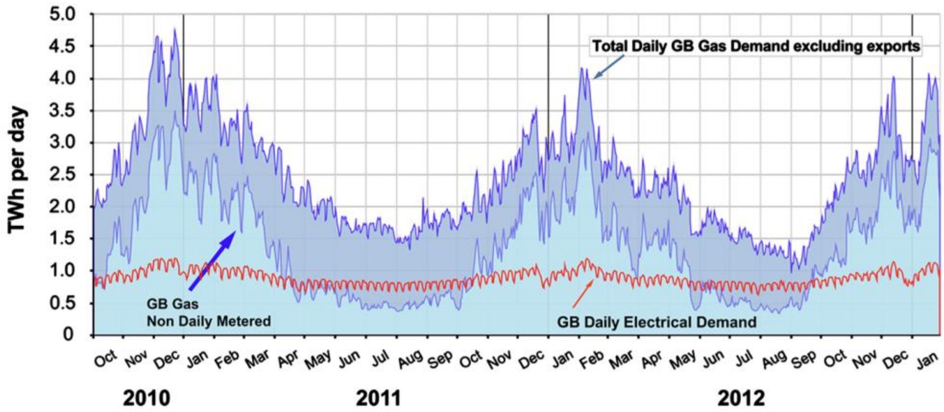

Figure 4. Daily UK Gas and Electricity Demands (TWh) [80]

2.3.3 UK Implementation Context

In stark contrast to other northern European nations, where policy-supported DHNs supply up to 98% of heating demand in cities like Copenhagen [83] and 90% in Sweden's multi-family residences [84], the UK's adoption remains limited. Figure 5 illustrates the spatial distribution of existing DHNs across the UK, revealing concentrated deployment in urban centres with notable gaps in potential high-demand areas [75]. While estimates suggest there are around 14,000 heat networks in the UK, including 2,000 considered to be district heating schemes serving multiple customers, comprehensive data remains elusive [85]. This data fragmentation exemplifies the institutional coordination challenges facing UK DHN deployment. A 2015 Department of Energy and Climate Change (DECC) survey identified only 1,765 networks, with fuel-type data available for just 715 [86]. This discrepancy reflects differences in data collection scope: the 14,000 figure includes all heat networks regardless of size, while the 1,765 represents only those systems with comprehensive operational data suitable for detailed analysis. Most critically, only 5.6% of documented systems employed renewable energy sources, revealing a contradiction between DHN deployment patterns and decarbonisation objectives, with natural gas dominance across network scales directly undermining the low-carbon rationale for district heating (Figure 6).

Figure 5: Spatial distribution of existing heat networks in the UK [75]

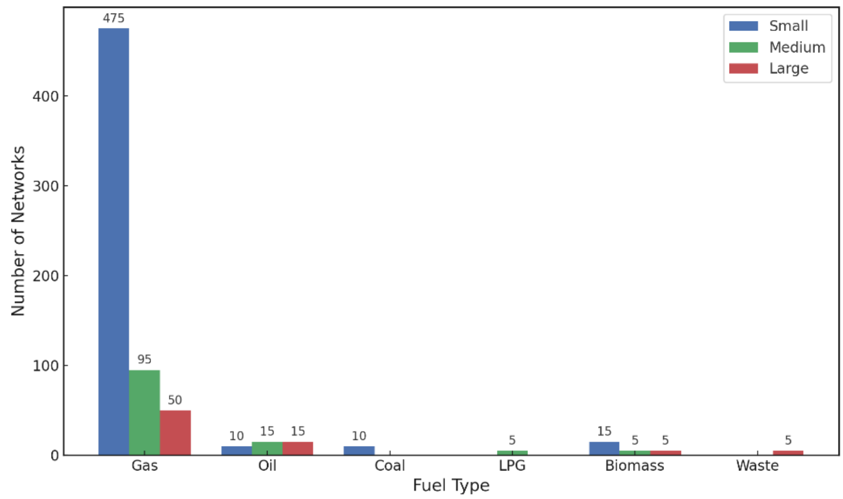

Figure 6: Distribution of fuel types used in DHNs by network size [86].

This data fragmentation reflects broader implementation challenges. The UK's market-oriented environment complicates large-scale DHN investments. Unlike countries such as Denmark, Finland, and the Baltic states where connection rates exceed 50% [51], the UK has no tradition of centrally planned DHN development. Danish success reflects early municipal ownership, mandatory connection zones, and sustained policy support following the 1970s oil crisis [87]. In contrast, the UK's liberalised energy market leaves DHN financing largely to private utilities requiring clear profitability margins and stable regulatory frameworks before committing to major infrastructure projects [88] [89].

This institutional divergence creates a risk allocation optimisation problem that impedes project development in the UK. Danish municipal ownership enables long-term strategic investment where initial network segments may operate at a loss whilst building toward system-wide viability, with cross-subsidisation across profitable and developmental areas. UK private developers, however, must demonstrate profitability for each development phase independently, creating a mismatch between DHN economics (which favour staged expansion) and financial structures (which require immediate returns) [90]. This manifests practically in developers demanding guaranteed heat offtake agreements (from commercial and residential customers) before construction begins, whilst property developers resist long-term commitments before network performance and economics is demonstrated, creating coordination deadlocks that stall promising projects regardless of technical viability [91].

Beyond institutional misalignment, policy instruments themselves create contradictory incentives that fragment deployment efforts. The Green Heat Network Fund prioritises early-stage demonstration projects with clear technical viability, whilst Heat Network Zoning proposals seek to establish mandatory connection areas where DHNs become the preferred solution [44]. This creates temporal tensions where developers await zoning decisions to guarantee market certainty, whilst GHNF funding timelines require immediate project initiation, resulting in policy instruments working at cross-purposes rather than reinforcing deployment momentum. More fundamentally, voluntary incentive mechanisms remain inadequate when confronted with the coordination challenges inherent in spatially-clustered infrastructure deployment, explaining the persistent gap between technical potential and deployment outcomes despite sustained policy attention [92].

Historically, UK local authorities pursued small-scale DHN schemes primarily to address fuel poverty rather than strategic decarbonisation. While this garnered local support, the projects were typically transferred to private energy service companies (ESCOs) upon completion and rarely expanded into fully decarbonised district-wide systems [93]. This pattern highlights the fragmented approach that has characterised UK DHN development where individual projects succeed locally but fail to generate the systematic, large-scale deployment momentum seen in successful international examples. The result is a portfolio of small, isolated schemes that cannot leverage network effects or economies of scale essential for sector transformation and decarbonisation targets.

The stark contrast between UK implementation and successful international examples demonstrates why technical feasibility assessments alone are insufficient. Despite clear technical advantages in dense urban areas, barriers including fragmented financing mechanisms, regulatory uncertainty, and stakeholder coordination challenges prevent translation of technical potential into deployment success. Successful DHN deployment requires integrated assessment approaches that capture the complex interplay between technical performance, economic viability, and socio-political implementation challenges, precisely the methodological gap this research addresses through ABM of coupled socio-technical dynamics.

2.3.4 Challenges and Opportunities

DHNs currently supply only about 2% of the UK's annual heat demand [54]. Although 166 new projects have been proposed, fewer than 53 have advanced beyond initial planning [94] - a 68% project delay rate that reflects inadequacies in planning. This failure to implement demonstrates how feasibility studies rely on oversimplified technical models that fail to capture the operational complexities, such as the use of thermal storage to manage peak demand (Figure 7), essential for reliable infrastructure design and economic projections.

The lack of standardised, publicly accessible operational data creates barriers to evidence-based technical assessment. Even large, well-established networks like Veolia's Sheffield waste-to-energy plant [95] or Nottingham's CHP systems offer limited transparency regarding actual performance characteristics, thermal efficiency, or operational reliability [96]. Smaller schemes often go undocumented entirely, preventing validation of modelling approaches or identification of performance benchmarks across different technical configurations and heat sources. These data gaps undermine technical model validation and prevent development of reliable assessment frameworks essential for the correct infrastructure investment decisions now, to avoid delays later [73][83].

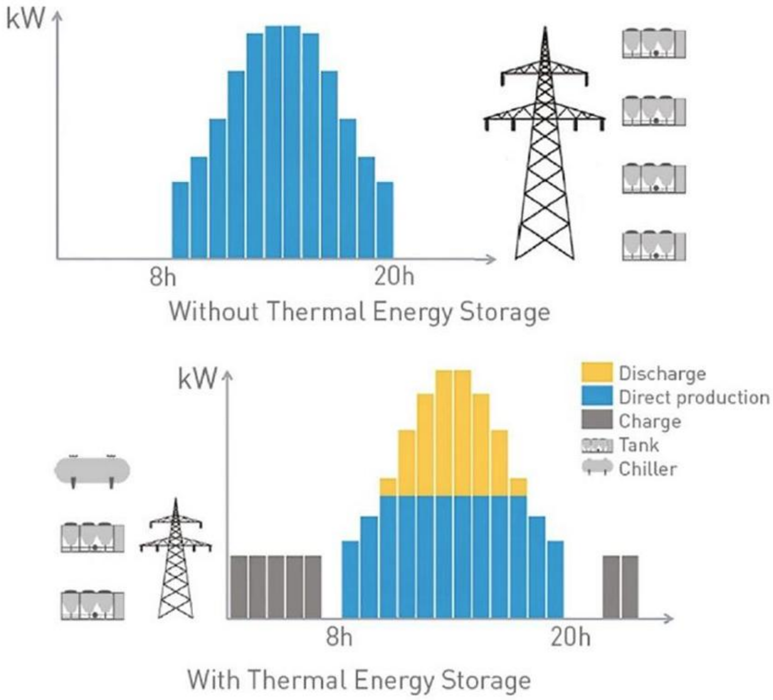

Figure 7: Thermal dispatch with thermal storage [14]

The technological promise of lower-temperature operation (around 45°C) and novel heat sources including industrial waste streams [81] and municipal solid waste [97], [98], reveals how technical advances compound assessment challenges rather than resolving them. While these innovations reduce emissions, improve utilisation and economics, comprehensive techno-economic evaluations remain limited for mine water energy, for example [22]. More fundamentally, the implementation gap between proposed and realised projects reveals that technical feasibility assessments underestimate performance complexities under dynamic operational conditions, particularly for novel heat sources that lack established performance precedents and standardised technical assessment frameworks.

2.4 Technical modelling Foundations: Simulation Approaches and Network Design Complexities

Most district-heating studies still use a two-stage workflow [99]. Stage 1 is a GIS-based spatial module that traces pipe corridors, applies road-crossing or land-use constraints, and sizes diameters from heat-density rules of thumb. Stage 2 is a thermal-hydraulic (TH) simulator that, for a fixed topology, solves mass, momentum, and energy-balance equations to predict pressures, velocities, and supply-return temperatures. The two stages often run independently: the GIS optimiser assumes idealised operating conditions (e.g., fixed flow or temperature), while the TH model evaluates performance on a topology that can no longer change [100]. This one-way coupling is problematic because routing decisions alter hydraulic resistance and heat loss, and, conversely, temperature and pressure constraints can dictate viable routes. When design and performance modules are not allowed to iterate, the result is layouts that look cost-optimal on a map yet prove unworkable or need expensive re-sizing once realistic hydraulics and transients are applied [101].

The same integration challenge forces computational trade-offs that erode accuracy. To keep run-times acceptable, many studies also down-sample time series from hourly to weekly and merge multiple demand nodes into one profile [102] [103]. Such averaging smooths exactly the peaks and fronts that govern pipe sizing and pump selection, leading to systematic under-prediction of performance variability, an effect magnified for low-temperature sources like mine water, where system COP is highly sensitive to short-term temperature swings [104].

Validation studies confirm the scale of the problem. In Gleisdorf, Austria, an automated GIS-to-thermal workflow under-predicted annual heat plus DHW demand by –36.5 % for multi-family houses and –60.6 % for commercial buildings, mainly because coarse three-zone building models and generic internal-gain schedules could not capture the demand diversity [105]. Current DHN tools can import network layouts from GIS shapefiles or CityGML city models [106], however, a recent review of 219 DHN papers found that only 44 % used GIS at all, and 58 % relied on annual time steps [16] showing that spatial and temporal simplifications remain the norm.

Beyond numerical error, current frameworks treat the network topology itself as static. They cannot explore how early choices such as radial versus looped pipes configurations [107], phased build-out, or land-parcel constraints become path-dependent commitments that lock in future costs and carbon. Untangling that spatial temporal feedback is central to this thesis: the hybrid modelling approach developed in Paper 1 and coupled to the agent-based framework in Papers 2 and 3 is designed precisely to iterate between layout, hydraulics, and stakeholder decision-making rather than confining them in separate silos [104].

2.4.1 Thermal-Hydraulic Fundamentals

The challenge in DHN simulation stems from the coupled nature of thermal-hydraulic phenomena, governed by interconnected energy, mass, and momentum conservation equations that create complex non-linear optimisation problems where design variables such as pipe sizing and network topology are intertwined [108]. Mathematical complexity arises because energy balance tracks heat supply and losses, mass balance ensures flow conservation, and momentum balance governs pressure drops. Consequently, researchers face a trade-off between mathematical rigour and computational feasibility [10].

To navigate this computational complexity, quasi-dynamic approaches that decouple flow rate calculations from temperature distribution are commonly adopted by researchers [109]. While this decoupling substantially reduces computational overhead, it omits critical transient phenomena such as thermal inertia and transport delays that significantly impact system performance under realistic operating conditions. Guelpa et al. demonstrated the practical significance of these omissions, reporting discrepancies of up to 20% between simulated and observed thermal peaks when dynamic effects such as overnight shutdowns and morning heating boosts were neglected [10]. Most critically, these errors compound through the project lifecycle: 20% underestimation in peak demand leads to undersized pipes, creating pressure drops that necessitate increased pumping power, reducing system efficiency and undermining economic projections that justified initial investment.

Current thermal-hydraulic modelling approaches reveal a persistent computational optimisation that prioritises mathematical tractability over predictive accuracy for dynamic operational scenarios. This creates a methodological limitation where models become simultaneously too complex for rapid scenario analysis yet too simplified for reliable performance prediction under transient conditions [110]. The resulting computational trade-offs compromise accuracy precisely during critical operational phases such as startup transients, peak demand periods, and emergency scenarios, where reliable performance prediction is most essential for robust infrastructure design and future expansion strategies.

2.4.2 Dynamic Modelling Methods and Limitations

Network modelling methods reveal a trade-off where computational feasibility, predictive accuracy, and practical applicability exist in tension, forcing researchers to sacrifice essential capabilities regardless of modelling choice. Table 2 summarises the key characteristics of major modelling approaches, exposing how each method presents different but equally problematic trade-offs that undermine reliable performance prediction. This review of dynamic modelling methods demonstrates that, although advances in computing power and parallel processing have reduced some runtime constraints, current approaches still struggle to simultaneously achieve the accuracy required for infrastructure design confidence, the computational efficiency necessary for comprehensive scenario analysis, and the accessibility needed for evidence-based policy development.

Table 2: Comparison of DHN Modelling Approaches

Method	**Accuracy**	**Runtime**	**Scalability**	**Data Requirements**	**Best Application**	**Key References**
Fully Dynamic	High	Hours (10h/day)	<50 nodes	High	Detailed design	[108][111][112][113]
Quasi-Dynamic	Medium (20% error)	Minutes	100+ nodes	Medium	Scenario analysis	[114][115][113][10]
Wave-Equation	Medium-High (±2°C)	~1h/24h	~50 nodes	Medium	Intermediate studies	[116]
Hardy Cross (HCA/MHCA)	Low-Medium (±5-10°C)	Fast	Variable	Low	Steady-state analysis	[118][117][118][119]
Aggregated	Low	Very fast (99% reduction)	High	Low	System scheduling	[109]
Plug-Flow	Medium-High (±0.5-1°C)	Variable	~100 nodes	Medium	Transient analysis	[106][120]
Characteristic Methods	Medium-High	$O(N^2)$ scaling	~42 nodes	Medium	Small networks	[118]
Hybrid Approaches	Medium	30-65% reduction	Variable	Medium	Selective accuracy	[121]

Fully dynamic approaches solve the complete mass, momentum and energy PDEs to capture transient thermal fronts and flow inertia but become increasingly computationally demanding as network size grows [108] [111]. Jäkle et al. [112] derive a high-dimensional DAE model and show that simulating a 100-node urban network for a single 24 h period can require several hours and multiple GB of RAM on a modern workstation. Steinegger et al. [113] compared their quasi-dynamic implementation with a near-fully-dynamic Modelica Standard-Library pipe model (slightly analogous to van der Heijde's plug-flow dynamic [116]) on the 298 m "Pongau" test grid. The dynamic configuration needed an average 130 s to complete the entire 168-step, 24 h simulation (≈ 0.8 s step^{-1}), while their quasi-dynamic solver finished in 2.9 s on identical hardware (Ryzen 5 4650U, 16 GB RAM). Even this modest-sized network therefore consumes about 15 min of CPU time per simulated day when modelled fully dynamically, which can limit the practicality of such methods for large-scale studies or extensive scenario analysis.

By decoupling hydraulic flow from thermal calculations on fixed intervals (e.g. 10–30 min), quasi-dynamic schemes accelerate runtimes by up to 80 % compared with full PDE solvers. These methods often treat heat movement as propagating "waves" based on calculated travel times, avoiding full PDE resolution [115]. Li et al. show that adding transport delays to steady-state simulations improves end-user supply-temperature predictions by roughly 20 % over a static baseline, with absolute node-temperature errors kept within 1–2 °C. However, this efficiency gain comes with a recognised accuracy penalty [114]. Lu et al. [122] arrive at a similar decoupled strategy through a physically informed aggregate model. By contrast, Steinegger's quasi-dynamic approach delivered a mean-absolute-percentage-error of 3.7 % on generator power and node-temperature errors within ±2 °C, trading a small loss in fidelity for a 45 × speed-up [113]. Guelpa et al. [10] still report up to a 20 % under-prediction of peak supply temperature. Such 10–25 % discrepancies can lead to undersized pipes or pumps and distort techno-economic projections, limiting quasi-dynamic models to preliminary design rather than final validation. These persistent errors underscore the core trade-off: computational accessibility often compromises sizing reliability, deepening the tension between practical utility and technical validity.

The computational efficiency of quasi-dynamic approaches stems from eliminating the need to discretize pipes into numerous segments, enabling near-linear scaling with network size in certain implementations. This characteristic makes them particularly attractive for extensive scenario simulations or long-term planning studies. However, this efficiency comes at the cost of reduced accuracy in wave diffusion phenomena and the omission of second-order dynamic effects, making them most suitable for analyses where computational speed takes precedence over sub-hourly precision [114].

Wave-equation methods, as employed by van der Heijde et al. [116] implement this in Modelica on an 18 km DHN, can halve runtime relative to a full PDE solver while maintaining ± 0.3°C accuracy. However, even this approach requires ≈ 1h of computation per 24h simulated, and scaling beyond ≈ 50 nodes or 30 km demands additional simplifications, reintroducing error in peak-demand estimation and thus limiting its broader applicability.

To address the limitations of quasi-dynamic approaches while avoiding the full complexity of PDE solvers, contemporary research has increasingly adopted plug-flow (Lagrangian) modelling frameworks. These approaches explicitly track discrete water volumes as they traverse the network, preserving their thermal history throughout transit [106]. Notable implementations include the Modelica libraries developed by Giraud et al. and van der Heijde et al., with the latter demonstrating accurate delay and heat loss prediction through experimental validation on physical test networks [120] [116]. These models typically assume convective dominance, allowing axial thermal conduction in water to be neglected without compromising accuracy under standard DHN operating conditions. By treating pipe walls as separate thermal capacities and fluid as moving plugs, these models also capture thermal inertia effects, where pipe materials and water thermal mass moderate temperature fluctuations, a crucial consideration given the substantial heat storage capacity of DHN.

Classical techniques such as the Hardy Cross Approach (HCA) [123] and Loop Equation Method (LEM) [117] iteratively solve steady or quasi-steady flows by enforcing conservation within loops. Del Hoyo Arce et al. [118] validate HCA/MHCA on small networks (≤ 42 nodes), showing steady-state temperature errors < 0.02 % but noting substantial inaccuracies when dynamics are significant. Under rapid transients (e.g., 5°C inlet-temperature ramps in 30 min), loop-by-loop corrections cannot capture wave effects, leading to mismatches at distant nodes. Modified HCA (MHCA) [119] accelerates convergence but still fails to represent sub-hourly phenomena in 4GDH/5GDH networks, limiting accuracy to ± 5–10°C under dynamic loads, making them unsuitable for detailed performance analysis of modern, responsive DHNs.

Aggregated network models simplify DHNs by collapsing adjacent nodes and short pipes into "super-nodes." Larsen et al. [109] reduce a 1,079-branch (20.2 km) network to ≈ 10 branches, achieving ≈ 99 % runtime reduction (runtime ∝ node count). Plant-level heat production remains "very close" to the full model, making AggM ideal for daily scheduling. However, the approach assumes proportional mass flows and equal return temperatures which are never met in practice, so the equivalent network cannot exactly reproduce original results. Reducing below ≈ 10 branches exponentially increases error (e.g., standard deviation in plant heat can double), and fixed-sample-time platforms miscalculate delays vs. variable-step solvers. Consumer-level losses and local temperature dips are masked, limiting AggM's accuracy for detailed performance assessment or for understanding localised impacts within an expanding network.

Characteristic methods (often called Method-of-Characteristics, MoC) solve the one-dimensional, hyperbolic energy equation by integrating temperature and enthalpy along lines that travel with the bulk water velocity. In practice, a pipe is discretised into segments; at each time-step the algorithm traces a "characteristic" back to the previous time layer, interpolates the upstream temperature, and then applies a semi-implicit heat-loss term to account for conduction to the surrounding soil [118]. Pressure and flow are updated in a coupled Newton-Raphson or Hardy-Cross loop, while the MoC handles the pure advection part of the energy equation, eliminating the numerical diffusion that plagues simple finite-difference schemes. Del Hoyo Arce et al. validated this approach on small networks (≤ 42 nodes) and achieved ±0.5–1 °C accuracy [118] but because every pipe segment requires its own interpolation and matrix operation each time-step, runtime and memory grow roughly with $O(N^2)$. Extrapolations from van der Heijde et al. on a 50-node network (~1 h per 24-h simulation) suggest scaling to ~100 nodes would take several hours, making CharM impractical for ABM loops or extensive scenario testing [116].

The computational burden of fully dynamic simulations has led researchers to pursue hybrid modelling strategies that selectively deploy dynamic modelling where essential while employing simplified approaches elsewhere. Falay et al. exemplify this approach by developing frameworks that automatically identify pipes where transient effects are negligible, such as short branches with minimal delay and substitute static heat loss models, achieving computational effort reductions of 30-65% while preserving acceptable accuracy [121]. Beyond identifying fewer dynamic sections, this principle of selective simplification can also extend to applying different levels of model fidelity to distinct network components based on their functional importance for overall simulation goals. For instance, primary supply lines, where accurate temperature delivery and transient effects are paramount for assessing service quality and expansion viability, might warrant detailed wavefront tracking, while return lines or secondary circuits could potentially be represented with more abstracted, computationally lighter models if their detailed dynamics have a lesser impact on the strategic questions being addressed. Despite advances in such hybrid thinking, the consistent and scalable representation of temperature wave propagation, especially in large and complex networks, remained a critical limitation, as noted by van der Heijde et al. regarding the ongoing gap in DHN simulation capabilities [116].

A key limitation in many quasi-dynamic and plug-flow schemes is their treatment of temperature fronts as uniformly advancing waves, without resolving finer spatial mixing or branching effects. In DHNs, time delays arise because temperature changes travel with the water flow, taking several hours to reach end consumers, up to 10–12h in the pipes of large systems. Pressure disturbances, by contrast, propagate nearly at the speed of sound and affect the network almost instantaneously [108]. Traditional plug-flow (Lagrangian) approaches track discrete "water parcels" or temperature segments through each pipe, merging or splitting them at junctions to approximate these fronts. While this reduces artificial numerical diffusion and captures time delays more precisely than node-based methods, it can still mask sub-segment mixing and exhibit significant complexity when applied to meshed topologies [113] [108]. As Guelpa et al. demonstrate, neglecting transient thermal effects causes models to over-predict peak power demand by over 25% (Figure 8), while other simplifications in tracking thermal fronts can still reintroduce errors of up to 7% [10]. Crucially, none offer a scalable way to maintain sub-pipe resolution across a city-scale, meshed network under deep uncertainty, precisely the gap that a truly effective hybrid dynamic framework should address.

The importance of accurate delay and wavefront treatment in DHN modelling cannot be overstated, as these phenomena represent make-or-break factors for simulation accuracy and operational reliability. As Guelpa et al. observed, the outcomes of planning and optimisation studies exhibit high sensitivity to network model accuracy, emphasizing that modelling compromises can propagate into significant errors in infrastructure investment decisions [102].

While advanced control strategies, particularly Model Predictive Control (MPC), have been integrated into quasi-dynamic models to continuously adjust flow and temperature in real-time [118], partially mitigating the impacts of underlying model simplifications in operational contexts, research on Danish energy systems demonstrated the potential of sophisticated control strategies, indicating that prioritising industrial waste heat recovery over combined heat and power (CHP) plant output could reduce excess heat production by up to 99% [124] [77]. However, even with advanced controls, the fundamental accuracy of the simulation method used to model thermal front propagation and capture transient effects remains critical; if these are poorly represented by the model, the perceived or actual effectiveness of control strategies can be compromised. Thus, methodologies for robustly modelling these phenomena while maintaining computational feasibility remain constrained in current DHN literature.

No existing method simultaneously delivers sub-hourly thermal accuracy, multi-scenario runtimes (≤ 24 hours per year of simulation time), and robustness to sparse, uncertain data. Fully dynamic and CharM approaches provide high fidelity but collapse under network size and iteration requirements. Quasi-dynamic, HCA, and MHCA run quickly but incur 15–20% errors in peak-loss estimation, risking undersized infrastructure design. Aggregated models enable rapid runs but mask local hot spots and transient mismatches. Reduced-order surrogates offer promise but depend heavily on high-quality training data and lose accuracy outside training envelopes. These trade-offs point to a clear research need: a hybrid dynamic framework that couples a reduced-order thermal model, able to capture transient fronts with a lightweight hydraulic solver for rapid flow updates. The method must work with sparse field data and run fast enough to support multi-scenario planning.

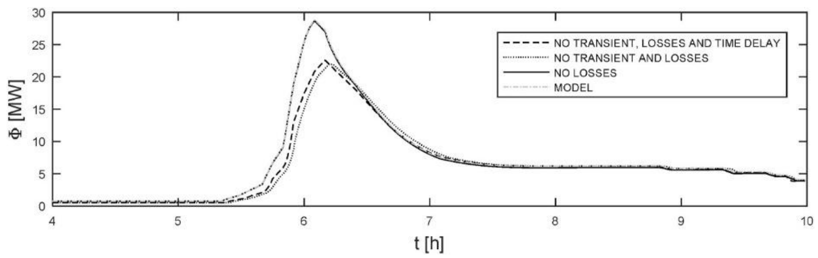

Figure 8: Demand peak comparison with and without transient behaviour in models [10].

2.4.3 End-User Demand Modelling and Validation Challenges

End-user demand modelling significantly affects DHN performance, with differences between residential and commercial demand profiles creating complexity for system design and operation [125]. Residential systems typically exhibit pronounced morning and evening peaks corresponding to occupant schedules, whereas commercial demand tends to follow standard business hours.

Methodological approaches to demand modelling face trade-offs between efficiency and precision. Top-down models using aggregate indicators prove computationally efficient but may oversimplify occupant behaviour and building diversity [126]. These models rely on macro-level indicators, such as heat demand density, population data, and building construction periods, to provide aggregate demand estimates [124], [98], with Heiple and Sailor [126] demonstrating the viability of top-down estimates demonstrating their viability through publicly available datasets.

Bottom-up approaches incorporating building-specific attributes offer greater precision but face substantial scalability limitations due to extensive data requirements [127]. Advanced techniques including ABM and artificial neural networks (ANNs) show promise but remain constrained by data scarcity and computational demands [128]. Some researchers incorporate stochastic elements, assigning probability distributions to key parameters such as indoor temperature set-points and occupant schedules, enabling more realistic predictions of peak-load events [129] [130] [131].

A critical validation gap emerges across all demand modelling approaches: while technical optimisation methods require accurate demand profiles for network sizing and operational planning, validation of demand predictions against actual DHN consumption data remains limited. This validation deficit becomes particularly problematic when demand models must interface with thermal-hydraulic simulations, as inaccuracies in demand prediction can propagate through network performance calculations and compromise infrastructure investment decisions.

2.4.4 International Approaches and Building Archetype

International experience demonstrates diverse methodological approaches, with data availability and regulatory frameworks often determining practical choices. Table 3 synthesises these approaches from different regions, illustrating how local constraints influence the selection between top-down, bottom-up, or hybrid strategies, while revealing significant variations in sophistication that reflect both data availability and institutional capacity.

Table 3 - Comparison by country of method, modelling framework, and outputs for demand modelling showing how local data and context drive choice.

Location	Method	Framework	Output	Reference
Switzerland	Bottom-up	Building archetype and normalized HDD analysis	Total energy consumption patterns	[132]
Italy	Bottom-up	Regression analysis based on comprehensive survey data	Space heating energy consumption as a function of surface/volume ratio	[133]
Italy	Bottom-up	Regression analysis based on comprehensive survey data	Aggregate heat consumption profiles	[134]
USA	Hybrid	Comprehensive building-type based modelling	Diurnal and total energy consumption patterns	[126]
Germany	Stochastic	Integration of probabilistic methods into bottom-up framework	Prediction of peak-load events with confidence intervals	[129]
Netherlands	ABM	Simulation incorporating socioeconomic and demographic factors	Dynamic demand profiles capturing occupant behaviour variability	[128]
France	ANN	Artificial neural network (ANN) demand forecasting	High-resolution hourly load predictions with	[135]

			adaptive learning capabilities	
UK	Top-down	Regression analysis of secondary data sources	Daily and sub-daily heat demand profiles relative to external temperature	[136]
Norway	Bottom-up	Panel data regression analysis	Daily heat and electricity load profiles as functions of ambient temperature and temporal patterns	[137]

The UK has predominantly employed top-down models due to data granularity limitations [136], contrasting with more sophisticated approaches developed elsewhere. Notably, Kouhia et al.'s approach [128], represents a methodological bridge between the demand modelling challenges discussed here and the broader ABM integration requirements outlined in Section 2.4.1. Figure 9 illustrates the trade-off between computational efficiency and demand accuracy, where top-down approaches enable rapid assessment of large building stocks but sacrifice the behavioural detail necessary for capturing occupant-driven demand variations that significantly affect DHN performance.

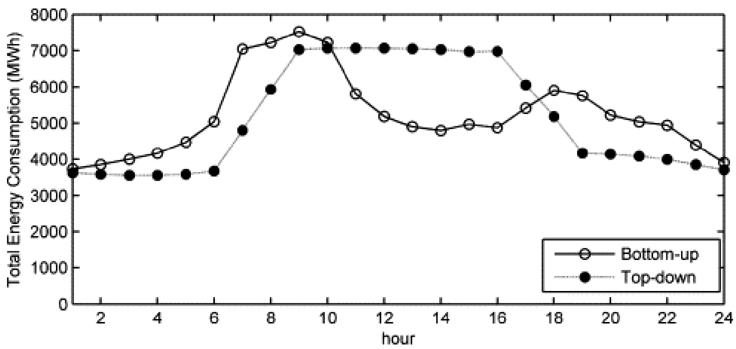

Figure 9 - Bottom-up vs top-down comparison for consumer demand modelling approaches [126]

Building archetype approaches represent a compromise between computational efficiency and demand accuracy, grouping structures by thermo-physical characteristics to simulate large-scale DHNs without modelling each building individually [132]. However, current archetype methodologies frequently exclude commercial and institutional loads that may be critical for network viability. Watson et al. [136] developed empirical regressions for domestic buildings using RHPP data but did not account for non-domestic users, limiting applicability in mixed-use districts, while Lindberg et al. [137] focused on residential archetypes while omitting leisure and industrial properties.

This exclusion is problematic since large commercial and institutional buildings serve as anchor loads, stabilising heat demand and improving network economics [138]. In urban UK contexts, facilities like sports centres significantly influence peak loads and seasonal profiles, creating demand patterns that residential-only models don't accurately capture. The omission of commercial loads from archetype frameworks represents a gap in the literature that constrains the development of viable mixed-use DHN assessments essential for urban deployment.

Addressing these archetype gaps is therefore a prerequisite for credible demand projections in mixed-use DHN scenarios. Having outlined the limitations of current demand models, the review now turns to the mine-water heat resource that will underpin the network configurations evaluated later in this thesis.

2.5 Mine Water as a Low-Carbon Heat Resource

Mine water represents a compelling opportunity for decarbonising DHNs, offering substantial thermal potential with unique characteristics that distinguish it from other renewable heat sources. However, transitioning from technical feasibility to operational implementation reveals complex interdependencies between resource characteristics, assessment limitations, and deployment barriers that current evaluation frameworks struggle to capture systematically.

2.5.1 Resource Characteristics and Thermal Potential

Among various low-grade heat sources suitable for DHN integration, mine water stands out due to its significant potential and underexplored nature. Groundwater in abandoned coal mines equilibrates with the geothermal gradient, typically maintaining temperatures of 10–20°C throughout UK coalfields [139]. While this is below the temperature required for direct space heating, it can still act as a low-temperature heat source that is upgraded to useful supply temperatures within a district heating system. The scale of this opportunity is substantial: the UK Coal Authority estimates these flooded mines contain approximately 2.2 million GWh of heat [140], equivalent to 9% of the UK's residential heating demand, with this resource position directly underneath 25% of UK homes, predominantly in densely populated former industrial regions [141].

Mine water offers consistent year-round temperatures, providing inherent stability that translates into operational advantages and long-term price stability while maintaining insulation from volatile global energy markets [16]. Heat extraction typically employs closed-loop systems where water pumped from flooded mine shafts undergoes thermal energy transfer at the surface before reinjection to maintain hydrogeological balance [142] [143].

Performance characteristics are promising. Due to consistent thermal conditions, mine water systems typically achieve coefficient of performance values ranging from 3–6 [144], substantially outperforming air-source heat pumps during peak demand periods. As grid electricity decarbonisation continues, these efficiencies translate into substantial carbon savings, with documented reductions of 59–76% relative to conventional natural gas heating systems [145] [139].

2.5.2 Modelling Challenges in Mine Water DHN Assessment

From a modelling perspective, mine water systems present unique challenges beyond the generic limitations of DHN simulation. While recent operational projects such as Seaham Garden Village and Hebburn [141] validate technical feasibility, these implementations rely on simplified analytical methods that neglect critical transient thermal dynamics. Jardon et al. [146] demonstrated up to 30% cost reduction when transitioning from 5 MW to 20 MW systems, yet these conclusions relied on steady-state conditions, potentially misrepresenting real-world performance. The thermal inertia characteristics of mine water sources create complex dynamic responses that steady-state models cannot capture, leading to errors in feasibility assessments and economic analyses that inform investment decisions.

The importance of spatial configuration and phased development strategies emerges as a critical factor determining mine water DHN viability. Spanish case studies demonstrate this criticality: the economically successful Barredo-Figaredo colliery achieved positive returns due to limited pipe infrastructure costs, while extended networks such as Calderón exhibited prohibitive costs [147]. High linear heat densities consistently emerge as essential for economic viability, yet existing DHN modelling predominantly treats infrastructure development as single-phase deployment, failing to capture the iterative expansion characteristic of real-world projects that creates critical feedback mechanisms between network performance, adoption rates, and subsequent expansion decisions [148].

This limitation becomes particularly problematic for mine water systems where initial anchor loads near extraction points must demonstrate viability before expansion to more dispersed demand centres become economically feasible. Current assessment frameworks cannot adequately model how initial network performance affects stakeholder confidence and subsequent connection decisions that determine long-term system viability.

Limited availability of detailed mine water thermal and hydrogeological data undermines accurate feasibility assessments [149]. Monaghan et al. [150] emphasize that thermal processes under varying pumping conditions remain poorly quantified, amplifying uncertainties and investment risks. This data scarcity creates challenges for integrated assessment: thermal models require detailed resource characterization that is often unavailable, while economic models must incorporate uncertainty ranges that current deterministic approaches cannot adequately represent.

Integration with complementary heat sources offers significant potential for addressing both technical performance and economic viability constraints, yet evaluation of hybrid system configurations remains inadequately analysed. Hybrid approaches combining mine water with solar thermal, biomass, or waste heat recovery could enhance system reliability and economic performance while reducing dependence on single resource characteristics. However, current research lacks frameworks for evaluating trade-offs between enhanced performance and increased system complexity, particularly regarding operational coordination and maintenance requirements across multiple heat sources.

2.6 Socio-Technical Adoption Dynamics and Spatial Equity in District Heat Networks

DHN uptake is driven by nested socio-technical processes that operate across three levels [151]. At the household level, income, tenure and technological awareness condition the willingness to connect. Neighbourhood peer influence and developer sequencing then translate these micro-choices into spatial clusters. The resulting city-scale patterns drive equity outcomes and the economics of further network expansion. While technical analyses dominate DHN research, household characteristics, spatial inequalities, and social dynamics create significant barriers that optimisation models alone cannot address.

These dynamics underscore the need to integrate social realities into planning rather than relying solely on engineering-optimal solutions.

2.6.1 Household-Level Adoption Barriers

Large-scale surveys confirm that housing tenure is one of the strongest predictors of low-carbon-heating uptake. In England, owner-occupied dwellings account for roughly 50% of the 103 000 homes with heat-pumps, whereas private-rented homes represent only 11 %—a 4.5-to-1 disparity [152]. A similar pattern appears for district heating: a nationally representative Heat Network Zoning social research survey found that 73 % of owner-occupiers would be very or fairly likely to connect to a DHN, compared with 62 % of social-housing tenants [153]. DESNZ's 2024 Public Attitudes Tracker likewise reports that 61–63 % of private renters say the choice of low-carbon heating system "is not mine to make," versus just 8–9 % of owner-occupiers [154]. Qualitative studies by Hawkey & Webb [155] attribute this gap to the landlord–tenant split-incentive: landlords bear the connection cost while tenants receive the bill savings. Together, these data indicate that tenure-sensitive instruments (e.g., minimum energy-efficiency standards, landlord incentives, cost-sharing) are essential for equitable DHN deployment.

2.6.2 Community Dynamics and Peer Effects

Beyond individual decisions, community-level social dynamics create powerful influences on adoption, driven by mechanisms like trust and information diffusion. Dutch studies indicate that higher community trust accelerates adoption via shared experience effects [17]. Public awareness is also a material driver: while direct UK DHN evidence is limited, studies of solar PV adoption suggest that increasing public awareness can be more effective than upfront financial incentives by addressing non-economic motivations and correcting misconceptions [18] [26]. In fact, recent UK surveys indicate that public awareness of DHNs remains very low; fewer than half of respondents had heard of "heat networks" prior to being given an explanation, underscoring a major informational barrier to community buy-in [153]. These social dynamics manifest spatially through peer effects and clustering: renewable energy adoption consistently exhibits spatial patterns driven by neighbour-to-neighbour interactions [156], and GIS-based analyses confirm that these clusters emerge directly from local diffusion processes [26]. This process of social contagion, with its reinforcing feedback, is a dynamic that ABMs are particularly well-suited to capture through the integration of social network effects [157] [21].

Positive or negative "first-mover" experiences propagate quickly through neighbourhood social networks. Empirical analysis of 29,000 Californian households shows that each new solar PV installation increases the probability of a further adoption in the same postcode by 0.78 percentage-points [158]. Conversely, Finnish survey evidence documents that negative word-of-mouth about high upfront costs can stall diffusion and even reverse previously rising adoption trajectories [151]. Comparable reinforcing and balancing feedbacks are expected in DHN roll-outs, where early performance perceptions can either catalyse or constrain local uptake. In the UK context, research into DHN deployment barriers (interviews with 63 stakeholders across 44 schemes) emphasised the importance of community involvement and trust in successful adoption [159]. The Sutton Dwellings project in Chelsea, for example, demonstrates how retrofitting 100-year-old social housing with ground-source heat pumps can challenge public perceptions and build community acceptance of low-carbon technologies [153], this illustrates how visible local "success stories" can generate demonstration effects in DHN contexts.

2.6.3 Spatial Equity and Market Dynamics

DHN economic viability is tightly coupled to energy price trajectories and urban form. Agent-based simulations for Dutch neighbourhoods show that sustained rises in natural gas prices (especially when electricity prices remain flat or fall) are a necessary trigger for households to abandon gas heating and connect to district systems [17]. Yet most UK feasibility studies still treat fuel prices as fixed sensitivities, leaving the strategic adjustments of users and developers untested in their forecasts. Cost benchmarking of 413 Danish schemes highlights the spatial penalty of low density: average annual heat charges in 2016 were £1,605 for urban networks versus £1,749 in rural systems [160] [161]. Evidence from Hawkey & Webb indicates that such economics concentrate new UK schemes in dense city cores, reinforcing pre-existing socio-economic divides [49]. The distributional impacts are clear; England's 2023 statistics record a rural fuel poverty incidence of 15.5 % with an average fuel poverty gap of £778, almost double the national shortfall [162]. Technical studies further show that when linear heat density falls below ~0.5 $MWh\ m^{-1}\ yr^{-1}$, relative heat losses can exceed 50 %, rendering expansion uneconomic [163]. This implies a double exposure: volatile gas prices can improve DHN competitiveness overall, but the capital logic of network layout still favours affluent, high-density districts. Without intervention, market-driven deployment may therefore bypass less-profitable low-density communities, exacerbating spatial inequities in the transition. Current optimisation models rarely couple demand-density dynamics with endogenous fuel-price responses, limiting evaluation of equity-focused strategies.

2.6.4 Institutional and Policy Challenges

UK DHN deployment faces substantial coordination challenges stemming from fragmented funding, misaligned incentives, and governance constraints [164]. The UK's liberalised energy market contrasts with the municipally controlled, coordinated expansion seen in Northern European countries, creating structural barriers beyond technical and economic considerations. While schemes like the Green Heat Network Fund offer support, they favour isolated projects rather than the comprehensive city-wide approaches found in Denmark and Sweden [164]. These barriers appear at different project phases: the initial feasibility stage faces data scarcity and regulatory uncertainty; development phases encounter planning permission complexities and multi-stakeholder coordination hurdles; operational phases must address ongoing maintenance responsibilities and expansion planning spread across multiple actors with differing objectives.

The tension between social objectives and commercial viability also creates split incentives that affect network expansion decisions [155]. Local authorities often serve as lead enablers of heat networks yet frequently encounter mismatches between their climate responsibilities and their practical capacity to act. Budget constraints and reduced in-house technical expertise have left many councils dependent on external consultants, whose priorities may diverge from long-term decarbonisation goals [14]. Community-led heat networks can, in principle, enhance public trust and local buy-in [165], through high capital costs and limited successful examples pose scaling challenges. This fragmented institutional landscape mirrors the regulatory complexities identified in innovative schemes like mine water heating projects, where considerable technical potential has struggled to translate into implementation reality due to unclear ownership and risk-sharing arrangements.

In response, new policy measures aim to better align actors and de-risk investments. Notably, the UK is implementing heat network zoning: specific geographic zones will be designated where heat networks are expected to be the most cost-effective decarbonisation solution, and certain building types within these zones can be required to connect [166]. By mandating a critical mass of anchor loads (such as large public or commercial buildings) in each zone, this policy aims to ensure sufficient demand and economies of scale, providing the certainty needed to attract long-term investment. Alongside zoning, comprehensive consumer protection regulations are being established through a new Heat Networks Market Framework. Ofgem will take on the role of regulator for heat networks, with powers to enforce fair pricing, transparency, and service standards. These steps are designed to build consumer confidence and accountability in a sector that until now lacked dedicated oversight. Together, zoning and the incoming regulatory framework seek to emulate coordinated, consumer-centric aspects of successful DHN markets abroad, potentially mitigating the institutional barriers identified above.

2.6.5 Methodological Integration Requirements

The above challenges highlight a critical gap in existing research methodologies. Socio-economic analyses of heat transitions cluster around three model families: (i) top-down techno-economic equilibrium models (e.g. UK MARKAL) that optimise energy systems under fixed assumptions [167], (ii) system-dynamics frameworks that explore aggregate feedbacks in city-scale heat transitions [168], (iii) and bottom-up ABMs of DHN emergence and consumer adoption [13]. Policy analyses still lean heavily on the first two families, whose deterministic structures assume uniform stakeholder behaviour and therefore overlook the dynamic, feedback-driven nature of consumer adoption and policy learning. This creates a methodological divide: macro-scale energy models oversimplify social dynamics, while micro-scale thermal-hydraulic models provide engineering detail but neglect socio-economic factors entirely. [11] [169] [108]. The challenge of scale integration becomes particularly evident when considering how individual household decisions aggregate into community-level adoption patterns that subsequently influence developer investment strategies and local authority responses. Current modelling approaches cannot adequately capture these multi-scale feedback mechanisms, where micro-level choices produce emergent macro-level outcomes that in turn reshape the context for subsequent decisions.

ABM therefore emerges as a useful integrator because it represents heterogeneous stakeholder behaviour and complex socio-technical interactions. It proves particularly valuable for settings like the UK housing market, where occupant decisions, policy interventions, and utility strategies interact in ways that linear models struggle to capture. While ABM has been applied to energy transitions generally, applications to DHN expansion remain limited, and even state-of-the-art models must abstract away detailed network physics to remain tractable. Thus, the literature still lacks frameworks that couple thermal-hydraulic performance with stakeholder dynamics across spatial and temporal scales. Bridging this gap likely requires hybrid approaches, e.g., coupling ABMs with engineering simulation or multi-level models so socio-technical complexity (peer effects, equity, policy feedback) can be evaluated alongside infrastructure performance.

2.7 Dynamic Techno-Economic Integration: From Static Optimisation to Evolutionary Infrastructure Development

The challenge in district heating network implementation lies not merely in technical feasibility, but in the disconnection between engineering optimisation and economic reality that characterises current approaches. This limitation is critical because real DHN projects evolve iteratively via phased expansions, where early design choices create path-dependent constraints.

2.7.1 Static Assessment Limitations and Dynamic Reality

Current DHN planning methods suffer a key shortcoming: most techno-economic analyses assume a static, "final-state" optimisation rather than modelling iterative, time-phased development. In practice, real DHN projects expand over years in multiple phases, and early design choices (pipe sizes, topology, etc.) constrain future options. Traditional models often optimise a network for a single snapshot or equilibrium state, which fails to capture feedback loops over time between initial decisions, later expansion pathways, and long-term economic performance. For example, studies seeking optimal DHN designs often neglect or greatly simplify network dynamics, focusing on steady-state performance [10]. Consequently, they ignore how transient phenomena (e.g., heating-demand fluctuations, ramp-up of new connections, thermal inertia) accumulate economic impacts across the system's life cycle. Policy and literature document this disconnect. In the UK context, upcoming heat network zoning policies demand methods that evaluate both near-term technical performance and long-run expansion economics [166].

Falke et al. [170] developed a multi-objective DH system optimisation dividing the design into stages (network layout, generation units, etc.). This approach moves beyond single-step optimisation and recognises the need for iterative design evolution, but the model still optimises against fixed assumptions and lacks robust treatment of how real demand might deviate or grow over time. Similarly, Mertz et al.'s [171] proposed an MINLP framework optimising 30-year cost for a DHN, simultaneously solving network configuration and operation. This integrated approach outperforms separated designs, supporting the argument that simultaneous simulation is superior. However, Mertz's model remains a steady-state (equilibrium) analysis that computes an "optimal" design for assumed conditions, without simulating year-by-year evolution; such a design can lock in layouts that perform poorly or prove unrealistic once the system grows. Wang et al. [101] provide an example of steady-state thermal simulation that accurately captures instantaneous hydraulics but stops short of projecting the economic or technical consequences of phased expansion. Beyond these technical shortcomings, adoption is endogenous: Sovacool and Mukherjee [172] show that perceived reliability conditions household willingness to connect. Uptake trajectories emerge from feedback between social perceptions and service quality; feedbacks largely absent from conventional analyses.

2.7.2 Path-Dependent Infrastructure Development Constraints

Current techno-economic optimisation approaches optimise for idealised final states rather than evolutionary development pathways that characterise real infrastructure deployment. This creates misalignment between theoretical optimisation and practical implementation realities. While sophisticated multi-objective frameworks like Li et al.'s [173] cost-emission trade-off analysis demonstrate impressive technical capability, they do not capture the dynamic stakeholder decision-making processes that ultimately determine project success.

This limitation becomes particularly evident in pipe sizing optimisation, where Martin-Du Pan et al., [174] demonstrate technically sound approaches for minimising heat losses, yet their methodology assumes perfect foresight of future demand patterns; an assumption invalid for networks planned through phased expansion with uncertain adoption trajectories. Real projects like the Guelph Innovation District in Canada illustrate these path-dependent constraints: initial conservative pipe sizing limited subsequent expansion capacity, requiring costly infrastructure upgrades when demand exceeded original projections after successful community engagement increased connection rates [175].

Busch et al. [13] identify how developer strategies involve adaptive, sequential expansion based on evolving technical and economic assessments, yet few frameworks systematically model these dynamic stakeholder-infrastructure interactions systematically. Nava-Guerrero et al. [176] demonstrate complex stakeholder interactions that reshape expansion priorities over time, but existing methodologies lack capability to model such evolutionary development processes that characterise successful infrastructure deployment.

The "split incentive" problem identified by Bird and Hernández [177] shows how technical-efficiency requirements conflict with socio-economic adoption barriers: high connection density is needed for efficiency, yet incentive misalignment between property owners and tenants depresses adoption. Lower-than-expected connection rates raise per-unit infrastructure costs, risking economic unviability despite sound initial technical design.

2.7.3 Technical-Economic Coupling Requirements

Conventional economic evaluation frameworks employ static assessment approaches that cannot capture dynamic interactions between technical performance, economic feasibility, and system evolution. While Hast et al. [178] demonstrate how technology diversification impacts economic outcomes, their analysis exemplifies the broader limitation of treating economic assessment as separate from technical dynamics rather than as integrated system elements.

Madsen et al.'s [179] stochastic modelling approach attempts to address system uncertainties but still struggles with the complex interdependencies between technical performance and economic outcomes that characterise evolving infrastructure. This disconnection has quantifiable consequences: neglecting thermal-hydraulic dynamics like thermal losses, transient flows, and delay times, can lead to underestimations of peak thermal power requirements by up to 20% [10], subsequently affecting both capital cost projections and operational expense forecasts that determine project viability. Hansen et al. [27] identify this challenge explicitly, arguing that traditional economic validation approaches prove insufficient for systems with substantial behavioural components, precisely the characteristic that defines DHN deployment where adoption decisions shape system economics.

2.7.4 Method Limitations and Requirements

Static frameworks cannot capture four essential aspects that determine real-world outcomes: (i) temporal evolution, where development patterns affect economic performance over time; (ii) infrastructure-utilisation dynamics, where the relationship between connection density and utilisation creates path-dependent economics; (iii) socio-technical feedbacks, where technical performance and adoption co-evolve; and (iv) phased-deployment complexity, where sequential development creates cumulative economic effects beyond static analysis.

Current frameworks also miss three methodological requirements essential for reliable DHN assessment: (a) dynamic performance–economics coupling, capturing how thermal-hydraulic dynamics generate cumulative economic effects across development cycles; (b) stakeholder–infrastructure feedback integration, evaluating how adoption patterns affect network viability and how technical performance influences subsequent decisions; and (c) path-dependent development modelling, representing how early infrastructure choices constrain future technical performance and economics.

The convergence of these limitations necessitates integrated assessment frameworks that model dynamic feedback between technical-performance evolution, adoption patterns, and economic outcomes throughout development cycles. This motivates engineering-bounded, agent-based approaches that represent complex socio-technical dynamics while preserving essential thermal-hydraulic realism, bridging the gap between the technical-modelling capabilities outlined in Section 2.4 and the stakeholder dynamics in Section 2.6.

2.8 Agent-Based Approaches to Socio-Technical Infrastructure Transitions: Bridging Individual Decision-Making and System-Level Dynamics

The evolution from static techno-economic optimisation to dynamic infrastructure assessment reveals the critical need for methodological approaches capable of capturing complex interactions between individual decision-making and system-level performance outcomes that characterise real-world DHN deployment. No single modelling approach (pure optimisation vs. pure ABM) currently covers all dimensions; hybrid approaches are therefore needed [180]. ABM emerges as a useful approach for addressing these integration challenges. However, a thorough review of its current applications to DHNs reveals not only its conceptual promise but also implementation limitations and methodological gaps, that constrain practical utility for robust socio-technical integration and infrastructure development, which together motivate the integrated framework developed in Papers 2 and 3 of this thesis.

2.8.1 ABM Theoretical Potential for Infrastructure Transitions

ABM applications to district heating networks demonstrate both conceptual promise and critical limitations that constrain their practical utility for guiding infrastructure development. While ABM's theoretical capacity to represent heterogeneous decision-makers and emergent phenomena makes it conceptually suitable for DHN transitions [25], current implementations often fail to integrate technical performance dynamics with social adoption processes that determine system viability.

The multi-paradigm integration capability, as highlighted by Chappin and Dijkema [25], represents ABM's most significant methodological advantage: enabling optimisation algorithms to govern agent decision-making while system dynamics model subsystem behaviours within a single analytical framework. Their framework conceptually supports assessment of different "transition assemblage designs" and treats policy as an endogenous parameter (a government agent's decisions respond to system state). This offers a pathway to explore dynamic policy feedback loops, a key objective of Paper 3.

However, the existing DHN literature generally fails to exploit this capability fully. Chappin and Dijkema suggest combining ABMs with system-dynamics models for feed-forward scenario generation; yet interactive, real-time coupling of detailed technical performance (e.g., transient thermal-hydraulics from Paper 1) with agent decisions often remains superficial. Implementations frequently use simplified behavioural rules that cannot capture complex feedbacks between evolving technical performance and adoption decisions. Even in advanced conceptual frameworks, while agent decision-making leading to emergent system properties is central, explicit algorithmic designs for tightly coupling network-expansion optimisation with dynamic agent-based adoption under changing technical conditions are sparse. The authors acknowledge the difficulty of modelling endogenous policy due to data scarcity and focus on evaluating pre-defined design alternatives rather than fully emergent, co-evolutionary designs driven by optimisation inside the ABM loop. This integration challenge reflects the technical–economic coupling requirements identified in Section 2.7, where static optimisation fails to capture dynamic feedback between infrastructure performance and stakeholder responses. Accordingly, Paper 2 seeks tighter coupling of ABM-driven adoption with a dynamically evolving (abstracted) expansion logic informed by Paper 1.

Current DHN modelling approaches reveal a methodological divide with critical gaps in expansion analysis. Broadly, they fall into two categories, each missing essential DHN dynamics [181]. Diffusion models, rooted in Rogers' innovation theory and Bass frameworks, examine technology spread under social learning and policy stimuli but assume predetermined infrastructure [157] [182]. These misrepresent DHN expansion where infrastructure development and household adoption must occur simultaneously through iterative, spatially constrained processes. Conversely, exploratory models address long-term infrastructure questions but typically focus on single-stakeholder optimisation, lacking modelling of bi-directional feedback between household decisions and developer strategies [13]. For example, Pagani et al.'s EnerPol framework [183], which, while sophisticated in its scenario-based routing and IRR calculations for a single utility, does not model heterogeneous developer agents with differing decision-making. This constitutes the core dynamic driving real DHN expansion.

This gap is acute because DHNs require spatial contiguity and minimum-density thresholds, creating interdependencies absent in other energy technologies. Unlike rooftop PV adoption where individual decisions are largely independent, DHN expansion requires coordinated commitment from spatially clustered households before infrastructure investment becomes viable [184]. This collective-action requirement mirrors challenges identified in mine water implementations (Section 2.5).

Current ABMs also often rely on ad hoc behavioural rules insufficiently grounded in social theory, creating gaps between assumptions and empirically validated adoption processes [184] [185]. Kiesling et al. [186] reviewing innovation-diffusion ABMs, note that many simplify social interactions and calibrate to S-curves rather than employing empirically grounded network structures. This is especially problematic for DHNs, where adoption reflects interactions between economic constraints, social influence, and perceived technical performance. Developing theoretically grounded agent rules, e.g., social-learning mechanisms parameterised from survey/census data, remains a key gap.

In short, the absence of theoretically grounded social-learning mechanisms prevents ABMs from addressing the community dynamics and peer effects documented in Section 2.6. While innovation-diffusion research shows neighbourhood-patterned adoption via social networks, many DHN models lack integration of established consensus-dynamics and peer-influence theories [183].

2.8.2 Current DHN Applications and Critical Limitations

Pioneering works such as Busch et al. [13] and Fouladvand et al. [187] establish important foundations but also demonstrate persistent gaps in current DHN modelling. Busch et al.'s methodological positioning highlights tensions in ABM infrastructure modelling beyond computational trade-offs. Their deliberate exclusion of detailed pipe-network modelling aimed to preserve explanatory power for policy and focus on institutional/governance barriers as primary leverage points. While valuable, complete abstraction of technical dynamics introduces a blind spot: it obscures feedbacks whereby evolving network performance (e.g., delivery quality, costs affected by transient thermal-hydraulics; see Paper 1) shapes adoption and expansion viability. Given that perceived and actual technical performance influence stakeholder confidence and connection economics, this is a non-trivial omission. This limitation echoes the thermal-hydraulic constraints in Section 2.4, where accuracy–scalability trade-offs can preclude comprehensive technical representation if not carefully managed.

Fouladvand et al.'s [187] integration of social value orientation (SVO) with Ostrom's IAD framework is innovative yet reveals application tensions. Their operationalisation of SVO; categorising households by motivations (environmental vs financial), allowing shifts via peer pressure in monthly meetings adds useful behavioural mechanisms. However, applying SVO to multi-decadal infrastructure investments raises questions about the temporal stability of orientations and their interaction with structural factors not well captured by SVO alone. Their IAD adaptation; specifying rules-in-use (Dutch policies), community attributes (single CES per neighbourhood, peer pressure), and biophysical conditions (district heating technology, ATES) risks overlooking differences between DHNs and classic common-pool resource settings: DHNs exhibit increasing returns to scale, lock-in, and multi-stage development with complex leadership/technology choices. The emergent outcomes (e.g., community boards with trade-offs between security and community benefit, continued reliance on gas) are insightful and attributable to SVO/IAD, but the extent to which such governance structures can be tested without more dynamic technical feedback remains uncertain. Both approaches illustrate a broader gap: limited capacity to model dynamic feedback between evolving technical parameters and multifaceted social processes.

This pattern of socio-technical disconnection extends across broader building heating transition literature. Nava-Guerrero et al.'s [188] [176] [21] analysis of Dutch neighbourhood transitions integrates multi-level governance and collective decision-making (e.g., quorum constraints, HOA voting), and treats heterogeneity (implicit discount rates, multi-criteria perceived utility). They acknowledge limited quantitative validation and reliance on simplified technical representations. Such simplifications (e.g., any technology fits any dwelling; constant demand; ignoring performance gaps) can bias estimates of governance efficacy, overstating policy impacts when technical constraints are binding. Sensitivity analysis and expert comparison lend credibility to exploratory findings, but the need remains for frameworks that test governance and policy under more realistic technical conditions.

ABM applications across energy transitions reveal two methodologically distinct approaches that reflect a broader trade-off between techno-economic detail, explicit actor heterogeneity, and transition pathway dynamics (Figure 10), each with specific limitations for comprehensive DHN modelling [173]. Diffusion-oriented models excel at quantifying adoption rates through economic decision-making and social contagion mechanisms. For example, Faber et al.'s micro-CHP analysis, for example, demonstrates policy threshold identification, revealing how subsidies below €1,400 produce negligible adoption effects while increases beyond €3,250 yield diminishing returns [189]. This non-linearity, as their findings suggest, arises from interactions between upfront cost reduction, learning-by-doing effects on price, and a "bandwagon effect" boosting technology visibility through market share. However, while energy-price sensitivity is explored, installation-cost and perceived-reliability uncertainties are not varied separately, both salient in practice. The strength in locating policy leverage points is offset by treating infrastructure as exogenous and abstracting supply-side/risk-perception dynamics. Conversely, exploratory socio-technical models better represent staged, multi-actor infrastructure development but produce scenario-specific narratives that are hard to validate and generalise, limiting policy utility [13] [190].

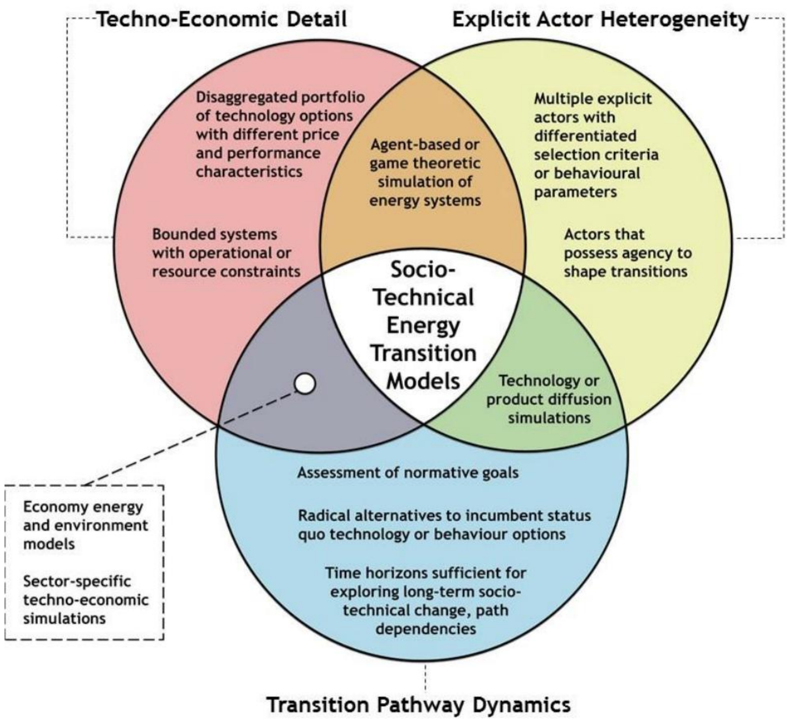

Figure 10: A taxonomy of socio-technical energy transitions models [173].

Empirical evidence from renewable energy adoption studies reveals spatial clustering patterns that extend beyond simple socioeconomic predictions [191] [17], indicating local social networks influence diffusion through mechanisms not yet adequately represented in DHN models. This spatial dimension creates methodological challenges that current approaches fail to address. While ABM–GIS integration could enable spatially explicit modelling across scales [156], effectively linking decisions from individual buildings to district-level planning remains a significant gap [192]. These spatial constraints reflect the linear-heat-density requirements identified in mine water assessments (Section 2.5), where infrastructure costs and proximity to source determine viability. Paper 2 targets this gap by linking individual adoption to spatially explicit expansion logic in a GIS-integrated ABM.

2.8.3 Socio-Technical Integration Gaps

The coupling of thermal-hydraulic models with agent-based frameworks presents distinct computational and methodological challenges that current approaches have not addressed. In an agent-based approach, each building or substation could theoretically be represented as an agent with its own logic (e.g., thermostat control or occupancy-driven heating patterns), while the network simulation provides the resulting supply temperatures and pressures. Cai et al. [193] introduced an agent-based distributed demand-response approach using the exchange ADMM protocol, where "load agents" (buildings) iteratively optimise schedules based on dynamic price profiles from a "network agent" (DHO) to achieve joint optimisation, reduce costs, and alleviate network congestion. Their work demonstrated robustness to typical communication delays for hourly scheduling but focused solely on the DH distribution network, not broader electricity–heat coupling, and highlighted the need for mechanisms to ensure truthful agent reporting. These studies underscore the necessity of simplified yet accurate network models in an ABM context: if the network model is too detailed (taking seconds or minutes of CPU time per step), it may bog down agent interactions or require impractically large computation when scaled to city-level agents. Hence, most ABM integrations currently use quasi-dynamic or reduced-order network models. This motivates Paper 1's development of a computationally efficient yet dynamically responsive thermal-hydraulic model to inform Paper 2's ABM without prohibitive cost.

However, as ABMs move into operational coordination (e.g., real-time pricing or demand-response events), the need to simulate short-term network reactions grows. Synchronising differing time scales; rapid physical dynamics versus slower social learning is non-trivial. While conceptual frameworks like Chappin and Dijkema [25] acknowledge system evolution over decades and potential SDM–ABM hybrids for scenario generation, they do not detail mechanisms for managing time-scale differences or feedback sensitivities in a tightly coupled ABM run. One pragmatic option is co-simulation: the ABM runs on a coarse time step (e.g., 15 minutes) and, when agents trigger a significant change, a fast dynamic simulation (e.g., plug-flow-based) is executed to update state for the next interval. Agents then "sense" outcomes (e.g., delivery delay or temperature drop) and react. Such hybrid time-step approaches allow coupling without fully embedding a heavy model, but introduce complexities (data exchange, synchronisation, potential fidelity loss). In this thesis, while Papers 2 and 3 do not implement full co-simulation, insights from Paper 1 parameterise and constrain the ABM's abstracted network, a pragmatic step toward tighter integration.

These coupling challenges contribute to several limitations in current ABM applications for DHN modelling and transition analysis. First, technical abstraction: most models simplify pipe networks, demand dynamics, and capacity constraints, potentially over- or under-estimating feasibility as technical performance evolves [192]. Second, static technical representation: approaches lack dynamic sub-models for business-case evolution with changing adoption patterns, missing feedbacks where added connections improve economies of scale and reduce per-unit costs [187]. Paper 2 addresses this via a dynamic expansion algorithm coupled to agent adoption.

Third, inadequate social-learning integration: while solar-PV models show peer effects and normative change, DHN ABMs often lack established social-learning mechanisms [184]. These limitations reflect the integration requirements in Section 2.6, where scale fragmentation prevents comprehensive assessment combining micro-scale technical detail with macro-scale socio-economics. Paper 2 incorporates theoretically informed social learning and peer influence to address this.

Existing models also constrain bi-directional stakeholder interactions essential for realistic DHN analysis. While acknowledging multiple stakeholder types (households, developers, policymakers), many frameworks treat interactions as uni-directional developers propose projects and households respond, missing iterative adaptation as developers modify strategies in response to adoption signals, market conditions, and evolving technical constraints.

The limitations in developer representation exemplify this issue. Busch et al. [13] represent instigator types (Local Authorities, Commercial, Community) with distinct heuristics, capabilities, and feasibility criteria (e.g., social viability for LAs/community groups). This nuance is a strength. However, their framework does not model how strategies evolve with observed adoption and performance feedback. Static representation prevents analysis of learning and strategic adaptation that shape expansion patterns and viability over time.

Contemporary developer decision-making frameworks reveal limitations in representing adaptive strategy evolution. While approaches range from economic optimisation models to multi-objective frameworks incorporating environmental and social criteria, yet many, like the EnerPol framework detailed by Pagani et al. [183], employ static decision rules from the perspective of a single optimising entity, even if they incorporate sophisticated scenario analysis for heat demand, connection likelihood, and phased, granular network routing. EnerPol, as described, does not model heterogeneous developers with differing financial hurdles or evolving risk preferences. Similarly, even if Fouladvand et al. [187] model leadership types (community vs municipality) with distinct objectives, but strategies do not adapt to unfolding simulation states. Paper 2 begins to address this gap by allowing developer archetypes whose expansion decisions respond to evolving local conditions and adoption signals.

2.8.4 (Lack of) Residential Stakeholder Representation

Residential representation still constrains analytical utility. While models acknowledge heterogeneity in homeowner decision-making and recognise collective processes in multi-dwelling buildings, they often lack integration of established social-learning theories explaining how peer influence and consensus dynamics shape neighbourhood adoption [21]. For example, Nava-Guerrero et al. [176] [188] model HOA decisions via simplified quorum/threshold voting and handle heterogeneity through implicit discount rates or multi-criteria utility but often assume scenario-level homogeneity. This captures "group lock-out" yet not the nuanced learning and negotiation processes. Coordination challenges in multi-dwelling buildings, e.g., Amsterdam's two-year consultation delays, reveal complex group dynamics (information sharing, preference evolution, collective action) that simplified rules cannot capture [194]. Paper 2 improves on this by integrating more robust social-influence and learning mechanisms based on established theory.

Contemporary residential frameworks move beyond simple economic rationality, yet gaps remain in modelling social learning that drives spatial clustering. Multi-attribute utility frameworks are advances: Nava-Guerrero et al. [188] include finance, environment, space, and installation duration as factors shaping household technology choice; Frontier Economics quantify "hassle factors" associated with heat-pump adoption at approximately £600 [185] [188]. However, preferences and weights are often treated as static, not evolving via social interaction and experience, despite empirical evidence of clustering beyond socio-economics.

Current models also show limitations in social-learning representation despite drawing on opinion-dynamics theory. Some implementations use DeGroot consensus and Hegselmann–Krause models [195] [196], yet integration with infrastructure-development dynamics is limited. Stylised (rather than empirically grounded) network structures fail to capture spatial characteristics of information flows crucial to DHN adoption, where neighbourhood coordination determines connection decisions [156]. Realistic social-network modelling is data- and compute-intensive, creating trade-offs between theoretical sophistication and practical implementation.

2.8.5 Developer Strategy Representation

As highlighted above, current developer-strategy representation reveals additional constraints that exemplify broader ABM failures to capture adaptive decision-making essential for realistic transition modelling. Existing approaches span institutional-governance frameworks [187] [13], technical-economic optimisation [183], and market-dynamics analyses, yet few capture integrated, adaptive decision processes characteristic of developers operating in complex stakeholder environments.

Busch et al.'s [13] multi-stage instigator model advances beyond purely techno-economic optimisation by representing heterogeneous agents with organisation-specific heuristics. However, while it captures varied motivations and initial capabilities, it does not model strategy evolution with experience (adoption patterns, cost changes, performance feedback) over the project lifecycle. This static representation prevents analysis of how learning and adaptation influence expansion patterns and long-term viability.

Similarly, techno-economic frameworks such as EnerPol [183] provide detailed routing based on predicted demand and IRR over phased expansions but typically optimise from a single decision-maker's perspective and do not model multiple, competing developers with heterogeneous, evolving strategies or constraints. Multi-objective frameworks (e.g., Fouladvand et al. [187]), incorporate broader criteria, yet often rely on static decision rules that cannot capture strategic evolution under market responses, technical feedback, and changing stakeholder dynamics. This mirrors the dynamic techno-economic integration gaps in Section 2.7 and motivates the adaptive developer agents and dynamic expansion logic explored in Paper 2.

2.8.6 Limitations in Policy Representation and Analysis

These methodological limitations extend critically into policy analysis, where existing evaluation frameworks reveal constraints that prevent effective assessment of dynamic intervention strategies essential for successful DHN implementation. The challenge reflects a deeper structural problem: the absence of frameworks that capture continuous, iterative network growth alongside evolving stakeholder decisions under changing market conditions. This creates a "chicken-and-egg" problem where infrastructure development requires sufficient demand, while demand creation depends on infrastructure availability [14].

Policy analysis for district heating networks demonstrates limitations in existing evaluation approaches. Traditional cost-benefit analyses assume static stakeholder responses to policy instruments, failing to capture how policy effectiveness evolves through stakeholder adaptation and complex feedback mechanisms that characterise real-world infrastructure transitions. This is particularly true if technical simplifications in the models, as seen with Nava-Guerrero et al. [176], such as not accounting for the energy performance gap or assuming constant energy prices, lead to overly optimistic financial projections, thereby misrepresenting the true impact or necessity of policy interventions. This fragmentation, treating technical optimisation and stakeholder coordination as separate domains, complicates planning and necessitates coordinated efforts between policymakers, industry, and consumers. It mirrors the institutional challenges in Section 2.6.

ABM offers significant capabilities for simulating dynamic policy scenarios where infrastructure developers and users respond to evolving incentives, representing important theoretical advances over static policy evaluation approaches [181], Faber et al.'s [189] work on micro-CHP subsidies clearly illustrates this potential by identifying non-linear responses and policy "sweet spots" that conventional CBA would miss, driven by their model's inclusion of learning-curve price effects and bandwagon-driven technology awareness. However, their model's sensitivity to energy price assumptions and its exclusion of perceived reliability risks highlight that even dynamic ABM policy insights are contingent on the completeness of behavioural and contextual factors modelled.

Furthermore, many ABMs lack frameworks for adaptive policy responses—where interventions evolve based on feedback and implementation outcomes. Castro et al. [197] reinforce that most ABMs explore fixed policy scenarios and call for more adaptive approaches. Current approaches rarely evaluate how policy timing, sequencing, and adaptive adjustment affect long-term expansion trajectories, capabilities essential for designing effective intervention strategies in complex socio-technical systems. This is a core challenge that Paper 3 aims to address by using the integrated socio-technical ABM from Paper 2 as a testbed for evaluating dynamic and adaptive policy scenarios.

The spatial clustering requirement means DHN expansion cannot simply target early adopters or high-income households, networks must achieve minimum density thresholds within geographically constrained areas, creating equity and coordination dilemmas absent in other energy transitions [185] [198]. Lower-income households face higher relative cost burdens and retrofit disruption risks, but their participation may be essential for network viability in mixed-income areas [19] [199]. This creates a gap in understanding how heterogeneous barriers across income, tenure, and demographics affect neighbourhood-scale coordination, central to viable DHN expansion and reflects the spatial disparities in Section 2.6..

Regulatory-instrument analysis reveals additional limitations. While Nava-Guerrero et al. [176] [188] show how gas-network disconnection policies can guarantee demand [21], their simplified technical representations and validation challenges mean regulatory effectiveness may evolve in ways not captured by long-horizon simulations. This matters because regulatory interventions often produce cascading effects that emerge only over extended implementation.

Policy-synergy analysis faces similar constraints. Although ABM could model multiple instruments simultaneously, current implementations often lack frameworks for adaptive policy combinations that change with observed outcomes and feedback. Time-sensitive sequencing is another gap: few frameworks evaluate how policy timing and ordering should adapt based on expansion results [13]. Most importantly, present ABM policy evaluation lacks mechanisms to identify and model responses to unintended consequences. Models may reveal perverse incentives and distributional inequities, but they seldom represent how policy frameworks adapt to address emerging challenges through iterative adjustment and stakeholder feedback [181].

2.8.7 Validation of Socio-Technical Models

The validation of ABMs in socio-technical transitions demands a fundamental shift in perspective away from traditional predictive accuracy. Unlike deterministic engineering models, these ABMs are primarily exploratory tools, designed to investigate plausible futures, uncover complex feedback mechanisms, and test the systemic impact of interventions under deep uncertainty. Consequently, their credibility hinges not on forecasting specific outcomes, but on their ability to generate mechanistically plausible explanations for emergent phenomena [200]. Thus, explanatory power and behavioural realism matter more than numerical precision. This section outlines validation challenges and the established credibility-building strategies used in this thesis.

The obstacles to traditional validation are twofold, stemming from both data scarcity and inherent system complexity. The first challenge is the acute lack of relevant empirical data, especially for emerging technologies like DHNs in the UK where historical precedents are few. As Busch et al. [13] highlight, while data exists for successful schemes, records of failed or stalled projects which are crucial for understanding barriers are almost non-existent, making robust back-casting "close to impossible." Secondly, the complexity of socio-technical systems, with their non-linear feedback loops and emergent properties, defies simple validation with analytical solutions, necessitating qualitative and structural assessments.

Given these constraints, the literature recommends alternative techniques to build confidence. A primary strategy is extensive sensitivity analysis to stress-test model logic and ensure qualitative conclusions are robust across plausible assumptions [188]. This is complemented by pattern-oriented validation, judging models on their ability to reproduce stylised facts (e.g., S-shaped adoption; dampening from landlord–tenant split incentives) [200]. A particularly powerful approach when quantitative data are lacking is participatory validation with domain experts. Following the “companion modelling” method used by Busch et al. [10], conceptual frameworks can be vetted in practitioner workshops, grounding assumptions and structure in real-world experience and aligning with recommendations for complex systems [190] (e.g. Moss 2008). Nevertheless, two frontiers remain. Transferability: a model validated with UK stakeholders may not generalise to other governance regimes. Dynamic policy: most models treat policy as static, failing to capture real-world adaptive learning where interventions change in response to outcomes. Incorporating dynamic policy feedback is an open research challenge.

Accordingly, the ABM in this thesis is explicitly positioned as an exploratory decision-support tool, not a predictive engine. Its purpose is to provide a what-if laboratory for testing relative strategy effectiveness and understanding path-dependent dynamics leading to success or failure. The framework has undergone the validation processes described above, including sensitivity analysis to support credibility. By stating the model’s exploratory role and documenting its theoretical grounding, this approach aligns with best practice for credible insight into complex socio-technical futures [13] [200].

2.9 Conclusion: Research Gaps and Thesis Contribution

2.9.1 Identified Research Gaps

The preceding review reveals four critical methodological requirements that current modelling approaches fail to address adequately:

1. Dynamic socio-technical coupling: Frameworks must model how thermal-hydraulic performance evolves and influences stakeholder perceptions and adoption decisions, while changing adoption patterns reshape network economics and expansion strategies.
2. Theoretically grounded behavioural representation: Rather than ad hoc rules, agent decision-making must be anchored in social theory capable of explaining and predicting spatial clustering and peer effects in energy transitions.
3. Adaptive policy modelling: Intervention analysis must capture how policy effectiveness changes through stakeholder feedback, moving beyond static assumptions to dynamic evaluation.
4. Validation in data-scarce contexts: Given limited historical DHN data, models must build confidence via theoretical robustness and systematic uncertainty analysis, not rely solely on empirical fit.

Although ABMs could in principle bridge these scales, current implementations often sacrifice hydraulic detail or agent heterogeneity to remain computationally viable [113] [116] [193].

2.9.2 Thesis Aim and Contribution

To close this gap, the thesis advances an integrated socio-technical framework designed for city-scale DHN expansion. Paper 1 (Chapter 6) presents a hybrid dynamic simulation that combines reduced-order heat-loss equations with a wave-front algorithm, achieving hourly thermal-hydraulic accuracy at runtimes suited to scenario analysis. These outputs parameterise and constrain a conceptually linked ABM in Paper 2 (Chapter 7), designed to capture path-dependent network growth. In the model, household and developer agents adapt through social learning, allowing technical service levels and adoption choices to interact. Building on this analysis, Paper 3 (Chapter 8) utilises the agent-based framework in a policy-simulation layer that tests tariffs, zoning, and subsidy timing against stochastic fuel prices and emergent stakeholder responses.

The resulting framework captures dynamic hydraulics, phased spatial growth, and behavioural feedback, providing a stronger evidence base for equitable, financeable heat-network planning. Collectively, these contributions address O1 (dynamic thermo-hydraulics), O2 (heterogeneous adoption under social learning), and O3 (strategy and policy evaluation under uncertainty). Chapter 3 details the integrated methodology; Chapters 6–8 present the publications; Chapter 5 synthesises findings and future work.

Chapter 3 - Integrated Research Methodology

This chapter details a technically informed, socio-technical approach developed through a sequential research pathway. It clarifies how the three publications relate and where information can flow between them, without implying a single integrated co-simulation. The chapter first outlines the two primary modelling frameworks: one focused on short-term network dynamics and the other on long-term socio-economic adoption; it then describes the relationships and potential (non-executed) information flows between them (Papers 1–3 correspond to Chapters 6–8).

3.1 Framework 1: The Network Dynamics Simulation

The network dynamics framework addresses thermal-hydraulic limitations noted in Chapter 2. By simulating hourly temperature decay and peak-load events, this framework enables district-scale representation of transient thermal-hydraulic behaviour for feasibility-stage planning:

- Integration of low-grade heat sources: incorporates mine water and industrial waste heat, with temperature decay, distribution losses, and variable-load pumping represented at hourly resolution.
- Demand-driven transient flow allocation: uses time-varying demand profiles.
- Techno-economic evaluation: tests sensitivity to energy prices, demand fluctuations, and CO_2 emissions to quantify economic and environmental trade-offs.
- GIS-based heuristics: enable pipeline sizing and layout comparisons for multiple generation technologies, facilitating step changes in network configurations.

This hourly-resolution model provides a platform to assess short-term operational conditions, such as peak-load events and partial-load operation, and to evaluate economic and environmental trade-offs. It enables rapid feasibility calculations and design screening, allowing planners to test robustness to weather-driven demand peaks, electricity-price variability, network structure, and other uncertainties.

3.2 Framework 2: The Residential Adoption Framework

This model's iterative, feedback-driven processes simulate stakeholder interactions across policy phases and quantify how socio-demographic characteristics shape adoption trajectories over years and decades. The framework targets the long-term evolution and infrastructure expansion of DHNs with the following capabilities:

- Long-term DHN expansion: simulates adoption trajectories under socio-demographic constraints, policy incentives, and consumer decision-making.
- GIS-driven analysis: identifies high-priority expansion areas from heat-demand density, building stock, and socio-economic factors, including behavioural willingness-to-connect.
- Growth pathways: generates phased network expansions for different operator strategies, enabling assessment of early high-return investments and equitable, sustainable scaling.
- Policy alignment: guides infrastructure choices to meet stakeholder requirements, local planning considerations, and national policy goals.

By capturing long-term adoption patterns, this second framework seeks to describe how small pilot projects can evolve into large-scale deployment, offering evidence-based policy and investment guidance. It complements the hourly network model by highlighting strategic and behavioural drivers of system expansion rather than short-term operational issues. It is suited to 'chicken-and-egg' contexts, where investment depends on anticipated demand while consumer uptake depends on build and timely infrastructure, and it provides insights for policymakers, local authorities, and ESCOs.

3.3 Relationship and Potential Information Flows

Using both frameworks in sequence provides a technically informed socio-technical approach:

- Short-term (hourly) simulation: Offers insight into thermal-hydraulic constraints, system reliability, and pumping strategies under changing load conditions.
- Long-term (multi-year) adoption: Investigates infrastructure expansion, stakeholder engagement, and policy influences over extended periods.

In this thesis, common household-demand inputs are used by both frameworks. Potential sequential use: where the ABM proposes staged expansion, and the thermal-hydraulic model runs a one-year segment to refine cost estimates or provide validation checks, is outlined conceptually but was not executed in the published papers. Likewise, metrics such as Levelised cost of heat (LCOH) and net-present value (NPV) and network efficiency informed exploratory parameter ranges but are not reported in Papers 1–3. Figure 11 summarises the actual links (solid arrows) and potential but unused flows (dashed arrows).

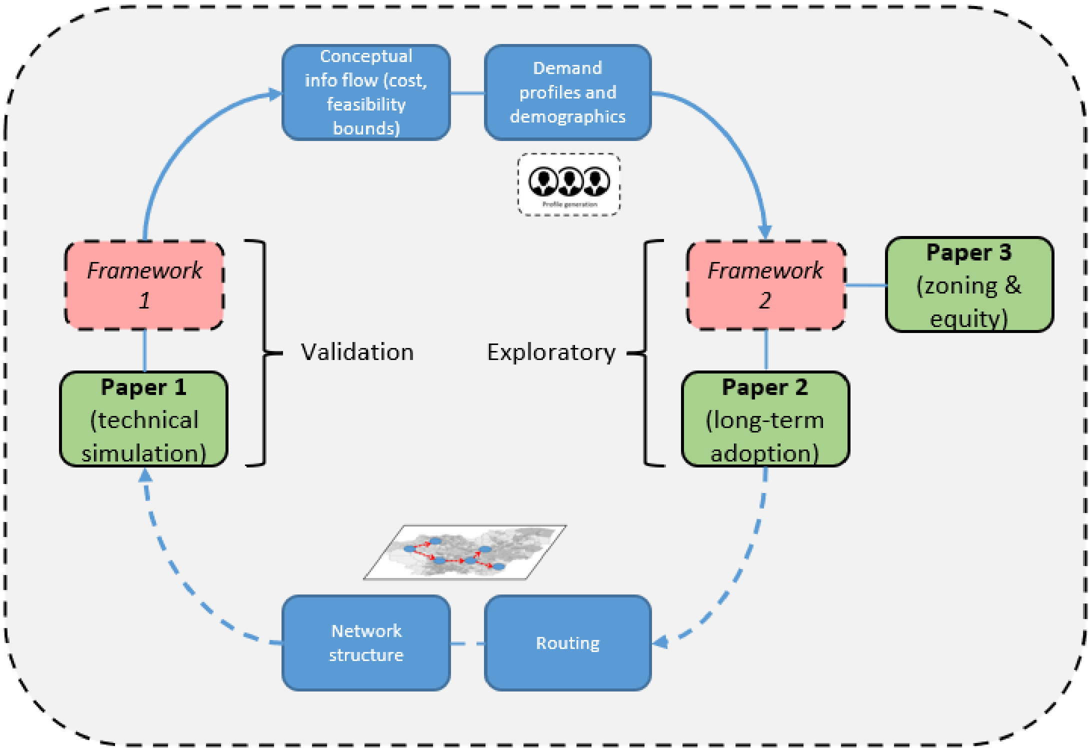

Figure 11. Relationships between the two modelling frameworks and the three publications. Solid arrows = actual links used in the thesis (shared demand inputs; network dynamics → ABM (socio-technical) conceptual constraints; both informing Paper 3). Dashed arrows = proposed, not executed sequential back-and-forth uses (e.g., ABM-drawn staged network feeding a one-year thermal-hydraulics run for refined costs/validation, with cost/efficiency priors informing ABM settings).

Conceptually, transferring hourly operational outputs from the technical simulation to the socio-technical ABM would bridge the divide between 'hard' engineering constraints (e.g., thermal losses [10]) and 'soft' behavioural drivers (e.g., policy incentives [45]). In such a transfer, the technical simulation would ground and constrain the ABM's decision space, capturing how grid reinforcement costs influence willingness to connect; feedback that siloed models often miss [16], [12].

The two-framework, sequential methodology described in this chapter addresses the key research gaps identified in the literature. It supports dynamic socio-technical reasoning, grounds agent behaviour in established theory, facilitates adaptive policy exploration, and builds analytical confidence in data-scarce contexts. By combining high-resolution engineering simulation with long-term behavioural dynamics within a consistent research programme, this approach provides a socio-technical evidence base that siloed models lack. The following chapters present the peer-reviewed publications that implement this programme to analyse the complex challenges of DHN deployment.

Chapter 4 – Introduction to Publications

This chapter provides overviews and contribution statements for the three publications forming the core of the thesis. Chapters 6–8 reproduce the articles as permitted by publisher policies; formatting and minor typographical errors are retained to preserve the record.

4.1 Paper 1:

Achieving Emission Reduction through the Utilisation of Local Low-Grade Heat Sources in District Heating Networks

4.1.1 Statement of Contribution

This first paper is published in Applied Thermal Engineering. The publisher has provided confirmation that the journal article can be posted publicly by the awarding institution with a DOI link back to the formal publication on ScienceDirect. The publication was accepted on 3 January 2024 and represents the foundational technical component of the thesis.

As lead author, I conceived the research design, led the model development, and wrote the manuscript. Joseph Hammond undertook pipe-sizing optimisation; Dr Timothy Hutty advised on mathematical formulations and code review. I analysed Coal Authority mine-water maps to verify geothermal availability and capacity, conducted the Barnsley case study, and interpreted the results. Professor Solomon F. Brown supervised the work.

4.1.2 Context and Role in Thesis

This paper's core technical contribution is the development of a hybrid dynamic simulation model. The approach, implemented in AnyLogic simulation software, combines reduced-order heat-loss equations with a dedicated water-front agent methodology. This design achieves a balance between thermal-hydraulic fidelity and computational efficiency suitable for year-long, city-scale scenario analysis.

The central role of this work within the thesis is to provide a validated "technical engine." By overcoming the trade-off between accuracy and speed, the model produces detailed techno-economic and engineering metrics, e.g., hourly losses, storage duty, network efficiency, and LCOH/NPC, that inform parameterisation and constraints for the socio-technical analysis in Paper 2.

4.2 Paper 2:

Accelerating Residential Decarbonisation: How Stakeholder Decision-Making and Socio-Economic Dynamics Affect Multi-Decadal District Heating Network Expansion

4.2.1 Statement of Contribution

This second paper is published in Energy and was accepted on 24 April 2025. The publisher provided confirmation that the published journal article "can be posted publicly by the awarding institution with DOI link back to the formal publications on ScienceDirect". This work represents the core socio-technical integration component of the thesis, building directly upon the technical foundation established in Paper 1.

As lead author, I was responsible for the entire research lifecycle as detailed in the CRediT authorship statement, including ABM design, coding, data curation, and analysis. Joseph Hammond assisted with GIS post-processing; Dr Timothy Hutty supplied calibrated demand data from the Cambridge Housing Model. Supervision was by Professor Solomon F. Brown.

4.2.2 Context and Role in Thesis

Building on the foundation of Paper 1, this paper addresses a gap in which existing models overlook the dynamic, iterative co-evolution of residential adoption decision-making and developer strategies. The model captures feedback consistent with established behavioural theories, including social learning and heating-system lifecycles, and applies a multi-attribute utility framework to represent heterogeneous decision drivers. It shows how household uptake and developer investment reshape system viability. It provides the socio-economic layer required for the policy stress-tests in Paper 3

This work advances the thesis narrative by adding the essential socio-economic and behavioural layer to the technical engine developed in Paper 1. It creates an integrated model that simulates how a network grows organically in response to the feedback between consumer choices and developer investments. This provides the robust, socio-technical simulation environment required for the final stage of the thesis: using this platform in Paper 3 to stress-test the impact of heat zoning on the long-term success of DHN deployment and social equity.

4.3 Paper 3:

Heat Zoning Aligns Profit and Equity in District Heat Networks.

4.3.1 Statement of Contribution

This final paper, titled "Heat Zoning Aligns Profit and Equity in District Heat Networks" is currently under review for publication at One Earth. As lead author, I designed and implemented the policy-testing methodology, developed the agent-based simulation model, conducted scenario analyses specific to Sheffield, interpreted the outcomes, and wrote the manuscript. Dr Timothy Hutty contributed calibrated residential demand profiles from the Cambridge Housing Model and provided reviews on methodological rigour. Joseph Hammond assisted with GIS data processing and spatial visualisation. Professor Solomon F. Brown supervised the research.

4.3.2 Context and Role in Thesis

This paper addresses strategic, policy-oriented gaps highlighted in Papers 1 and 2 by examining how governance and operator strategies influence DHN expansion, sustainability, and spatial equity. It directly responds to the need for integrated socio-technical frameworks capable of evaluating complex interactions between economic viability, stakeholder decision-making, and policy interventions, including the newly introduced UK heat network zoning mandates. The core contribution is a spatially explicit, socio-technical ABM that represents dynamic interactions among stakeholders, ranging from purely commercial profit-driven developers to socially driven municipal utilities. The paper tests multiple operator strategies to show how exclusive pursuit of either extreme profit or social objectives can result in underperformance, specifically infrastructure redlining in profit-driven approaches and financially unsustainable equity traps in purely social-maximising scenarios. It identifies a balanced, socially leaning strategy as the most effective within this model for supporting sustainable, city-wide DHN expansion, highlighting the important role of supportive zoning policies. These outcomes form the final component of the thesis's integrated socio-technical modelling approach and support a nuanced understanding of the implications of policy strategies on long-term network expansion and social equity. By elucidating the mechanisms behind these emergent dynamics, the research offers policy-relevant insights for policymakers and operators, helping to position DHNs within broader decarbonisation and just-transition frameworks.

Chapter 5 – Conclusions & Future Work

This chapter synthesises the findings of the thesis and outlines a roadmap for future research. Section 5.1 presents the overall conclusion, integrating the key technical, socio-behavioural, and strategic insights. Section 5.2 details a programme of future work, progressing from immediate model integration to long-term policy application.

5.1 Conclusion

This thesis set out to develop and apply a technically informed, sequential socio-technical approach to district heat network expansion in UK cities. It addressed three objectives: (1) dynamic thermo-hydraulic modelling (Paper 1/Chapter 6); (2) residential adoption dynamics (Paper 2/Chapter 7); and (3) operator strategy and policy design (Paper 3/Chapter 8). To meet these objectives, two complementary models were built: a thermo-hydraulic network-dynamics simulation representing transient behaviour and operational constraints, and an ABM capturing heterogeneous household decision-making and social learning. The thermo-hydraulic model was used to inform the ABM; no fully coupled co-simulation was attempted in the publications. Taken together, the results from Chapters 6 to 8 indicate that, in the UK cases studied, deployment is constrained less by physical limits than by the configuration of markets and institutions and by persistent social frictions around connection: Chapter 6 shows that scale and connectedness suppress avoidable losses and enable the use of low-grade heat; Chapter 7 shows that tenure, trust and perceived disruption slow uptake even where the network is technically viable; Chapter 8 shows that policy and operator mandates determine whether commercially rational sequencing coincides with inclusive coverage. Within the sequential framework developed here, when thermo-hydraulic feasibility constrains empirically grounded adoption rules, policy packages that align operator incentives with density can produce expansion trajectories that are both financeable and equitable.

The studies address different parts of the same system. The technical work shows (Ch. 6) why scale and connectedness matter: larger, better-structured networks suppress avoidable losses, unlock non-traditional heat sources like industrial waste heat and mine water, and create the operational headroom that underwrites long-run viability. The adoption work shows (Ch. 7) that diffusion is not a smooth inevitability but is path-dependent and place-specific: early phases track high-return pathways while tenure, trust, and perceived disruption slow uptake elsewhere, widening uncertainty in long-term projections. The strategic study (Ch. 8) formalises the failure modes that follow from these facts. Results indicate that policies which align private returns with system efficiency make profitable sequencing coincide with inclusive coverage. Heat network zoning, predictable support, and transparent price frameworks can create a wide "performance plateau" (a parameter region where multiple strategies achieve comparable profitability and equitable coverage) where several balanced strategies deliver city-scale outcomes. Within that plateau, the most profitable path often coincides with the one that maximises durable inclusion, because anchor loads and dense corridors are explicitly harnessed to finance more difficult connections. A narrowly commercial strategy underserves poorer districts, a narrowly social strategy risks financial fragility.

A second contribution is methodological. The thesis transfers physical and operational constraints from the network dynamics model into the ABM so that behavioural adoption is bounded by what is plausible. In the present work, this coupling is unidirectional. The natural next step is to close the loop: allow the ABM to propose staged topologies and phasing which are then stress-tested for temperature discipline, losses, and cost decomposition. These results would then be returned as priors and feasibility envelopes that reshape subsequent adoption. In this way, the same framework that explains who connects and when also learns what can, in fact, be built and operated, moving it from explanatory analysis to a planning-grade decision aid.

There are limitations. The emphasis is on mechanism and inference rather than long-horizon point prediction. Competing technologies are treated exogenously, and some volatile economic factors are simplified to keep the dynamics legible. Data scarcity in the UK residential DHN context constrains historical validation. The modelling also assumes a single-operator context; multi-actor competition and imperfect information are left to future work. External validity remains bounded by UK urban governance settings; generalisability should be tested via the proposed multi-city benchmark suite. None of these caveats undermine the core results: balanced, policy-led strategies dominate extremes; customer-side frictions remain binding even when capital expenditure issues are addressed; and uncoordinated deployment reproduces structural inequity. The practical implication is to measure success by absolute coverage, bill stability, and service quality across all areas, not by connection rates in a handful of favoured zones.

In short, the work repositions DHNs as a market-design and coordination problem under uncertainty. When institutions reward technically efficient, density-oriented expansion while directly addressing the social costs of connection, the physics of heat networks becomes an asset rather than a constraint. The policy implication is to design incentives so that the privately most profitable path is also the path that delivers the most equitable and technically sound citywide system.

5.2 Future Work

The immediate priority is to fully integrate the two frameworks. A bidirectional loop will be formalised so that the ABM exports staged network graphs and connection sequences, which are then simulated in the network dynamics model. The technical model will return a compact bundle of performance indicators: temperature violations, pressure margins, thermal losses, storage performance, and cost components, which then become constraints and price signals for the next ABM phase. Iteration would continue until phasing stabilises under clear operating bounds and a consistent cost trajectory. This would close the design loop and yield a planning-grade tool in which in silico policy experiments are evaluated for physical feasibility, financial implications, and behavioural plausibility.

With the loop in place, the near-term focus is credibility and usability. Validation should triangulate across out-of-sample years, analogous European cases, and synthetic back-casts. Uncertainty should be reported with discipline through studies that show which mechanisms materially move outcomes. Customer-side frictions; trust, disruption, and tenure constraints, should be represented explicitly in the model and reported as a 'shadow price' per additional household to inform policy design. On the supply side, the value of waste heat should be priced operationally rather than assumed. Participatory validation with local authorities, operators, and community groups can calibrate social-learning parameters and improve the legitimacy of resulting policies.

The medium-term agenda is integration and sequencing. Electro-thermal coupling is required to understand how grid constraints and power-to-heat dispatch interact with DHN phasing. Future work will evaluate zoning as an ordering problem: which anchors and estates to connect, in what sequence, and under what service guarantees. Tariffs, indexation, and contract length need to be endogenised in the adoption space, with churn risk and fairness metrics tracked alongside standard economics. Competition between developers and procurement modes should be represented to test how franchises or concessions reshape the size and stability of the performance plateau in the model and assess the policy relevance of those changes. Finance and risk should be modelled more explicitly, including stochastic capital costs and interest-rate shocks to clarify bankability.

Longer-term work should embed equity directly in the optimisation. Distributional objectives such as fuel poverty relief and tenure parity can be integrated as explicit constraints. Building fabric and supply-temperature regimes should be allowed to co-evolve so the model can assess staged retrofit pathways and the feasibility of lower-temperature operation over time. A multi-city benchmark suite across several UK contexts will support external validity, replication, and policy comparison. Finally, the tool should be packaged for planning practice, with outputs aligned to heat network zoning regulation and an audit trail adequate for public inquiry.

Across all strands, the emphasis should remain on transparent data, reproducible calibration, and metrics that matter to citizens: absolute coverage, service quality, and bill stability. The intention is to turn the present explanatory framework into a robust decision aid that can steer real projects in real time. As UK zoning pilots mature, emerging datasets on adoption and social responses should be folded back into calibration to sustain decision-grade performance.

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Chapter 6

Achieving Emission Reduction through the Utilisation of Local Low-Grade Heat Sources in District Heating Networks

6.1 Abstract

Decarbonising heat provision is paramount in the global shift towards sustainable energy, and waste heat utilisation presents a transformative opportunity, especially in areas of industrial activity. Accordingly, this study examines the performance of District Heating Networks (DHNs) integrated with unconventional heat sources, specifically mine water and industrial waste heat, aiming to derive a comprehensive understanding of the techno-economic and environmental implications of various DHN configurations. To this end a refined network dynamics simulation model has been developed and employed to evaluate the cost and performance of several network size and heat source combinations, with a case study carried out for Barnsley, UK. Results indicate that large networks can achieve an average thermal efficiency of approximately 87%. Networks utilising mine water have a Levelized Cost of Heat (LCOH) in the range 11.6 – 11.9 p/kWh; introducing industrial waste heat reduces this to 10.6 – 10.7 p/kWh. Additionally, waste heat integration lowers the carbon factor of the supplied heat to 0.05 kgCO2/kWh. Transitioning from boilers to district heating in the region covered by the case study networks showed a marginal emission reduction ranging from 44.76% to 83.46%. The gas price at which these networks achieve economic viability varies from 8.6 – 8.8 p/kWh. In conclusion, the DHNs proposed, especially when augmented with industrial waste heat, emerge as a promising solution for areas like Barnsley in their pursuit of sustainable heating. These findings are pivotal for policymakers and local governing bodies as the UK gears up to meet its 2050 net-zero ambitions.

6.1.1 Keywords

Energy; Heat Decarbonisation; District Heat Networks; Agent-based Modelling; Mine Water

6.1.2 Nomenclature and terminology

Acronyms.

ASHP	Air Source Heat Pump
CAPEX	Capital Expense
CHP	Combined Heat and Power
COP	Coefficient of Performance
DC	Demand Centre
DEC	Display Energy Certificates
DHN	District Heating Network
GIS	Geographic Information System
GHG	Greenhouse Gas
GSHP	Ground Source Heat Pump
HIU	Heat Interface Unit
HP	Heat Pump
LCOH	Levelized cost of heat
LP	Linear Programming
LTC	Sum of costs over lifetime
MIDAS	Met Office Integrated Data Archive System
NON-DEC	None Display Energy Certificates
NPC	Net present cost
O&M	Operation and maintenance
OPEX	Operating Expense
RHPP	Renewable Heat Premium Payment
SEAP	Sustainable Energy Action Plan

Symbols.

Symbol	*Unit*	*Description*
$CO_{2_{MR}}$	%	Marginal reduction in emissions
h_{co}	$Wm^{-2}K^{-1}$	Convection coefficient

CC_t	£	Total capital cost
E_t	£	Total energy cost
L_T	m	Total network length
L_p	m	Route length
P_{GC}	pkW_{th}	Capacity of plant
P_{HP}	kW	Power consumption of heat pump
P_r	kW	Repressurising power
$\dot{Q}$	kW_{th}	Thermal power
R'	$(Wm^{-1}K^{-1})^{-1}$	Losses per metre of pipe per °K (reciprocal of)
R_{nom}	-	Nominal discount factor
$\hat{T}$	°C	boundary temperature
$\dot{V}$	m^3s^{-1}	Volumetric flowrate
a_{diff}	m^2s	Diffusivity coefficient
c_w	$kJkg^{-1}°C^{-1}$	Specific heat capacity of water
d_{in}	mm	Diameter
$\dot{m}$	kgs^{-1}	Mass flowrate
ε_A	m	Absolute roughness
ε_R	-	Relative roughness
ρ_w	kgm^{-3}	Density
ΔP	kPa	Pressure drop
E	$pkWh^{-1}$	Electricity price
i	%	Rate of inflation
r	mm	radius
R	-	Discount factor
T	°C	Temperature
C	£MWh^{-1}	Cost factor
CC	£	Capital cost
$CO2_{hp}$	kg	Emissions from a heat pump
$CO2_b$	kg	Emissions of boiler

$CO2_{bT}$	kg	Emissions from entire region of boilers
$CO2_{gc}$	kg	Emissions from a generation centre
$CO2_{p}$	kg	Emissions from repressuring pump
$CO2_{s}$	%	Carbon savings
$CO2_{total}$	kg	Emissions from the DHN
CSA	m^2	Cross sectional area of pipe
F	-	Shape factor
Nu	-	Nusselt number
Pr	-	Prantl number
Q	kJ	Thermal energy
Re	-	Reynolds number
SA	m^2	Surface area
d	m	Burial depth
e	kW	Error term
f	$tMWh^{-1}$	Carbon factor
q	Wm^{-2}	Flux
t	hours	Time
v	ms^{-1}	Flow velocity
μ	-	Friction factor
ν	mm^2s^{-1}	Kinematic viscosity

Subscripts	
hp	Heat pump
A	Ancillary equipment
B	Borehole
BP	Main buried pipe
BR	Business rates
DC	Demand centre node
GC	Generation centre node
$HIUM$	HIU maintenance

HM	Heat meter
HMM	Heat meter maintenance
IP	Internal pipe
N	network
NM	Network maintenance
SC	Staff maintenance
SS	Substation
WH	Waste heat
b	Boiler
$casing$	Pipe parameter for casing
ext	External pipe parameter
$flow$	Flow (heated) pipeline
g	Generated heat
gc	Generation centre
gen	Heat generation
i	Node identifier
$insulation$	Pipe parameter for insulation
m	Monthly
max	Max value/limit
p	Repressuring pump
$pipe$	piping infrastructure
$return$	Return pipeline
s	Supplied heat
$total$	Combined cost factor

6.2 Introduction

It is widely recognised that carbon dioxide significantly contributes to climate change, driving leading economies to reduce carbon emissions [1]. The UK, amongst others, has pledged to reach net-zero greenhouse gas emissions (GHG) by 2050 [2]. While the UK has made progress towards decarbonisation of its electricity grid, the heating sector, responsible for 23% of all UK emissions, remains a challenging target [3] [4]. Given this scenario, district heating networks (DHNs) are gaining interest, intending to connect large sets of customers to low-carbon heat generation systems [5] [6], especially at a community or district level, with typical sizes of up to 10's MW at peak demand [7]. Yet, they compete with other low-carbon technologies like air source heat pump (ASHP) or ground source heat pump (GSHP) [8] [9], whose implementation is slowed by the perceived skill gap in design and installation, and associated costs [10] [11]. Across Europe, the proliferation of DHNs underscores their potential as enablers of low-carbon heat generation. This study shows that the majority of the successful systems leverage local heat demand and access to generation sources [13]. As the UK considers the adoption of DHNs, it's essential to incorporate these findings, informed by the European experience and compare them to alternative heating options [12]. Currently, the utilisation of heat networks in the UK is limited, with only 2% of the total heat demand being met by DHN, indicating minimal experience with this technology in the UK [13].

The adoption of DHN systems in the UK is fraught with challenges; the most significant is their uncertain techno-economic feasibility [14]. While network dynamics models are instrumental in grasping these systems, they frequently simplify techno-economic analysis, like K. Sartor et al. which bases its economics on peak power demand only [15]. Conversely, techno-economic studies do not include any form of network dynamics simulation to accurately obtain results. A vast majority of these models either lack the necessary generality to accurately represent performance across different regions and network sizes, or they are not computationally efficient enough to simulate across an entire year. Work by B. Back et al. simplify their model to only simulate 1 week for each month, stating that this gave 'a number of issues' in the results [16]. Although numerous studies delve into various DHN layouts, many overlook the economic consequences of fluctuating demand, [15] [17] [18], as well as complex network dynamic functionality such as thermal transience and time delay. The work of E. Guelpa et al analyses the relevance of implementing network dynamics into DHN modelling and the impact of neglecting it. Thermal losses, time delay and thermal transients, were compared in two scenarios; during steady-state operation; and variable control. The most significant phenomenon was the heat lost when there was no flow and the time it took to replenish the water when demand was requested [19]. Keirstead et al.'s. work reviewed 219 papers and found that only 44% of models incorporated geographic information systems (GIS) features, and 58% used a yearly temporal scale or greater [20]. In the context of regional heat networks, historical trends have shown that fluctuations in natural gas prices can significantly influence the adoption of DHNs, especially in regions like the UK where natural gas dominates the heating market [21]. Additionally, the increase of heat costs with certain heat generation technologies such as combined heat and power (CHP), as seen in the case of St Bride's Community Centre's efficient modulation during demand fluctuations, further highlights the intricate balance between technology choice and gas pricing, and major increases in demand [6]. This highlights the importance of techno-economic analysis of alternate heat sources, not just CHP if we want to advance the field in the UK, and assessing breakeven gas prices when considering that as networks expand so does the demand [22] [23]. Recent studies highlight the complexities of energy system assessments, especially when balancing economic and environmental concerns [24] [21]. Sensitivity analyses reveal the system's susceptibility to changes in fuel and CO2 quota, cautioning against a narrow focus. A significant insight is the economic feasibility of expanding district heating networks to harness wasted energy. Yet, the research advises in such expansion to try an encompass a well-rounded assessment, including changes in demand and scale [25] [26].

Recent advancements in Europe's DHN technology emphasize the evolution towards 4th and 5th-generation networks (4GDH, 5GDH) [27] [28] [29] [30] , and are notable for their integration with electricity grids, smart systems, and low-temperature functionality [31] [29] [27] [32]. A specific study highlighted that transitioning the district heating (DH) system to function at lower temperatures can lead to enhanced building efficiency and a notable decrease in reliance on natural gas [30]. The research further indicated that such modernisations can substantially reduce network losses, offering both environmental and operational benefits. Work by P. Ostergaard et al in Aalborg is a prominent example of a network that uses low-temperature geothermal energy, wind turbines with a grid connection, and biomass [33]. It shows independence from natural gas and flexibility to align its production with the demand of the network while also being very economical by taking advantage of electricity price fluctuations. This can help recuperate the high capital costs, often borne by local authorities. To address this user-friendly tools that are flexible enough to be applied to different regions and topological layouts of DHNs while also uncovering complex systems like in Aalborg can break down some of the barriers for implementation [34], enabling a broader range of decision-makers to understand the potential of DHN and leverage their local topology [35].

As the UK considers integrating these advancements, understanding these outputs becomes crucial for informed decision-making in DH system adaptations. While low-temperature DHNs have shown adaptability in older European buildings [30], their potential in the UK, remains untapped, highlighting a significant research gap and emphasising the value of this study. Considering Barnsley's older infrastructures, findings indicate that even 70s-era houses can benefit from such DH networks. These networks, with operation temperatures as low as 45°C for 4GDH [36], permit connection to low-grade heat sources like mine water, in areas like Barnsley with a rich mining history [37] [38]. Abandoned coal mines contain groundwater heated by the earth's geothermal gradient and provide an estimated 2.2 million GWh of heat stored below 25% of UK homes [39] [40]. The extracted heat can be utilised for warming nearby homes, with minimal thermal losses due to the proximity to demand [37]. The temperatures of flooded mines typically range between 10-20°C but can reach up to 40°C [38]. Currently, only a few large schemes, such as Seaham Garden Village, Gateshead, Hebburn, Holburn, and Caerau, are operational [41] [42]. The utilisation of these sources within low-temperature networks [36] particularly under the principles of 4th and 5th-generation district heating, presents promising techno-economics and ample opportunities for significant carbon reduction [43] [44]. These solutions form an integral part of the broader smart energy systems that encompass integrated systems for electricity, heating, and cooling [28].

Comparative studies underscore the potential of harnessing mine water energy for district heating. While some approaches have shown operational advantages, such as achieving high coefficients of available output, they also encounter challenges like significant energy losses [45]. Delving deeper into geothermal mine water systems, their sustainability, versatility, and reduced carbon footprint stand out, but these benefits also have challenges related to data scarcity, increased pumping costs due to depth, and potential infrastructure modifications [46]. The Laciana Valley's exploration of flooded mines as a source of geothermal heating has shown potential, with certain mines offering significant thermal benefits. However, these ventures face hurdles related to water quality and high initial investments, emphasizing the role of subsidies for profitability [47]. Research into heat extraction from flooded coal mines suggests that the efficiency of these systems is intricately tied to site-specific geological conditions. The overarching conclusion, though, underscores the potential of using flooded mines for heat storage, with some models indicating long-term benefits [40].

Transitioning to the topic of waste heat, this by-product from industries and data centres presents a promising solution for decarbonizing the heating sector [48][49]. Its potential integration with other heat sources, like mine water, offers an innovative approach yet remains largely uncharted territory. Globally, countries like Sweden have tapped into this potential, with waste heat accounting for a significant portion of their DHN [50]. In the UK, the Bunhill Heat and Power network exemplifies the possibilities, offering both environmental and economic benefits. The system has reduced carbon emissions by 500 tonnes per year as well as providing a minimum 10% reduction in heating charges for tenants [51]. However, the operational nuances of waste heat in DHNs have challenges, from geographical mismatches between sources and demand areas to the variable availability of waste heat. In areas like Barnsley, waste heat from local industries could bolster DHN efficiency, but a comprehensive techno-economic evaluation remains a gap in the existing literature [52]. Addressing these challenges may hinge on the development of user-friendly tools, promoting easier feasibility assessments and overcoming inherent barriers in DHN implementations [53] [54].

Researchers have investigated industrial waste heat and mine water energy independently. However, these studies tend to focus on either waste heat or mine water energy independently, rather than examining the combined effect on DHN performance, economics, and environmental impact. Both A. Matas Escamilla et al. [47] and Antonio Atienza-Márquez et al. [55] emphasize the potential of unconventional sources in district heating. Escamilla and colleagues pinpoint the merits of mine water discharges for heating public buildings, highlighting the open-loop geothermal system as the most efficient. Their findings resonate with the results from the earlier mentioned study on the Laciana Valley, which showed that while the initial investment for geothermal use of mine water is considerable, the environmental and economic returns in the long run make it a viable option. On the other hand, Atienza-Márquez et al. delve into the capabilities of absorption systems in transporting heat within district networks, emphasising how industrial waste heat, similar to that from mine water, can be effectively upgraded and channelled. By integrating the insights from these studies, especially in areas like Barnsley, one can envision a future where the combined benefits of both these low-carbon sources lead to improved environmental, economic, and efficient use of waste heat in district heating and cooling networks.

This study explores the integration of mine water and industrial waste heat into district heating networks, using Barnsley, UK as a focal case study. By incorporating advanced network dynamics and conducting an in-depth techno-economic analysis, the research presents a model that is both adaptable and versatile, suitable for various regional characteristics. The approach taken holistically addresses the changing scale of networks, their economic ramifications, and their emissions impact. The broader implications of this research could steer Barnsley, and similar regions, toward sustainable heating solutions, empowering local authorities, and decision-makers. This offers a unique perspective on heating solutions that align with the UK's ambitious 2050 net-zero GHG emission goals.

The paper is organised as follows: Section 3 describes the construction of the simulation model and its sub-models. Section 4 provides the case study setup and data used as input to the developed model and operational parameters of the heat networks. The results are presented in Section 5, with comprehensive sensitivity analyses to identify and quantify the main techno-economic drivers and implications of different alternatives under different scenarios. Finally, the conclusions drawn from the studies and insights for future work are presented in Section 6. This work aims to measure the effectiveness and feasibility of the potential new DHN in Barnsley to understand the trade-off between cost and emissions for large-scale mine water heat pumps and how that meets the heat demand in the region, consisting of standalone gas boilers. This will help to answer the following research aims and objectives:

- Develop and refine a network dynamics simulation model accounting for thermal fronts, to accurately capture the performance of DHNs when integrating non-traditional heat sources.
- Investigate the trends and patterns as the network expands and understand the implications of integrating industrial waste heat.
- Quantify the economic benefits and challenges of integrating mine water and industrial waste heat into DHNs, focusing on factors like fuel cost savings, Net Present Costs (NPC), and Levelised Cost of Heat (LCOH).

Assess the environmental benefits of the proposed DHNs, particularly in terms of emission reductions, and understand the relevance and viability of using low-carbon sources

6.3 Methodology

6.3.1 Overview

The following section describes the developed network dynamics simulation of a DHN. The purpose of the model is to simulate the extraction of mine water heat from unused coal mines, for distribution via the DHN to various heat demands, both domestic and non-domestic. A high-level overview of the model, which is implemented in AnyLogic simulation software [56], is given in Figure 1; shown are the data inputs, various sub-models and agents, and modelling outputs, which include both physical and techno-economic metrics.

The network simulation employs an agent-based approach; thus, the behaviour of the model is determined by the actions of the individual agents situated at heat network nodes, rather than employing any form of top-down control or optimisation. For instance, demand agents observe the flow temperature at their location, and adjust the flow at their own node to attempt to meet demand; these control actions can affect flow and temperature throughout the network, leading to feedback effects.

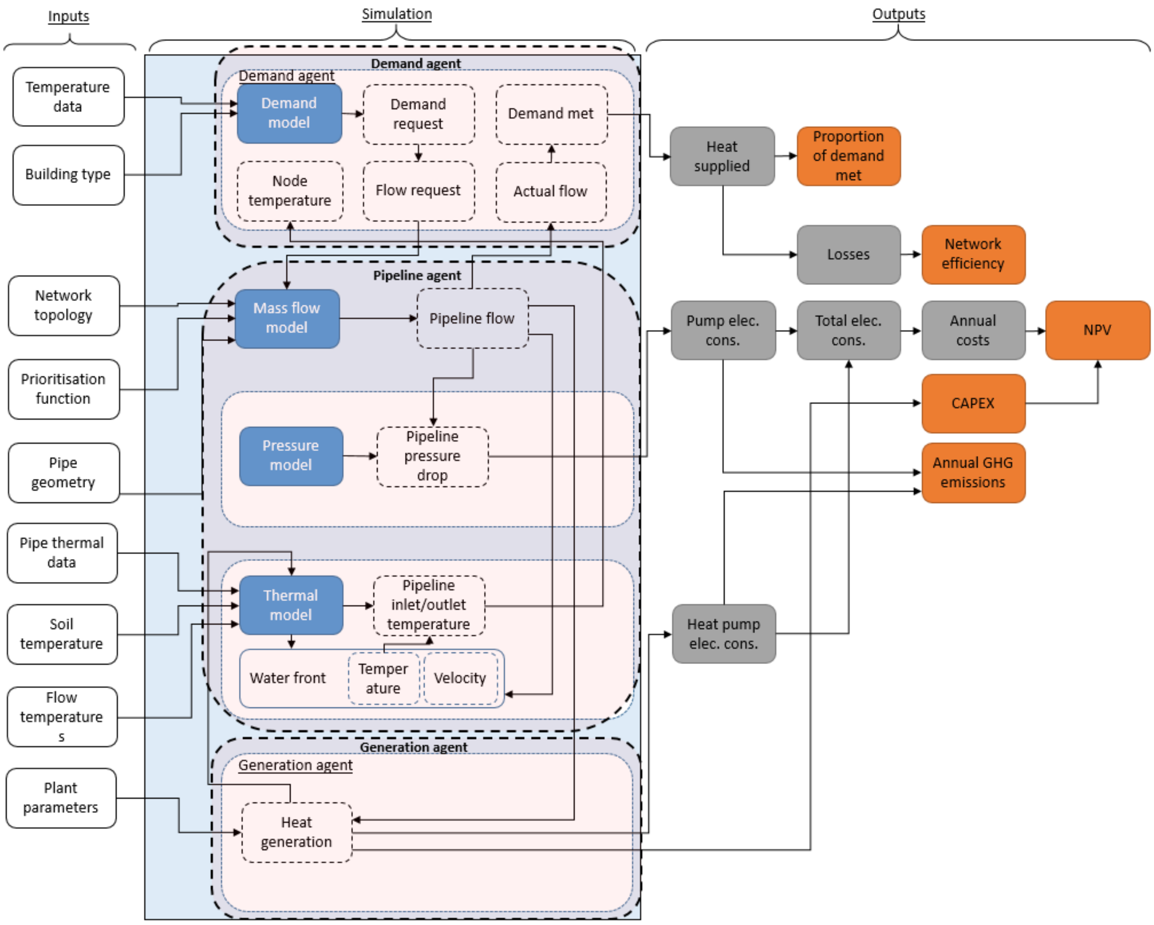


Figure 1. *An overview of the network dynamics simulation model. 'Plant parameters' includes locations and capacities of both boreholes and mine water sources (see Section 4).*

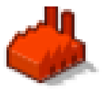
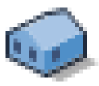
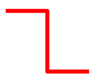
Table 1 provides an overview of all agents included in the model. Primary agents of the model are nodes (demand centres, generation centres, and junctions), and pipelines, which link the nodes. The model also includes water fronts as secondary agents; the motion of these through the network helps to capture the dynamic behaviour of the DHN (see Section 2.6).

The modelling of mass and energy conservation is approached as follows. The mass flow model is handled by AnyLogic's fluid library. This employs LP to maximise mass flow through the network at discrete points in time, within the constraints imposed by valve settings and pipe flow limits. Valve settings depend on the flow requested at demand nodes (see Section 2.4). Propagation of heat through the network occurs at finite speed; this behaviour is captured by the 'water front' agents. When the mass flow model alters the flowrate in a particular pipe, a water front is created which moves along the pipe at finite speed, experiencing thermal losses (see equations 14 and 15). Fronts are also generated when changes to inlet temperature occur. On the arrival of the front at the end of the pipeline, the temperature at the outlet node is updated. Whilst this model is a simplification, it provides an improvement on equilibrium models [57]. Water pressure throughout the network is calculated as specified in Section 2.6.1, to check that the pressure remains in acceptable limits and assess the energy requirement for pumping. Pumps are located at junctions and generation centres.

The model can work with arbitrary heat sources and network scales / layouts. Here, the identification of locations for mine water or industrial heat sources is extraneous to the model: see Section 4. The specified network topology is imported to GIS, and pipe routing is decided by the model itself.

More details on the behaviour of demand agents can be found in Section 2.4; more details on the pipelines and water front agents are found in Section 2.6.

Table 1. *Definition of agents used in model.*

Model Icon	Agent	Description
	Generation Centre	Industrial waste heat source, or large scale heat pump extracting heat from boreholes.
	Demand Centre	Domestic, commercial, leisure and industrial buildings with demand for space heating and hot water
	Junction	A node that allows pipe flows to split or combine.
	Pipeline	A length of pipe that connects demand and generation centres allowing for the transfer of heat.
-	Water fronts	Volumes of water that move through the pipeline

6.3.2 Model assumptions

To reduce the computational intensity only the phenomena that have a significant impact on the accuracy of the simulation are accounted for; therefore, the following simplifications have been made, similar to work of Duquette et al [58]:

- Water properties such as conductivity, specific heat capacity, and density are constant parameters.
- Water is considered an incompressible fluid.
- Flow within pipeline agents is one-dimensional.
- Heat loss to the surroundings is one-dimensional.
- There is no degradation of piping material or insulation over the simulation time.
- Axial conduction along pipes is considered insignificant.
- The pressure drops in the pipeline agents have negligible viscous heating effects.
- Perfect mixing and adiabatic operation are assumed when flows combine at junction agents.
- All heat is extracted from the supply and return temperature difference.
- When two flows combine, pressure is assumed to match the lowest inlet pressures to ensure no backflow.
- Pumps for pressurisation are installed at generation centres and junctions only.
- Non-constant terms in the momentum equation are neglected.
- Pressure loss within the HIU at the demand centres is not considered.
- HIU is 100% efficient. Cooling is not considered.

The following sections provide further detail on the sub-models.

6.3.3 Generation Centres

Generation centres are assigned a capacity P_{GC} in kW_{th}. The maximum volumetric flow of water $\dot{V}_{GC,max}$ from the generation centre is a function of C_{GC}, flow temperature for the generation (which is assumed constant) and the return temperature. It is also constrained by the radius r_{GC} of the pipeline connecting to the generation centre:

$$\dot{V}_{GC,max} = min\left(\frac{P_{GC}}{c_w\, \rho_w (T_{GC,flow} - T_{GC,return})}, \pi v_{max} {r_{GC}}^2\right) \quad \text{Eqn. 1}$$

where c_w and ρ_w are respectively the specific heat capacity and density of water, and v_{max} is the maximum flow velocity allowed in the pipeline. $\dot{V}_{GC,max}$ is passed to the fluid model. The actual value of $\dot{V}$ in the interval $\left[0, \dot{V}_{GC,max}\right]$ is determined by the level of demand downstream.

6.3.3.1 Geothermal plants

The geothermal plants use boreholes to extract mine water energy. They are equipped with large-scale heat pumps that supply heated water to the distribution network at a defined network temperature. The sustainable annual heat extraction from the borehole is calculated as:

$$Q_{annual\_max} = \frac{8760}{1000} \cdot q \cdot SA \qquad \text{Eqn. 2}$$

where SA is the total surface area of the mine workings; q is the heat flux from surrounding ground to the mine water; and the factor 8760/1000 converts Watts to kWh/a. Designed annual heat extraction should be below this level, as specified in Equation 3:

$$\int_0^{8760} \dot{Q}_{borehole} \cdot dt \leq Q_{annual\_max} \qquad \text{Eqn. 3}$$

where $\dot{Q}_{borehole}$ is heat extraction from the borehole in kW_{th}. Heat pumps are used to increase the mine water temperature to the required flow temperature. Owing to the steady temperature of the mine workings, these are expected to have relatively constant COP in the range 3 – 6 [46]. Electrical power consumption of the heat pump P_{HP} and total heat supply $\dot{Q}_{gen}$ are linked to $\dot{Q}_{borehole}$ via equations 4 and 5 [59].

$$\dot{Q}_{borehole} = \dot{Q}_{gen} \frac{COP - 1}{COP} \qquad \text{Eqn. 4}$$

$$P_{HP} = \frac{\dot{Q}_{gen}}{COP}$$

Eqn. 5

6.3.3.2 Industrial waste heat

Industrial waste heat sources function similarly to other generation centres, but with variations in the parameter values for costs, efficiency, and maximum power generation output. Industrial waste heat refers to the unused heat produced as a by-product of various industrial processes.

6.3.4 Demand Centres

As noted above, demand centres attempt to procure the required amount of heat $\dot{Q}_{DC,demand}$ by adjusting the flow rate of water through the valve.

$$\dot{V}_{DC,max} = \frac{1000 \cdot \dot{Q}_{DC,demand}}{c_w \rho_w (T_{DC,flow} - T_{DC,return})} \quad \text{Eqn. 6}$$

Actual supply may deviate from demand: this is because constraints on flow at generation centres and in pipelines may lead to $\dot{V}_{DC} < \dot{V}_{DC,max}$; and also because values of T_{flow} and T_{return} may vary from their values when the control action was taken. Thus the actual instantaneous heat supplied is given by Equation 7:

$$\dot{Q}_{DC,demand} = \frac{1}{1000} c_w \rho_w \dot{V}_{DC} (T_{DC,flow} - T_{DC,return}) \quad \text{Eqn. 7}$$

Demand centres are prioritised according to their distance from the generation. If the demanded hot water flow is more than the DHN can provide, supply is prioritised for the nodes nearest to the generation. For domestic demand, each demand centre represents the aggregation of tens to hundreds of houses; for non-domestic demand, one demand centre represents one building. The model for heat demand will now be detailed.

6.3.4.1 Demand model

Heat demand in the simulation is modelled using piecewise linear regression against ambient temperature T_{ext}, with a different regression for each building type, each of twelve daily time intervals, and each of two seasons; similar to the approach in [60]. Building types considered are: 'domestic', 'leisure', 'residential', 'commercial' and 'education'. ('Residential' refers to large demands such as hotels and blocks of flats and therefore differs from 'domestic'.) For a given building type, demand is given by Equation 8:

$$\dot{Q}_{demand}(t, \mathrm{T}_{ext}) = \begin{cases} (m_{t,1}\mathrm{T}_{ext} + c_{t,1}) + e_t, & for\ \mathrm{T}_{ext} \leq \hat{T}_t \\ (m_{t,2}\mathrm{T}_{ext} + c_{t,2}) + e_t, & for\ \mathrm{T}_{ext} > \hat{T}_t \end{cases} \quad \text{Eqn. 8}$$

Here t represents the timeslot within the day; $m_{t,i}$ and $c_{t,i}$ represent the coefficients for the piecewise linear model at time t; $\hat{T}$ represents the boundary temperature between the two linear sections; and e_t represents an error term. Figure 2 illustrates heat demand (measured in kW) on the y-axis and air temperature (°C) on the x-axis. Multiple lines are shown, each representing an average heat demand for specific two-hour intervals throughout a 24-hour day. For instance, there are distinct lines representing the intervals from midnight to 2 am, 2 am to 4 am, and so on for the entire day.

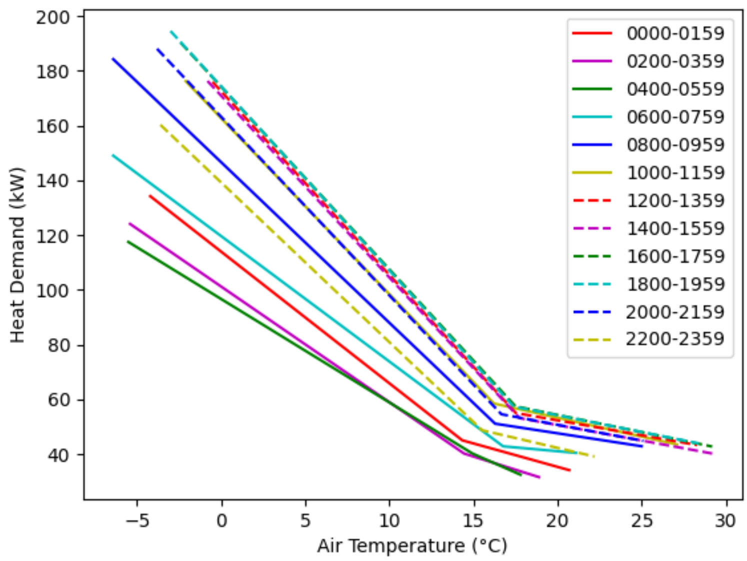


***Figure 2**. Piecewise linear regression of heat demand versus ambient temperature for the 'residential' category.*

It will be seen that the model depends on values for the parameters $m_{t,i}$, $c_{t,i}$ and $\hat{T}_t$. These were regressed against measured data to obtain a least squares fit. For the 'domestic' category, regression was carried out against data from the renewable heat premium payment (RHPP) scheme [61]. This demand was for heat pumps, so the assumption here is that demand profiles are relatively independent of heating system. Since the model is intended to represent domestic heat demand only at the resolution of hundreds of houses, the regression used 138 houses and 134 houses respectively for the winter and summer models, as dictated by the availability of good quality data. Domestic demand centres in the simulation have demand rescaled according to the number of addresses.

For the remaining building categories, regression was carried out against hourly heat network demand data procured from a third party; this data included 47 educational, 41 commercial, 15 residential and 9 leisure buildings. For these building types, each demand centre corresponds to one building, and demand is rescaled by floor area.

The MIDAS database [62] was used for temperature data, both for model-fitting and for the final simulation. Error terms e_t reflect the variance of the measured data around the piecewise linear fit and provide the final simulation model with an element of stochasticity. The final adjustment to heat demand is to ensure that it is non-negative (cooling is not considered in the model).

This study utilised third-party data to validate the model, aligning it with real-world conditions. To establish a robust validation framework, the network model was configured to precisely correspond to the nodes of this third-party data. However, specifics of the validation are protected under a Non-Disclosure Agreement (NDA), which restricts the direct representation of raw figures.

Despite the constraints of the NDA, overall validation results affirm the model's effectiveness and robustness. Minor temperature profile variances between the simulation and real-world data were observed. These discrepancies can largely be attributed to the simulated demand of non-domestic buildings, which had limited data available for validation.

Figure 3 showcases the comparison between the average modelled demand and the actual demand from the third-party data for domestic buildings. The results from the domestic demand centre model indicate an average heat demand of 12.3MWh per year for each building. This closely aligns with data provided by BEIS, which estimates an average heat demand of 12MWh per household annually [63]. The alignment of these figures underscores the model's fidelity to real-world observations, attesting to its reliability.

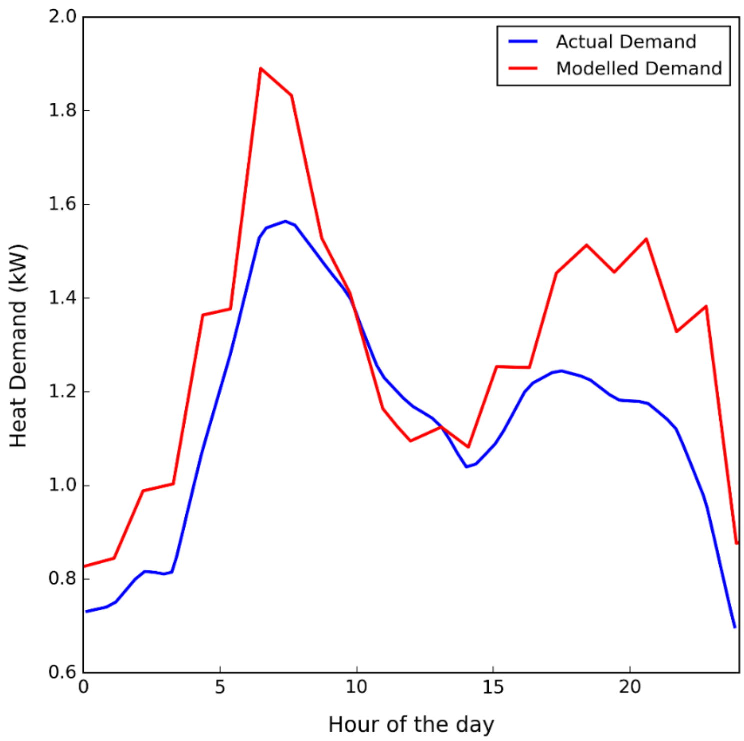


Figure 3. *Average daily profile for a single domestic building*

6.3.5 Junctions

Junctions allow the combination of two or more network pipes. To calculate the outlet pipe temperature under adiabatic conditions it is assumed that perfect mixing occurs instantly. The outlet temperature is then a weighted average of the inflow temperatures [64]:

$$T_{junc} = \frac{\sum_i \dot{m}_i T_i}{\sum_i \dot{m}_i} \qquad \text{Eqn. 9}$$

where T_{junc} is the temperature exiting the junction at time t, m_i is the mass flowrate into the junction at time t.

6.3.6 Pipelines

Pipelines are characterised by their route, length, diameter and the thicknesses of insulation and other layers. To adhere to vibration regulations and to decrease the friction/degradation of the pipework, each pipe is throttled to a maximum volumetric flow rate $\dot{V}_{p,max}$ [65] determined by cross-sectional area CSA_p and a maximum flow velocity v_{max}:

$$\dot{V}_{p,max} = CSA_p \cdot v_{max} \qquad \text{Eqn. 10}$$

Each pipe is linked to a unique start and end node. The route between these (and resulting pipe length) is obtained using the Open Street Map server [66].

The flow rate through the pipe is determined by the fluid model, as outlined in Section 3.1. Temperature dynamics in the pipe are modelled as follows. Input and output temperatures $T_{p,in}$ and $T_{p,out}$ are defined for the pipe at all times. The pipe operates under one of two modes: FLOWING and ZERO_FLOW. Under the first mode, the outlet temperature is dictated by the arrival of 'water front' agents. Under the second mode, outlet temperature decays continuously towards soil temperature.

R' describes the thermal losses of the pipeline as Watts per meter of length per °K. It results from the combination of five thermal resistances: the interface between fluid and pipe; the pipe wall, insulation and casing; and the interface between pipe and soil. Equation 11 gives the definition [58]:

$$R' = \frac{1}{(2\pi(r_{in} \times 10^{-3})h_{co})} + \frac{\log\left(\frac{r_{pipe}}{r_{in}}\right)}{2\pi k_{AB}} + \frac{\log\left(\frac{r_{insulation}}{r_{steel}}\right)}{2\pi k_{BC}} + \frac{\log\left(\frac{r_{casing}}{r_{insulation}}\right)}{2\pi k_{CD}} + \frac{1}{(Fk_s)} \quad \text{Eqn. 11}$$

Here k_{AB}, k_{BC}, k_{CD} and k_s are the thermal conductivities respectively of the pipe wall, pipe insulation, pipe casing and soil. r_{pipe}, $r_{insulation}$ and r_{casing} give the outer radii of the pipe, the pipe insulation and pipe casing. h_{co} is the convection coefficient with unit's W/K, and F is a dimensionless shape factor.

The value of R' and all related quantities is updated whenever the fluid flow through the pipe changes.

The convection coefficient h_{co} is dependent on the fluid and flow properties and is calculated by Equation 12 [58]:

$$h_{co} = \frac{Nu \cdot \sigma_w}{2(r_{in} \times 10^{-3})} \quad \text{Eqn. 12}$$

where σ_w is conductivity of water, r_{in} is the internal radius of the pipe and Nu is Nusselt's number. Details on the calculation of Nu can be found in Appendix 6.9.2. The shape factor F is calculated as in Equation 13 [67]:

$$F = \frac{2\pi}{\operatorname{acosh}\left(\frac{d}{r_{in} \times 10^{-3}}\right)} \quad \text{Eqn. 13}$$

where d is the burial depth of the pipe.

Change of flowrate or input temperature triggers the creation of a water front agent; this travels along the pipe with speed dictated by the water flowrate. The temperature of the water front evolves according to Equation 14:

$$c_w \cdot \rho_w \cdot A \cdot \frac{dT}{dt} = -\frac{T - T_s}{R'} \quad \text{Eqn. 14}$$

where T_s is the temperature of the surrounding soil, assumed constant. Equation 15 yields the exact solution:

$$T(t) = T_s \cdot (1 - \Lambda) + T_0 \cdot \Lambda \quad \text{Eqn. 15}$$

$$\text{with } \Lambda := exp\left(-\frac{t}{c_w \cdot \rho_w \cdot A \cdot R'}\right)$$

where T_0 is equal to the value of $T_{p,in}$ at the time of water front creation, and t is time elapsed since water front creation. This is similar to models found in Duquette et al [58] and others. Upon arrival at the end of the pipeline, the destination node temperature is updated with the temperature of the arriving waterfront. For simplicity, in FLOWING mode this outlet temperature remains constant in between the arrival of water fronts. Thus, the model operates as an equilibrium model after a delay while water fronts are in transit.

If flow in the pipe is zero, $T_{p,out}$ is expected to decay towards T_s. In this case, the mode of the pipe is switched to ZERO_FLOW and $T_{p,out}$ evolves according to equations 14 and 15.

For the network's return pipes, the water fronts are omitted and a 0D model is used. Return pipe temperature thus evolves according to Equation 16:

$$\dot{T}_{return,p}(t) = \frac{Q_{return,p}}{p_w \cdot c_w \cdot \pi \cdot r_{in,p}^2 \cdot L_p} \quad \text{Eqn. 16}$$

where $T_{return,p}$ is the return pipe temperature at time t, $Q_{return,p}$ is the energy transferred to the return pipe, p_w and c_w are the density and specific heat capacity of water, respectively, $r_{in,p}$ is the radius of the pipe, and L_p is the length of the pipe.

6.3.6.1 Pressure drop and pump requirements

Pressure drop ΔP occurs due to frictional losses and is dependent on the flow regime. The pressure drop is affected by the length of the pipe and the fluid velocity. Equation 17 describes this [68]:

$$\frac{\Delta P}{L_p}(t) = \mu\left(\frac{{v_x}^2(t)p_w}{4r_{in}}\right) \quad \text{Eqn. 17}$$

where μ is the unitless friction factor, r_{in} is the radius at the inlet of the pipe and p_w is the density of water. ΔP is the pressure drop in the pipe, L_p is the length of the pipe, v_x is the flow velocity at time t.

The overall pumping power requirement P_r can be expressed by Equation 18 [69]:

$$P_r = \frac{\int_0^{8760} \Delta P \cdot \dot{v}_x \cdot dt}{\eta_{pump} \cdot \eta_{motor}} \quad \text{Eqn. 18}$$

where η_{pump} and η_{motor} are the pump efficiency and electric motor efficiency, respectively.

6.4 Techno-Economics

6.4.1 Emissions

Techno-economics are concerned with the cost-effectiveness and environmental impact of the heat network. The GHG emissions are computed following the UK Government's GHG Conversion Report [70]. The efficiency of the heat network is calculated by Equation 19:

$$\eta = \frac{Q_s}{Q_g} \cdot 100\% \qquad \text{Eqn. 19}$$

where η is the overall efficiency of the network, Q_g is the total heat generation from geothermal plants, and Q_s is the actual heat supplied to demand centres.

The percentage of demand met is calculated by Equation 20:

$$Demand\ met = \frac{Q_d}{Q_s} \cdot 100\% \qquad \text{Eqn. 20}$$

where Q_d is the demand requested by the network.

Standalone boilers are used in the business-as-usual case, relative to which the DHN's carbon emissions are compared. Carbon emissions from boilers are calculated using a carbon factor from The Standard Assessment Procedure [71] that quantifies the CO_2 released per kWh of energy use. The same heat demand model is used as specified in 2.4. The emissions from boilers are calculated by Equation 21:

$$CO2_b = \frac{Q_d}{\eta} \cdot f_b \qquad \text{Eqn. 21}$$

where $CO2_b$ is the carbon emission from the boilers, η is the efficiency of the boilers, and f_b is the carbon factor of the boilers.

Table 2. Carbon factors [71].

Source	Carbon factor (t/MWh)
Geothermal plant	0.011
Industrial waste heat	0.011
Natural gas	0.210
Electricity (Monthly average)	0.136

The CO_2 emissions from the geothermal plants or industrial waste heat are calculated by Equation 22, the emissions from the heat pumps by Equation 23, and the emissions from the repressurising pumps by Equation 24:

$$CO2_{gc} = Q_{g,gc} \cdot f_{gc} \quad \text{Eqn. 22}$$

$$CO2_{hp} = \sum_{m=1}^{12} \frac{Q_{g,m}}{COP} \cdot f_{e,m} \quad \text{Eqn. 23}$$

$$CO2_{p} = \sum_{m=1}^{12} E_{p,m} \cdot f_{e,m} \quad \text{Eqn. 24}$$

where $CO2_{gc}$, $CO2_{hp}$, $CO2_{p}$, are the carbon emissions from the geothermal plants, heat pumps and repressurising pumps, respectively, $Q_{g,gc}$ is the heat generated at the generation centre, $Q_{g,m}$ is the monthly heat generation at the generation centre, $E_{p,m}$ is the monthly emissions from the pumps, f_{gc}, $f_{e,m}$ are the carbon factor for the generation centre heat source and electricity, respectively.

The total CO_2 emissions $CO2_{total}$ from the DHN are calculated by Equation 25:

$$CO2_{total} = CO2_{gc} + CO2_{hp} + CO2_{p} \quad \text{Eqn. 25}$$

Equation 26 gives the percentage carbon savings $CO2_{s}$ relative to boilers:

$$CO2_{s} = \frac{CO2_{b} - CO2_{total}}{CO2_{b}} \cdot 100\% \quad \text{Eqn. 26}$$

Marginal reduction in emissions for the region is calculated by Equation 27:

$$CO2_{MR} = 100 - \frac{CO2_{bT} - CO2_{b} + CO2_{total}}{CO2_{bT}} \cdot 100\% \quad \text{Eqn. 27}$$

where $CO2_{bT}$ is the emission from the entire region, and $CO2_{MR}$ is the percentage marginal reduction.

6.4.2 Costs

The following equations are used to calculate various costs of the network and any currency specified is originally in pounds or has been converted. The network piping costs are calculated by Equation 28:

$$CC_{N} = (C_{BP} + C_{IP}) \cdot L_{T} \quad \text{Eqn. 28}$$

where CC_{N} is the total network piping cost, C_{BP} is the main buried pipe cost factor and C_{IP} is the internal pipe cost factor and L_{T} is the total network length.

The demand centre cost is calculated by Equation 29:

$$CC_{DC} = (C_N + C_{SS} + C_{HM} + C_{HIU}) \cdot Q_d \quad \text{Eqn. 29}$$

where CC_{DC} is the total demand centre cost, C_{SS} is the cost factor of the substation, C_{HM} is the cost factor of heat meters, and C_{HIU} is the cost factor of the heat interface unit.

The cost of heat pump follows an affine relationship vs capacity in MW is obtained from Pieper et al [72], shown in Figure 12, in Appendix 6.9.3, thus calculated by Equation 30:

$$CC_{HP} = (0.6398 \cdot C + 0.50543) \quad \text{Eqn. 30}$$

where CC_{HP} is the capital cost of the HP, and C is the maximum capacity of the HP for the specific network.

The ancillary equipment cost is calculated using Equation 31:

$$CC_A = Q_d \cdot C_A \quad \text{Eqn. 31}$$

where CC_A is the capital cost of ancillary equipment and C_a is the cost factor of the ancillary equipment.

Total capital cost of the network is calculated by Equation 32:

$$CC_t = CC_N + CC_{DC} + CC_{HP} + CC_A \quad \text{Eqn. 32}$$

where CC_t is total capital cost of the network.

The O&M costs are calculated by Equation 33.

$$O\&M = C_B \cdot C + (C_{NM} + C_{HIUM} + C_{HMM} + C_{SC} + C_{BR})Q_g + P_{HP} \cdot E \quad \text{Eqn. 33}$$

where O&M represents the total operation and maintenance costs, C_B is the operational cost factor associated with borehole or source-side operation, $C_{NM}, C_{HIUM}, C_{HMM}, C_{SC}, C_{BR}$ are the operational cost factors for network maintenance, HIU maintenance, heat meter maintenance, staff costs and business rates, respectively. P_{HP} is the electrical power consumption of the heat pump, and E is the price of electricity.

Energy cost is calculated by Equation 34:

$$E_t = \frac{Q_g}{COP} \cdot E \quad \text{Eqn. 34}$$

where E_t is the total energy cost.

Inflation is taken into account; thus, the real discount rate can be calculated from the nominal discount rate and inflation rate using Equation 35 [73]:

$$R = \frac{(1 + R_{nom})}{(1 + i)} - 1 \qquad \text{Eqn. 35}$$

where r is the real discount rate, r_{nom} is the nominal discount rate and i is the inflation rate.

Net-present cost (NPC) is a metric to assess the costs of a heat network considering monetary outflows over time. For networks without industrial waste heat and with industrial waste heat the NPC is calculated using Equation 36 and 37, respectively [74], incorporating total capital, operational and energy costs. The model will be integrated into the electricity grid to realise profits and a positive NPV obtained in future work.

$$NPC_a = \sum_{t=0}^{n} \frac{CC_t + O\&M + E_t}{(1 + R)^t} \qquad \text{Eqn. 36}$$

$$NPC_b = \sum_{t=0}^{n} \frac{CC_t + O\&M + E_t + (Q_{WH} \cdot C_{WH})}{(1 + R)^t} \qquad \text{Eqn. 37}$$

where subscripts b and a denote with and without industrial waste heat respectively, and Q_{WH} is the industrial waste heat energy usage and C_{WH} its cost factor.

The Levelized Cost of Heat (LCOH) is a metric to assess the cost heat delivery to the network over it's lifetime and is calculated without industrial waste heat and with by Equation 38 and 39, respectively. It depends on the heat generation and demand requested, length of pipework, substations, and plants contributing to capital and operational costs [75].

$$LCOH_a = \frac{\sum_{t=1}^{n} (CC_t + O\&M_t + E_t)/(1 + R)^t}{\sum_{t=1}^{n} Q_t/(1 + R)^t} \qquad \text{Eqn. 38}$$

$$LCOH_b = \frac{\sum_{t=1}^{n} (CC_t + O\&M_t + E_t + (Q_{WH} \cdot C_{WH})/(1 + R)^t}{\sum_{t=1}^{n} Q_t/(1 + R)^t} \qquad \text{Eqn. 39}$$

where subscripts b and a denote with and without industrial waste heat respectively, LCOH is the levelised cost of heat achieved by the network and Q_t is the total energy.

6.5 Case Study

The model detailed in sections 2 and 3 is employed to assess the feasibility of a mine water district heat network in Barnsley. The local council of Barnsley has envisioned four distinct network layouts, each leveraging the latent thermal energy of the surrounding mine workings. This represents the evolution of a district heat network temporally. These networks share a constant baseload of non-domestic connections, but exhibit variations in the extension of domestic connections, thus affecting network lengths and heat densities. All networks have a consistent number of geothermal plants, but variants include an additional pipe from a glass manufacturer supplying waste heat, augmenting the network length and generation capacity.

Performance evaluations were based on a year-long simulation using 2021 temperature data [76], with supply and return temperatures set at 60°C and 30°C respectively but will vary depending on performance of the network. The network piping is assumed to be at a burial depth of 0.8 m with a soil temperature of 10°C [77].

Firstly, the potential sites for initial geothermal plants were identified, revealing four mine-working locations and four boreholes with adequate ambient temperatures. Further data on the boreholes intersecting these workings are presented in Table 3 obtained from old mine workings maps supplied by The Coal Authority [78]. A heat flux q value of 63.5 Wm^{-2} was used [79].

Table 3. *Borehole depth and temperature*

Borehole	Depth (m)	Temperature (°C)	Surface Area $(m^2) \times 10^6$
Grimethorpe	150	14.3	90.1
Houghton	243	14.9	64.3
Royston	332	17.9	84.3
Cudworth	132	18.2	34.3

6.5.1 Network classification

The selection and classification of demand is found in Appendix 6.9.1. The baseline COP is assumed to be 4.9 [80]. The areas in close proximity to the boreholes contain 12636 buildings, with each demand centre node containing between 65 and 375 domestic houses. A mixture of 25 non-domestic buildings (5 commercial, 11 education, 2 leisure, 7 residential) identified will be used as anchor loads. Table 4 shows each borehole and the number of nearby non-domestic and domestic buildings.

Table 4. Number of DC of each building classification and the total number of buildings

Village	Building Type	No. of DCs	No. of Buildings
Grimethorpe	Domestic	21	5650
	Non-domestic	16	-
Houghton	Domestic	15	3549
	Non-domestic	8	-
Royston	Domestic	13	3437
	Non-domestic	1	-

Four scenarios are outlined in Table 5, each with an increasing number of domestic demand centers attached; this is designed to scale the network.

Table 5. *Number of buildings in each scenario*

Scenario	1	2	3	4
Number of buildings	3184	6343	9502	12661
= 1000 buildings				
Network Length (m)	37512	42581	45451	52775

Network parameters and costs [81] are outlined in Table 6 and 7 with carbon cost taken from UK ETS [82] discount and inflation rate from The Green Book [83] and COP from Figure 13, in Appendix 6.9.4 estimated from the supply and return temperature values. Where p is used in p/kWh this refers to pennies (£0.01) per kWh of heat delivered.

Table 6. *Network parameters*

	Value
Pump efficiency (%)	80
Motor efficiency (%)	80

Table 7. *Cost parameters*

	Value
Electricity price (p/kWh)	13
Gas price (p/kWh)	4.94

Network pressure (kPa)	1,500
Supply temperature (°C)	60
Return temperature (°C)	30
Soil temperature (°C)	10
Water conductivity (W/mK)	0.598
Water diffusivity (mm^2/s)	0.16
Lifetime (years)	30
COP	4.9

Combined operation costs (£/kWh)	35.9
Combined demand Centre costs (£/kWh)	919
Substation cost (£/kWh)	16
Ancillary cost (£/kWh)	68
Combined pipework cost (£/kWh)	516
Boiler CAPEX and OPEX cost (£/kWh)	2.28
Inflation rate (%)	2.7
Discount rate (%)	3.5
Carbon cost (£/MWh)	52.56

6.5.2 Pipe sizing

To determine the appropriate pipe size for the DHN's a heuristic approach and Insulation Class 1 selection criterion [84] are used. The nominal pipe diameters are initially calculated based on the velocities prescribed by the UK Heat Network Code of Practice [85], as illustrated in Figure 14 in Appendix 6.9.5. Subsequently, trial simulations were conducted, and various performance indicators were recorded, including velocity, demand supply deficit, and network efficiency. The position of the pipe in the network and the number of downstream connections were also considered. In case any pipe was throttled due to the maximum velocity, it was adjusted to the next size, and similarly for undersized pipes. It is worth noting that pipe sizes remained unchanged for all scenarios.

6.5.3 Industrial waste heat

In addition to the network's mine water heat supply, an additional source of heat can be obtained from a nearby glass manufacturer, with a maximum capacity of 7 MW obtained through conversation with Barnsley region council [86], which can be utilised at any given time. This industrial waste heat resource presents an opportunity to supplement the overall heat generation. It operates with an efficiency of 90% [87] and adds an additional 1.11km of pipework to each network scenario.

The cost associated with utilising the industrial waste heat is 3 pence per kilowatt-hour (p/kWh) [88]. The industrial waste heat source was assumed to be available at 60°C in the model. This cost reflects the price charged for accessing and utilising the industrial waste heat output. It is important to note that the industrial waste heat option provides a cost-effective means of obtaining heat, considering its comparatively lower cost per unit of energy compared to other sources.

The chosen case study serves as an exemplary scenario for strategic investment in mine water heat networks, particularly due to Barnsley's proximity to geothermal heat sources and disused coal mines. This model has been designed specifically to evaluate diverse demand scenarios and scale of network, thereby assessing the feasibility of the region for decarbonisation and its potential for transformation. The assessment of cost-effectiveness in reducing CO_2 emissions from standalone boilers would provide valuable insight, with the ambition of informing the district about the possible innovation avenues within its heating sector.

6.6 Results

This section presents the results of applying the methods discussed in Section X, thereby developing DHNs that employ both mine water energy and industrial waste heat. Four network scenarios (S1-S4) of increasing complexity were evaluated, each represented by two variants - one with and one without industrial waste heat. The techno-economic aspects and environmental benefits are both assessed.

6.6.1 Network performance

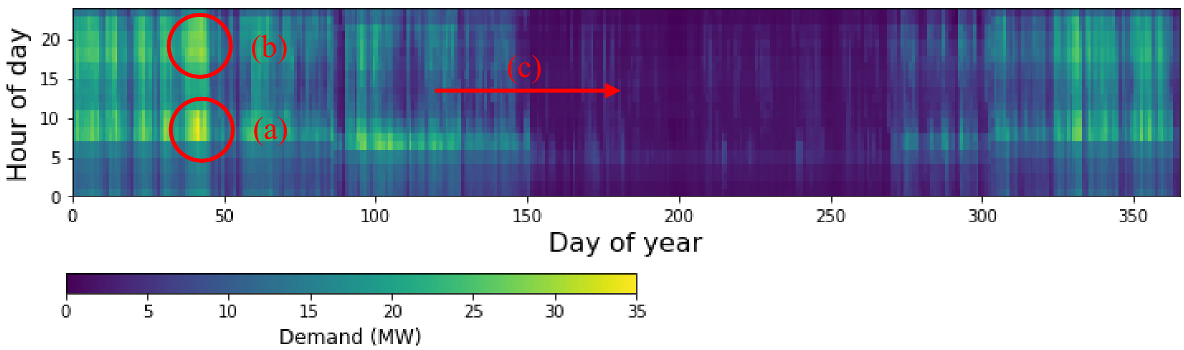


***Figure 4**. Heat plot of demand across the network for S1.*

Figure 4 provides a heat plot illustrating the dynamic daily heat demand patterns throughout the year, captured by the network. The time of day is plotted on the y-axis and days of the year on the x-axis, the plot corroborates the following well-established trends in DHN usage: firstly, an observable surge in heat demand during the morning hours, likely attributable to space heating needs after a cold night and hot water usage for daily routines (a). Secondly, a pronounced peak in heat demand during late afternoon and early evening hours, reflecting the increased usage of heat for activities such as cooking, bathing, or space heating (b). Finally, an appreciable reduction in heat demand during summer months, attributed to warmer outdoor temperatures and consequent decreased reliance on the DHN for space heating (c).

Table 8 outlines the key performance indicators of different network scenarios both with and without the incorporation of industrial waste heat. The parameters evaluated in these scenarios include heat generation (MWh), heat demand (MWh), heat supply (MWh), the percentage of demand met, emission savings (%), carbon factor (kgCO2/MWh) and pump power (MWh). The table shows the variations in these parameters as the network size increases from S1 to S4.

For networks without industrial heat, heat generation and heat demand increase with growing network size, S1 through S4. The demand met, however, declines as the network size increases, with a decrease from 99.2% in S1 to 87.9% in S4. Emission savings display an upward trend across the scenarios, indicating a higher emission reduction as the network size grows. Notably, the carbon factor decreases with the network expansion. Pump power, indicative of the energy used by the pump, escalates with increasing network size.

In scenarios incorporating industrial heat (S1WI-S4WI), the heat generation, heat demand, and industrial heat usage all increase with the network's size. However, the percentage of demand met decreases. This trend is also observed in scenarios without industrial heat The carbon factor increased from S1WI to S2WI by 7.4%, meanwhile from S3WI to S4WI there was a decrease by 9.6% indicating a mixed trend. Changes in LCOH from S1WI to S4WI decreased across the scenarios from, with a difference of 2.8%. Understanding these nuances allows us to better navigate the complexities and potential challenges in designing and expanding heat networks, especially when incorporating industrial heat.

Table 8. *Key performance indicators of scenarios.*

Network (w/o industrial waste heat)	**Unit**	**S1**	**S2**	**S3**	**S4**
Heat generation	MWh	111000	148600	168600	214200
Heat demand	MWh	97100	131300	150100	197200
Heat supply	MWh	96400	129200	147100	173400
Demand met	%	99.2	98.4	98.0	87.9
Emission savings*	%	80.57	80.60	80.68	80.83
Carbon factor	$kgCO_2eq/MWh$	50.50	49.58	48.95	41.43
Pump power	MWh	1620	3550	4980	7370
Network (w/ industrial waste heat)	**Unit**	**S1**	**S2**	**S3**	**S4**
Heat generation	MWh	106600	149400	170700	204700
Heat demand	MWh	96300	130000	149000	198800
Heat supply	MWh	90500	127900	146800	178000
industrial waste heat usage	MWh	31200	37300	40400	40500
Demand met	%	94.0	98.6	98.3	89.5
Pump power	MWh	1950	4040	5110	7270
Emission savings*	%	85.02	84.48	84.35	83.88
Carbon factor	$kgCO_2eq/MWh$	36.55	39.25	39.55	35.75
Change in LCOH	%	8.36	6.71	6.22	5.56

* Using the same demand of that specific network but consisting of boilers only.

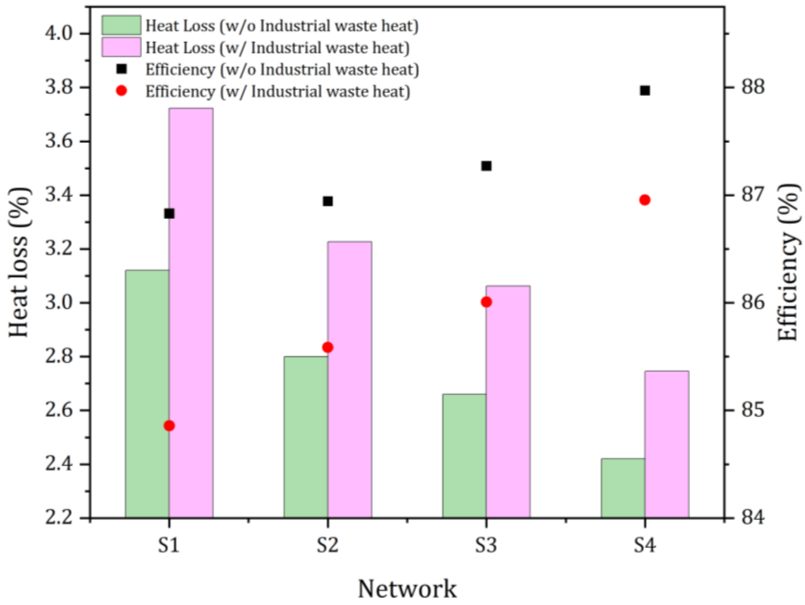


Figure 5*. Heat loss and overall network efficiency for all scenarios.*

Figure 5 represents the correlation between heat loss and efficiency all network scenarios, with and without the incorporation of industrial waste heat. It demonstrates a clear trend of increasing efficiency and decreasing heat loss as the network size expands, for both scenarios with and without industrial waste heat. This trend is indicative of the advantages of larger networks in enhancing operational efficiency and managing heat loss. However, an intriguing observation is that networks utilising industrial heat, despite following the same trend, consistently show lower efficiency than their counterparts without industrial waste heat. This drop in efficiency is attributed to the comparatively higher thermal losses observed when industrial waste heat is incorporated into the networks due to the higher supply temperature and additional pipe length. This discrepancy suggests that while the integration of industrial waste heat can aid in meeting the increased demand of larger networks, it may simultaneously incur a penalty in efficiency.

6.6.2 Net present cost

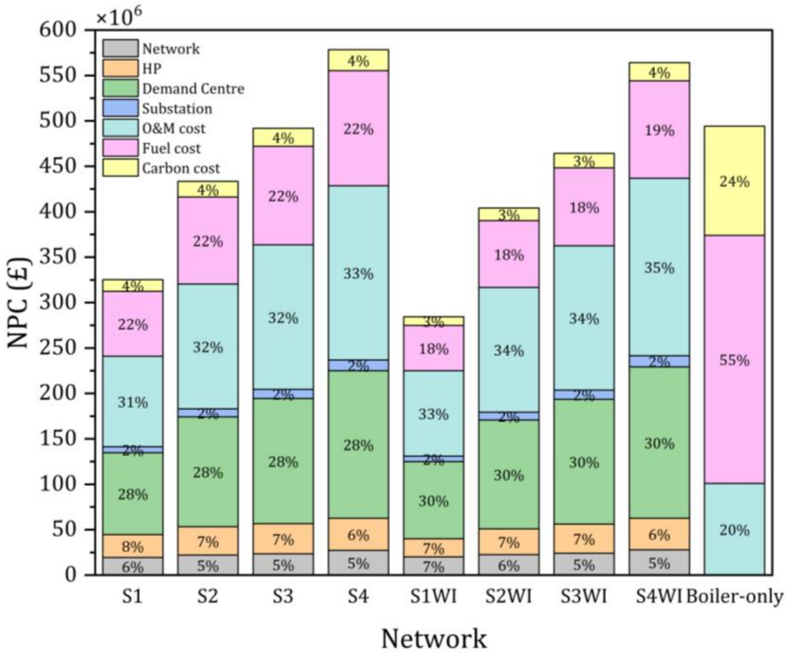


***Figure 6**. Breakdown of Network Present Costs (NPC) for all scenarios, including main network, demand centre, heat pump (HP), substation, operation, and maintenance (O&M), fuel, and carbon costs.*

Figure 6 shows the comparison of NPC for all scenarios. The costs are detailed in several categories, including main network, demand centre, HP, substation, O&M, fuel, and carbon costs. As expected, as the network size increases from S1 to S4 the costs across all parameters generally exhibit an upward trend. This can be attributed to the larger infrastructure requirements and increased energy demand associated with larger networks. Notably, the fuel costs demonstrate the most substantial increase, reflecting the greater energy consumption and corresponding fuel expenditure.

The addition of industrial waste heat, however, shows a noticeable reduction in fuel costs across all scenarios. For instance, fuel costs reduce from S1 to S1WI see a reduction of 30.2% saving £21.6 million, and similarly for other scenarios, although the reduction is less significant as the network scale increases. This cost reduction can be attributed to the more efficient utilisation of waste heat, reducing the reliance on the HP and thus electricity consumption. Similarly, the carbon costs decrease with the injection of industrial waste heat seeing an average reduction of 20.3%.

The total NPC for scenarios incorporating industrial waste heat exhibits a consistent reduction, emphasising the economic advantage of waste heat recovery, seeing a reduction of 12.6%, 6.8%, 5.6% and 2.48% reduction from S1-S4 to S1WI-S4WI, respectively. In the boiler-only scenario, substantial fuel and carbon costs are noted. These high costs, in comparison to other scenarios, underline the energy inefficiency and environmental impact associated with natural gas, and the high COP of the HPs really show the decreased fuel consumption and cost.

6.6.3 Levelized Cost and Emissions

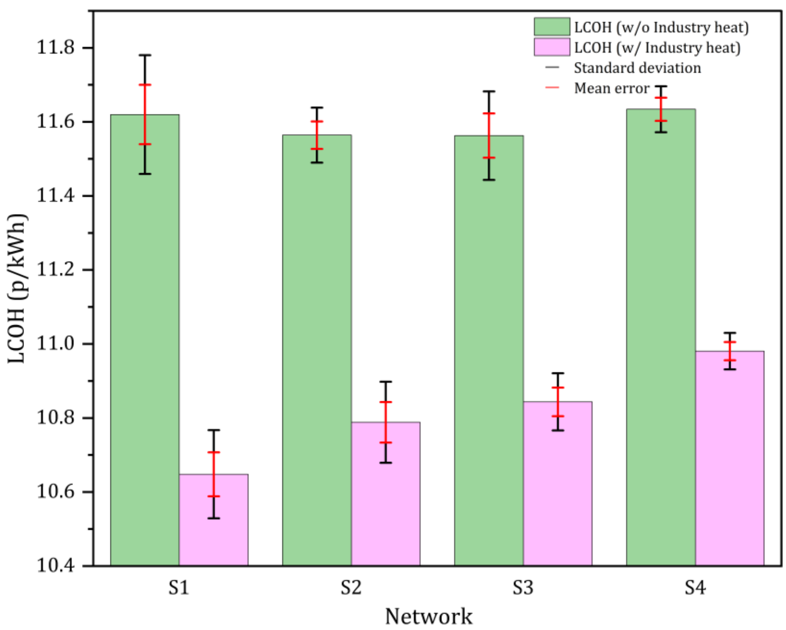


***Figure** 7. Levelized cost of heat for all scenarios.*

Figure 7 displays the LCOH for the network scenarios, with and without the incorporation of industrial waste heat as well as standard deviation and mean error due to multiple instances of simulations run for each scenario. When industrial waste heat is not included, the LCOH values exhibit a narrow range, with minimal fluctuations observed across the scenarios. The LCOH slightly decreases from S1 to S3, and peaks in S4, indicating that the cost of heat does not consistently increase or decrease with the scale of the network. This trend suggests that factors other than network size may influence the LCOH.

Contrastingly, when industrial waste heat is integrated, an evident upward trend in LCOH with increasing network size is observed. This is because the proportion of heat from the heat pump at a higher cost must increase as the industrial waste heat has a fixed capacity. Therefore, as the network size increases the LCOH will converge towards the networks with industrial waste heat price.

However, despite this upward trend, the LCOH values with waste heat inclusion are consistently lower than its industrial waste counterparts, despite the larger network scale requiring more extensive pipework. The additional pipework costs are offset by the capital cost reductions of the heat pumps (HP), which further exemplifies the economic efficiency of waste heat utilisation.

In the integration of industrial waste heat, it was observed that the impact on LCOH lessened as the network size increased. Specifically, S1 showcased the highest LCOH reduction of 8.36%, while S4 presented the smallest reduction of 5.62%. This outcome suggests that waste heat's influence on LCOH is more notable in smaller networks, where the waste heat proportion is relatively larger. Conversely, in larger networks, the waste heat proportion is smaller, thus having a smaller impact on the overall LCOH.

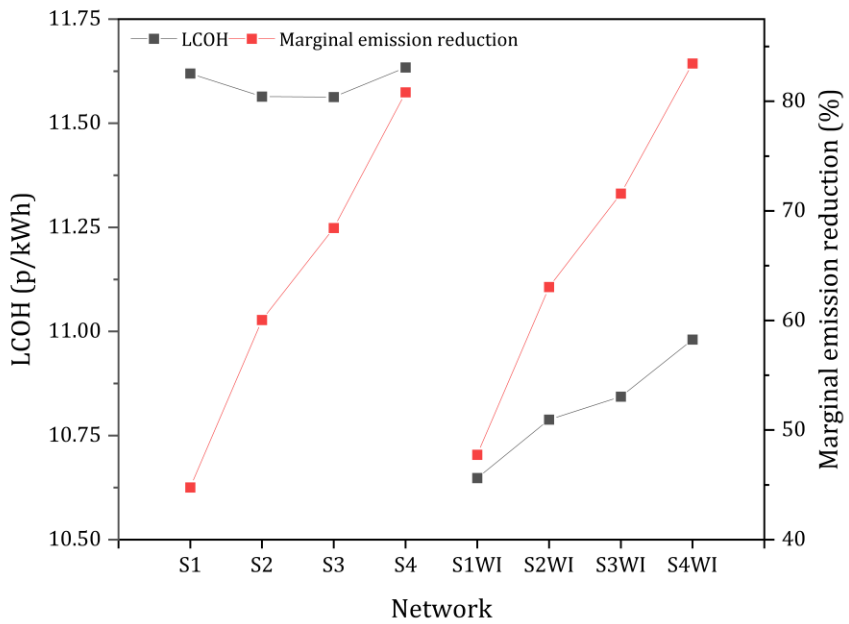


Figure 8*. LCOH and marginal reduction in emissions for scenarios*

Figure 8 presents the LCOH and the marginal emission reductions over all network scenarios, both without and with the integration of industrial waste heat. Marginal emission reduction, in this context, refers to the percentage decrease in CO_2 emissions achieved by each DHN scenario compared to the standalone boiler emissions of the region that isn't connected to the DHN. This calculation effectively quantifies the emissions reduction benefit provided by each scenario.

Marginal emission reductions exhibit a significant upward trend from 44.76% to 80.83% for S1 to S4, respectively. Consequently, leading to greater emission reductions, despite the cost of heat remaining relatively constant.

When industrial waste heat is incorporated, the marginal emission reductions continue their upward trend but now from 47.74% to 83.46% for S1-S4, respectively and see a reduced LCOH from 11.62p/kWh to 10.65p/kWh for S1-S1WI. This result exemplifies the combined economic and environmental benefits of integrating waste heat into the network, yielding lower costs and higher emission reductions.

In Scenario S1, the LCOH decreases by approximately 8.36%, while the marginal emission reduction increases by approximately 6.65%. This shows that the inclusion of industrial waste heat in S1 brings about a more significant economic benefit (as shown by the greater reduction in LCOH) compared to the environmental benefit (smaller increase in marginal emission reduction). Conversely, in Scenario S4, the LCOH decreases by approximately 5.62%, while the marginal emission reduction increases by approximately 3.27%. This indicates that while the inclusion of industrial waste heat still results in economic and environmental benefits, the relative improvements are less compared to S1. From this comparison, it's clear that the smaller network (S1) derives a greater relative economic advantage from the inclusion of industrial waste heat, while the larger network (S4) experiences a more balanced improvement between economic efficiency and environmental impact. However, the absolute environmental impact (in terms of marginal emission reduction) is higher in S4 due to its larger size and thus larger potential for emission reduction.

Of all the scenarios, the implementation of S4 with industrial waste heat presents a promising balance between cost-efficiency and environmental impact. It achieves the highest marginal emission reduction of 83.5%, equating to a total of 38,000 tCO_2e offset, and concurrently exhibits a significant reduction in LCOH to 10.98 p/kWh. The implementation of S4 thereby covers 89.5% of Grimethorpe, Houghton, and Royston's heat demand while only producing 7,530 tCO_2e. It is notable that the adoption of S4 could contribute to a significant 21.4% reduction in CO_2 emissions across the entire Barnsley metropolitan district [89]

6.6.4 Sensitivity Analysis

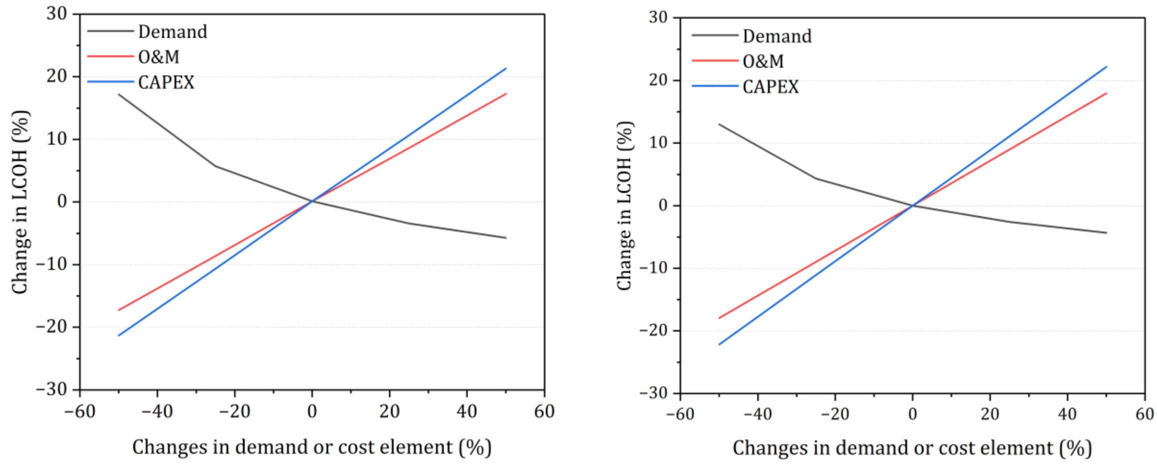


***Figure 9**. Sensitivity analysis of capital, O&M costs, and demand for scenario S1 without (left) and S1WI with (right) industrial waste heat.*

Figure 9 presents a sensitivity analysis of the capital costs, O&M costs, and demand for Scenarios S1 and S1WI. Specifically, the results demonstrate that a 50% reduction in total heat demand leads to an increase in LCOH by approximately 17% for networks without waste heat, and 13% for networks with additional industrial waste heat. Conversely, a 50% increase in total heat demand results in a decrease in LCOH by 5% without industrial waste heat, and 3.5% with industrial waste heat.

Additionally, the analysis reveals that when capital costs and O&M costs increase or decrease by 50%, the overall LCOH follows suit, with a corresponding change of 22% and 17% for networks without industrial waste heat, and similar results for networks with industrial waste heat, respectively.

Furthermore, the sensitivity analysis of the LCOH for networks with industrial waste heat indicates that incorporating waste heat from industries can help reduce the sensitivity of the LCOH to changes in heat demand. This finding implies that the integration of industrial waste heat as an energy source can enhance the resilience of the DHN, making it more stable and adaptable to variations in heat demand, and facilitating expansions or improvements in building insulation.

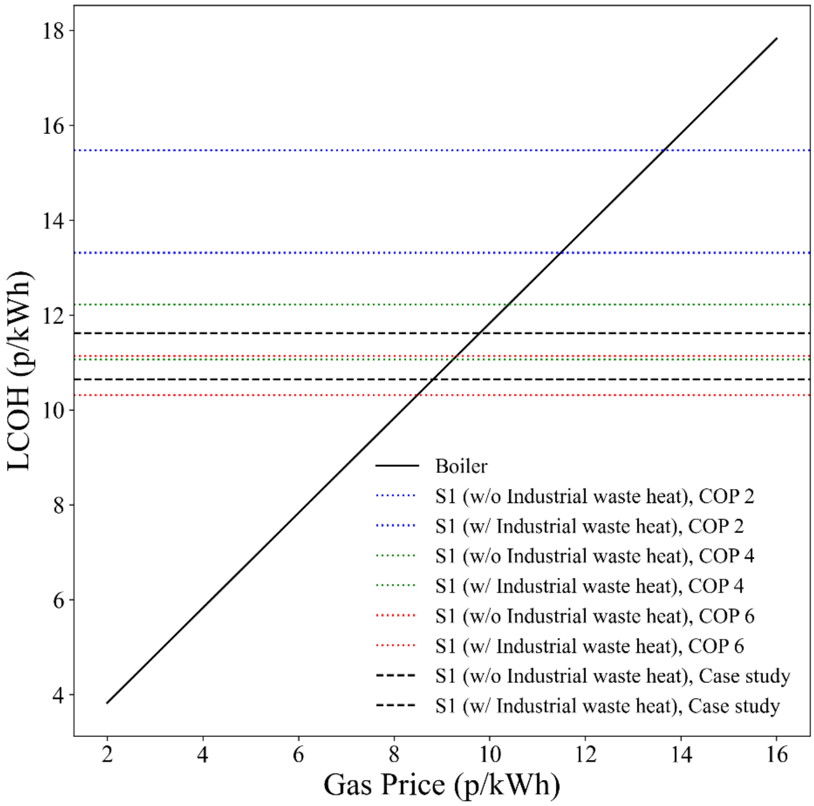


***Figure 10**. LCOH of network or boilers when changing COP or gas prices.*

Figure 10 shows the LCOH in relation to varying gas prices and COP of the HP. The figure shows the intersection S1 and S1WI. This intersection point represents the gas price at which the DHN becomes economically viable compared to boilers. Networks with industrial waste heat become competitive with boilers at a gas price of 8.7 p/kWh, whereas networks without industrial waste heat become competitive at a slightly higher price of 9.8 p/kWh. It is worth noting that natural gas prices have exhibited significant fluctuations ranging from 4.4 to 27.3p/kWh in 2021 [90]. Despite this volatility, district heating networks provide a stable LCOH.

6.6.5 Comparison of Heating Systems

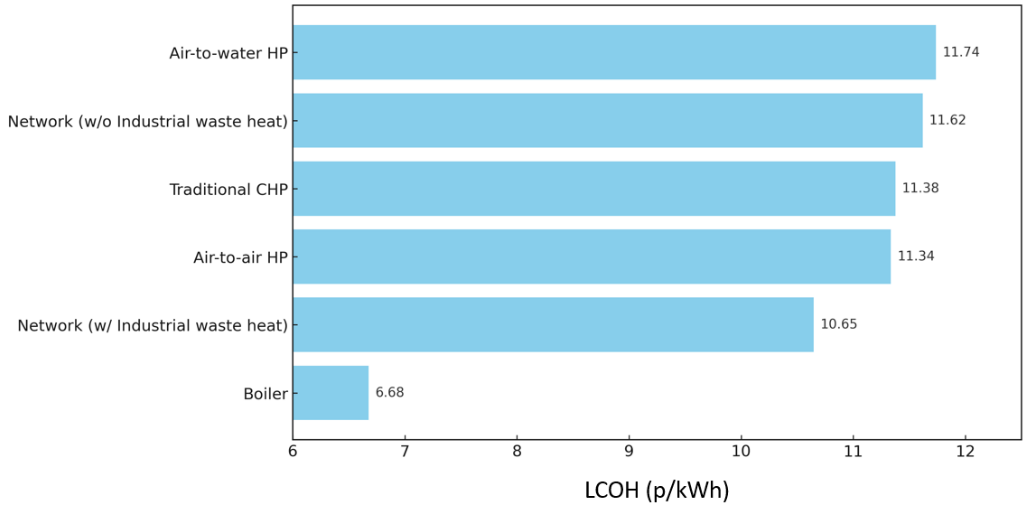


Figure 11. *Comparison of various heating systems and S4 [91].*

Figure 11 shows the LCOH, articulated in pence per kilowatt-hour (p/kWh), for a diverse set of heating systems. These systems span a conventional boiler, an air-to-air heat pump (HP), an air-to-water HP, a traditional CHP heat network, a DHN without industrial waste heat, and a DHN integrated with industrial waste heat.

While traditional boiler systems boast the most economical LCOH at 6.68 p/kWh, their environmental repercussions are significant. Transitioning to renewables, both the air-to-air and air-to-water heat pumps log LCOH values of 11.34 p/kWh and 11.74 p/kWh respectively. Notably, the traditional CHP heat network stands at 11.38 p/kWh, positioning itself competitively within the renewable technologies.

However, DHNs, as seen, shows environmental benefits with cost efficiency. Specifically, the mine water network with industrial waste heat registers an LCOH of 10.65 p/kWh, underscoring its economic promise and better performance compared to other renewable sources.

6.7 Discussion & Conclusion

6.7.1 Discussion

This research has highlighted the relationship between network size and DHN efficiency, with larger networks outperforming smaller ones, primarily due to reduced transient heat loss. Meanwhile, integrating industrial waste heat into the network offers substantial benefits but with trade-offs, moderately reducing overall efficiency due to increased thermal losses and additional piping. However, it significantly enhances the network's capacity to meet heat demand. This increased capacity is beneficial enough to outweigh the minor loss in efficiency. The assumption that "heat loss to the surroundings is one-dimensional" simplifies our understanding of these thermal losses. This foundational perspective on how these losses impact overall system efficiency influences the results, potentially underestimating multi-dimensional heat loss effects.

The value of waste heat extends beyond improved performance; it also helps make DHNs more cost-effective by reducing LCOH values. These LCOH values should, however, be interpreted as representing an unsubsidised case, as the effect of any government capital grant support was not explicitly modelled here. This cost-efficiency trade-off highlights the importance of waste heat as a key resource. It's important to consider the differing impacts of network size and waste heat integration on DHN system efficiency during design.

A comprehensive DHN model should factor in potential fluctuations in heat demand and cost, refining our understanding and optimisation of DHN efficiency, performance, and cost-effectiveness. The analysis of DHNs also requires understanding the interplay between economic and environmental factors. As networks expand, the balance between cost and emissions reduction becomes paramount. Larger networks, while more efficient, can incur higher operating costs, especially when integrating waste heat. Yet, they offer a significant advantage: greater reduction in emissions.

Certain scenarios, such as S1WI and S4WI, stand out due to their low LCOH and high emissions reduction capabilities. In fact, Scenario S4, when implemented with industrial waste heat, can substantially contribute to regional decarbonisation goals. DHNs also enhance energy security and sustainability, offering stable LCOH despite natural gas price fluctuations, thus reducing reliance on fossil fuels.

The viability of large-scale networks depends on location, with regions like Barnsley well-positioned for geothermal mine water heating. Despite some demand not being met, particularly in larger networks, boreholes didn't exceed their heat extraction limits. The average household energy consumption aligns with the demand model results, indicating accuracy.

Predicting non-domestic heat demand profiles is challenging due to factors like business type, activities, opening hours, staff numbers, and building characteristics. More accurate profiles could be obtained with more building categories, but this increases complexity and may impact computational time. Supply temperature changes and pipe sizing optimisation can ensure that all heat demand is supplied and will be present in future work.

Sensitivity analysis reveals that heat demand fluctuations impact LCOH more than cost changes. Anticipated shifts in demand patterns due to factors like climate change, population growth, and changing energy usage habits are thus crucial for long-term DHN management. On the other hand, integrating waste heat can reduce the impact of demand fluctuations on LCOH, making DHNs more adaptable and stable.

Alternative heating solutions, such as ASHPs, compete with DHNs. ASHPs offer high energy efficiency but suffer performance losses in colder periods due to varying efficiency with ambient temperature. In contrast, DHNs maintain stable efficiency by using waste heat and can offer more reliable heat delivery with advanced storage technologies. Future work will look more closely at the comparison between DHN and ASHPs.

6.7.2 Conclusion

In the presented research, an in-depth analysis of District Heating Networks (DHNs) was executed, focusing on the integration of non-traditional heat sources, specifically mine water and industrial waste heat. Utilising a refined network dynamics simulation model with water front functionality, the investigation for Barnsley, UK yielded the following key results:

- With the expansion of the network, a clear trend in heat generation, demand, and supply emerged. Without industrial waste heat, demand satisfaction decreased from 99.2% in Scenario S1 to 87.9% in Scenario S4.
- The integration of industrial waste heat resulted in a 7.5% reduction in the carbon factor by Scenario S4WI. Additionally, a transition from Scenario S1 to S1WI led to a 30.2% decrease in fuel costs, equating to savings of £21.6 million.
- The Net Present Costs (NPC) for Scenario S1WI was determined to be £284.46 million, indicating an advantage over the £325.36 million of Scenario S1.
- A significant 5.56% reduction in the Levelized Cost of Heat (LCOH) was observed by Scenario S4. In comparison to traditional boiler systems, which have

an LCOH of 6.68 p/kWh, the traditional CHP DHN, at 11.38 p/kWh, showcased competitive potential. More notably, upon the integration of waste heat, the LCOH for the network was further reduced to 10.65 p/kWh, reinforcing its economic and environmental appeal.

- Despite the complexities associated with integrating multiple heat sources, Scenario S4WI maintained a thermal efficiency of approximately 87%, even accounting for increased thermal losses.
- A critical techno-economic breakpoint was identified at a gas price of 8.7 p/kWh, emphasizing the conditions under which DHNs, utilizing mine water and industrial waste heat, can economically compete with traditional boilers.
- From an environmental standpoint, Scenario S4WI achieved a marginal emission reduction of 83.5%, showcasing the potential of the proposed DHN systems to significantly reduce regional carbon emissions, especially in areas characterised by low heat density and outdated infrastructure.

In summary, this research offers technical insights into the viability of low-carbon DHNs in the UK, with particular relevance to regions with a rich mining history such as Barnsley. As the UK progresses towards its 2050 net-zero GHG emission targets, the findings from this study provide a valuable reference for local authorities and policy makers. For future work it is recommended to perform sensitivity analysis or optimisation of the additional pipe length and waste heat temperature to achieve peak thermal efficiency and reduce heat loss, additionally to undertake a more detailed comparative analysis with alternative heating systems.

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6.9 Appendix

6.9.1 Selection and classification of demand

The following method was used within each of the three locations:

1) The postcodes within a selected village were identified using PostcodebyAddress [92].
2) The total number of properties within the village was identified by searching the EPC database for the identified postcodes [93]. An assumption was made that all the houses within each postcode had either been sold, rented, or had an EPC conducted since 2008 when the database began.
3) The villages were split into smaller postcode segments to aggregate the houses into reduced village sectors to enhance spatial accuracy. The sectors vary in size depending on the number of postcodes aggregated to obtain 200-300 houses per DC.
4) The process was repeated for each of the villages independently.

The following method was used to identify the any commercial demands within the specified region:

1) The EPC database [119] was searched for identified postcodes regions S72, S71 [93]. Both DEC and NON-DEC were obtained from the EPC database. Commercial buildings are required to have an EPC; therefore, all commercial buildings are assumed to be within the database.
2) The postcode sectors which were identified as not surrounding the 8 selected villages were removed.
3) The following categories were removed from the category type within the EPC database: a. Pubs b. Pharmacies, surgeries, and clinics. c. Retail – due to them mostly being local corner shops. d. Workshop businesses. e. Warehouse and

General Industry. 4) The removal of duplicate building reference numbers and addresses was completed to eliminate any duplication.

6.9.2 Calculation of Nusselt's number

Reynolds number is calculated to show which regime the flow of water in the pipe, described by:

$$Re = (4\dot{m})((\pi(d_{in} * 1 \times 10^{-3})(\nu * 1 \times 10^{-6})\rho_w)^{-1}$$

where $\dot{m}$ is the mass flowrate, Re is Reynolds number, d_{in} is the diameter of the pipe, ν is the kinematic viscosity, and ρ_w is the density of water.

Relative roughness is the amount of surface roughness that exists within the pipe and calculated by dividing the absolute roughness by the diameter of the pipe. The absolute roughness is pre-determined when sizing the pipes described by:

$$\varepsilon_R = \varepsilon_A {d_{in}}^{-1}$$

where $\varepsilon_{relative}$ is the relative roughness, $\varepsilon_{Absolute}$ is the absolute roughness and d_{in} is the diameter of the inlet pipework.

The friction factor is calculated by the Darcy-Welsbach Equation [94] and is used for calculating the friction loss in a pipe, the value is calculated by two methods dependent on the flow regime. Laminar flow is described by:

$$\mu = 64Re^{-1}$$

where μ is the friction factor, and Re is Reynolds number.

Turbulent flow is described by:

$$\mu = (\frac{1}{-1.8 \log_{10} 6.9 * Re^{-1} + (\frac{\varepsilon_{relative}}{3.7})^{1.11}})^2$$

where μ is the friction factor, and Re is Reynolds number, and $\varepsilon_{relative}$ is the relative roughness.

The Prandtl Number (Pr) approximates the ratio of momentum diffusivity and thermal diffusivity, it is described by [95]:

$$Pr = \nu \cdot {\alpha_{diff}}^{-1}$$

where α_{diff} is the water's diffusivity coefficient.

Nusselt's Number is the ratio of convective to conductive heat transfer across a boundary surface, this is because when a fluid is motionless is conduction and convection if it involves motion. The heat flux for conduction is calculated by Fourier's law of conduction, while for convective it is calculated using Newton's Law. The ratio of these two laws gives the Nusselt's number, due to the different flow regimes the calculations are calculated differently as outlined below [96]. For laminar flow (Re <= 2,300) Nusselt's number is calculated by:

$$Nu = 3.66 + \left(\frac{0.0668RePr(2r_{in}(L_{route}{}^{-1})}{1 + 0.04(RePr(2r_{in}(L_{route}{}^{-1}))^{\frac{2}{3}})}\right)$$

where r_{in} is the radius of the pipe, L_{route} the length and Nu is Nusselt's number, Pr is Prantl's number, and Re is Reynolds number.

While, for the turbulent regime within the model this equation is used for the case of Re> 2,300:.

$$Nu = 3.66 + \left(\frac{\mu 8^{-1}(Re - 1000)Pr}{1 + 12.7(\mu 8^{-1})^{0.5}(Pr^{\frac{2}{3}} - 1)}\right)$$

where Nu is Nusselt's number, μ is the friction factor, and Re is Reynolds number, and Pr is Prantl's number.

6.9.3 Heat pump CAPEX

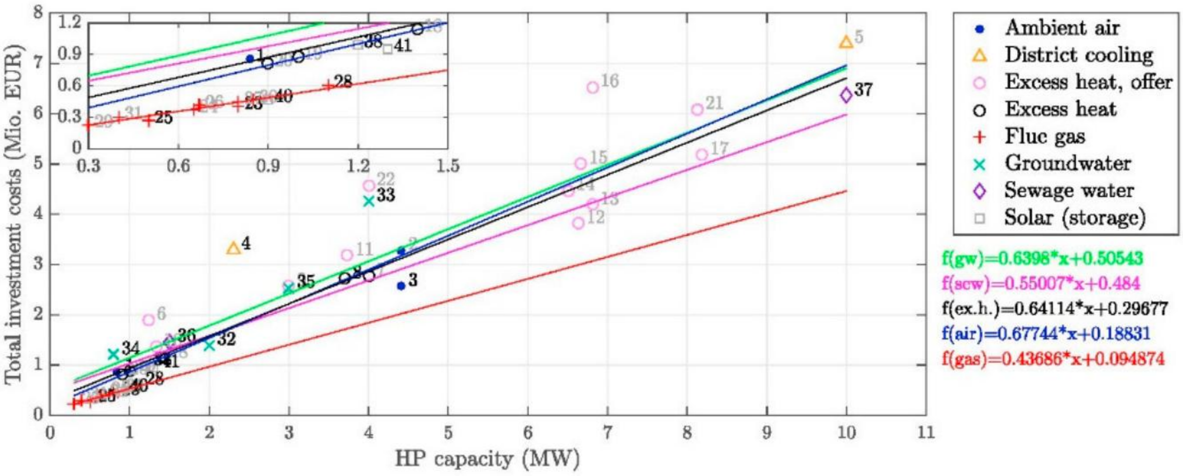

Figure 12. *Relationship of heat pump cost per MW.*

6.9.4 Selection of COP

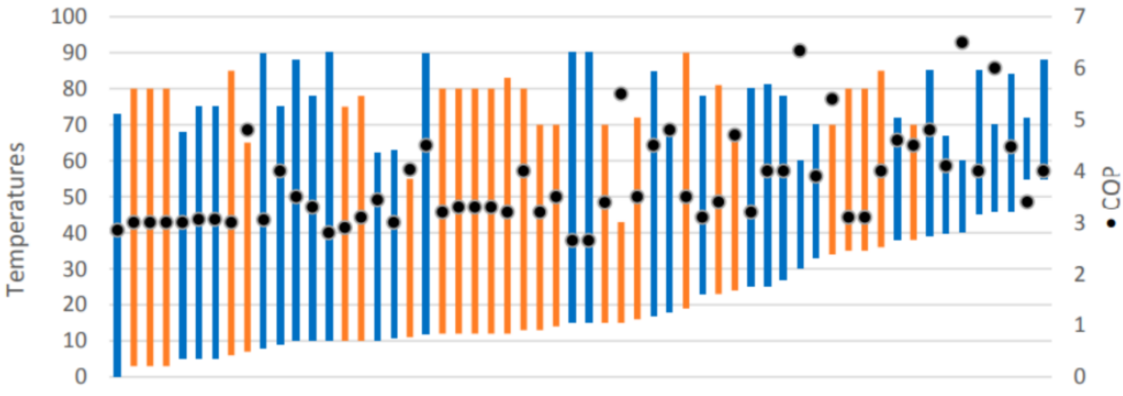

Figure 13. *Supply and return temperatures with associated COP.*

6.9.5 Pipe sizing

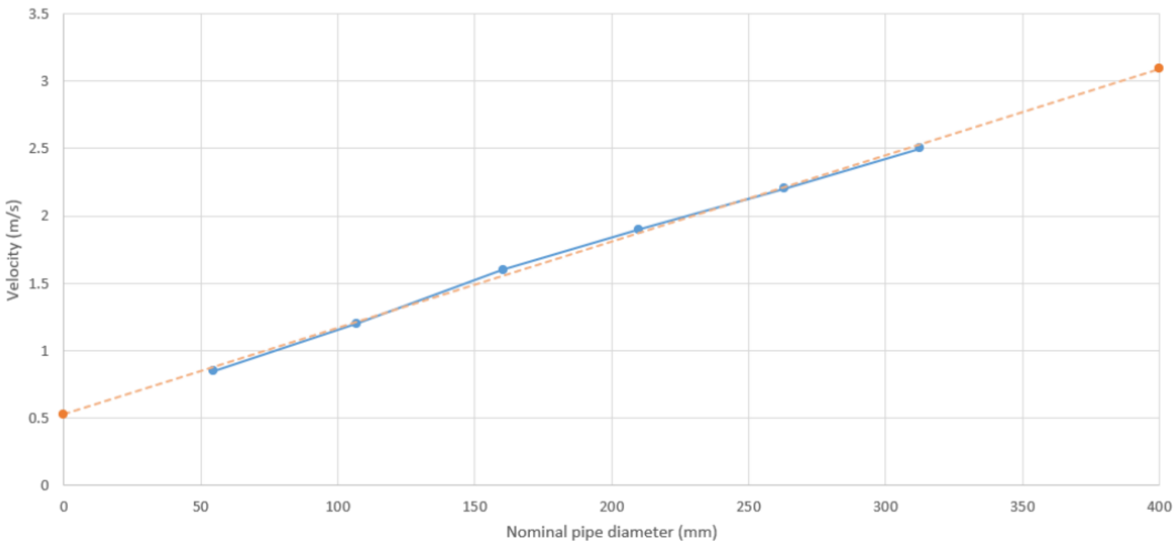

Figure 14. *Relationship of nominal pipe diameter and velocity of water.*

Chapter 7

Accelerating Residential Decarbonisation: How Stakeholder Decision-Making and Socio-Economic Dynamics Affect Multi-Decadal District Heating Network Expansion

7.1 Abstract

District heating networks (DHNs) are essential for decarbonising urban heating but face adoption barriers due to stakeholder complexities, infrastructure legacies, and consumer resistance. Existing models overlook the dynamic, iterative nature of infrastructure development and multi-stakeholder interactions. To address these limitations, this study develops an agent-based model (ABM) that continuously simulates DHN adoption and expansion. Unlike discrete optimisation approaches, this integrates evolving household decision-making, project developer strategies, and dynamic market conditions. Socio-economic factors, spatial dynamics, and temporal evolution are incorporated to provide a comprehensive understanding of DHN diffusion. The model projects that adoption in the studied urban area could reach 30.4 ± 2% of households by 2050. This highlights the substantial, but still incomplete, potential of DHNs to contribute to urban decarbonisation under the socio-technical conditions represented in the model. Heating bill savings range from 41.9% to 56.3%, while CO_2 emissions are reduced by 24.3% compared to existing gas heated systems. Through the quantification of temporal dynamics and multi-stakeholder interactions, this study offers insights for urban energy transition strategies. These findings can inform policies that accelerate DHN adoption, mitigate risks associated with large-scale infrastructure investments, and contribute to sustainable urban heating strategies aligned with international climate goals.

7.1.1 Keywords

District heat networks; Agent-based modelling; Urban energy transition; Socio-economic dynamics; infrastructure expansion

7.1.2 Nomenclature and terminology

Acronyms.

ABM	Agent-based Model
BMDHN	Blackburn Meadows District Heat Network
CAPEX	Capital Expenditure
CI	Confidence Interval
CO_2	Carbon Dioxide
DHN	District Heating Network
EPC	Energy Performance Certificate
GIS	Geographical Information Systems
KPI	Key Performance Indicator
LNG	Liquefied Natural Gas
OA	Output Area
OPEX	Operating Expenditure
PERT	Program Evaluation and Review Technique
PV	Photovoltaic
ROI	Return on Investment
TPB	Theory of Planned Behaviour

Symbols and Subscripts.

Symbol	Unit	Description
$a_i(t)$	years	Heating system age of household i at time t
$Adj(OA_i)$	-	Set of output areas adjacent to output area OA_i
$c_i(t)$	$\frac{£}{kg}$	Carbon cost at time t
$c_i^{heat}(t)$	$\frac{£}{kWh}$	Cost per unit of heat using existing heating system for household i at time t
$C_i(t)$	-	Normalised cost differential for adopting DHN for household i at time t
$C_{DHN,i}$	£	Capital cost of DHN installation for household i
$D_{gas}(t)$	kWh	Current gas consumption

$D_{gas,initial}$	kWh	Initial gas consumption
d_i	kWh	Annual energy demand
$d_{oa,i}$	kWh	Annual heating demand of household i in output area oa
$D_{acceptable}(O)$	days	Acceptable downtime based on ownership
D_{actual}	days	Actual installation downtime
e_{DHN}	$\frac{\text{kg}}{\text{kWh}}$	Emission factor for district heating
e_i	$\frac{\text{kg}}{\text{kWh}}$	Emission factor for the current heating system of household i
$E_{a,i}$	-	Encoded value for age of household i
$E_{DHN,i}$	$KgCO_2$	CO_2 emissions for household i
$E_{e,i}$	-	Encoded value for economic activity of household i
$E_{h,i}$	-	Encoded value for heating system of household i
E_i	$KgCO_2$	Annual CO_2 emissions for household i
$E_{p,i}$	-	Encoded value for property type of household i
f_c	-	Coefficient differentiating between connected and regular social circle peers, and perceived positive and negative savings.
F_{time}	-	Function representing improvement of installation quality over time
$gasPrice_{kWh}(t)$	$\frac{£}{\text{kWh}}$	Gas price per kWh at time t
$H_{oa,b}(t)$	-	Set of households using gas boilers in output area oa at time t
$I(\cdot)$	-	General indicator function (1 if condition is met, 0 otherwise)
$I_{built}(OA_i)$	-	Indicator function for DHN infrastructure in output area OA_i (1 if built, 0 otherwise)
$o_i(t)$	-	Opinion vector of household i at time t
$\bar{o}_{S_i}(t)$	-	Average opinion of peers within sphere of influence S_i at time t

O_t	-	Set of output areas where expansions have connected at time t
$OA_{optimal}(t)$	-	Optimal output areas based on conditions for initial DHN deployment
$P_{connect,i}(t)$	-	Probability of household connecting to the DHN
$p_i(t)$	$\frac{£}{\text{kWh}}$	Price per unit of energy at time t
$S_i(t)$	-	Savings ratio at time t comparing district heating costs to existing heating technology
$T_{peak}(O)$	days	Peak downtime based on ownership
$u_{i,oa}(t)$	$\frac{£}{\text{kWh}}$	Cost per unit of heat using the heat network for household i in output area oa at time t
$U_{economic,i}(t)$	-	Economic utility for household i at time t
$U_{environmental.i}(t)$	-	Environmental utility for household i at time t
$U_{hassle,i}(t)$	-	Hassle utility for household i at time t
$U_{social,i}(t)$	-	Social utility for household i at time t
$U_{total,i}(t)$	-	Total utility as a weighted combination of individual utility factors
x	-	Threshold probability for willingness to connect
β	-	Price elasticity parameter representing the responsiveness of gas prices to changes in gas consumption levels
γ	$days^{-1}$	Exponential decay factor representing the rate of improvement of installation quality over time
γ_i	-	Percentage subsidy for the capital cost of DHN installation for household i
$\delta_i(t)$	-	Influence on household i decision to adopt DHN at time t
$\Delta E(t)$	$kgCO_2$	Total emissions reduction achieved by DHN at time t
ϵ	-	Confidence bound within which households consider other opinions relevant

λ	-	Learning rate dictating the degree of opinion adjustment toward peer average
ω_{hassle}	-	Weighting for hassle utility factor
$\omega_{economic}$	-	Weighting for economic utility factor
Subscripts		
a		Age
b		Subset within an output area
e		Economic activity
h		Heating system
i		Index representing a specific household
oa		Index representing output area
OA_i		Specific output area
p		Property type
S_i		Sphere of influence for household i

7.2 Introduction

Heating and cooling constitute a significant share of global energy demand, with buildings responsible for 26% of global greenhouse gas emissions [1]. As nations work toward ambitious climate goals, district heating networks (DHNs) are increasingly recognised as a scalable, low-carbon alternative to traditional heating systems [2], offering up to a 69% reduction in emissions compared to existing gas heated systems [3] [4].

DHN adoption varies significantly across regions, influenced by policy frameworks, legacy infrastructure, and socio-economic conditions [5]. For example, in Northern Europe over 50% of houses in cities such as Copenhagen and Stockholm rely on DHNs [6]. This success is attributed due to strong policy support and the integration of diverse heat sources (e.g., industrial waste and large-scale heat pumps) [7]. Recent work by Lund et al. [8] on 4th Generation District Heating (4GDH) further emphasises how these advanced systems enable better utilisation of low-temperature renewable heat sources while providing heat supply with low grid losses, creating a framework for future sustainable expansions. Nevertheless, despite these benefits, barriers persist. Limitations such as inadequate policy support, complex stakeholder interactions, and outdated infrastructure hinder wider adoption [9] [10] [11]. Successful implementation demands a strategic balance between stakeholder investment, consumer adoption, and project management [12], while understanding the technological, economic, social, and institutional drivers is essential to accelerate DHN deployment and meet climate goals.

In regions like the UK and Germany, where DHN adoption has been slower, governments are intensifying efforts to expand DHNs as part of broader climate strategies [13] [14]. The UK, for instance, aims to increase DHN connections to cover 20% of total heat demand by 2050 [15], however, progress has been impeded by high upfront costs, fragmented policies, and consumer reluctance. Strategies such as mandatory connection policies for new developments and financial incentives in the form of regulatory mechanisms are being implemented [16]. Yet, convincing existing homeowners remains a significant challenge, particularly given the high upfront costs, complexity of retrofit, resistance to change, and perceived risks [17].

Socio-economic factors strongly shape household attitudes toward DHNs. Higher-income and more educated households are more likely to adopt DHNs, driven by greater environmental awareness and resources [18] [19], while lower-income households are often excluded from transitions to sustainable heating [20] [21] [22]. Policymakers must prioritize targeted strategies, including subsidies, low-cost financing, and community engagement, to ensure that DHNs benefit all demographics, aligning with broader goals of social and energy justice [23].

High upfront costs and the disruption associated with retrofitting homes for DHN connectivity consistently emerge as major barriers to adoption [24] [25] [26]. Although financial incentives exist to mitigate these barriers, their effectiveness across different socio-economic groups remains understudied, hindering the development of equitable policy measures [27]. Social dynamics and peer effects—such as house-to-house influence, social networks, and the diffusion of opinions—also play critical roles in shaping household decisions, as emphasized in the literature [28]. Positive spillover effects are observed in wider regional transitions; as cities witness successful DHN deployment in similar urban areas, this can accelerate adoption through peer influence. Such dynamics have been documented in multiple energy system transitions, including rooftop solar PV adoption and low-carbon transportation [29] [30]. Socio-demographic factors such as education and age play critical roles in shaping awareness and openness to adopting sustainable technologies [11] [31]. Education has been identified as a key driver of environmental awareness and pro-environmental attitudes, while age often serves as a proxy for generational differences in attitudes toward innovation and adoption of new technologies [32].

To explore these multifaceted transitions, researchers have turned to bottom-up complexity-based methodologies such as agent-based modelling (ABM) [24] [33] [34] [35] [36]. ABM is a stochastic, bottom-up computational approach simulating interactions among heterogeneous agents within spatial-temporal contexts, capturing emergent system dynamics arising from individual decision-making, this approach aligns with Lund et al.'s [8] concept of "smart thermal grids" within 4th Generation District Heating, which emphasizes the importance of consumer interaction, distributed intelligence, and flexible demand-side management within future energy systems. It accounts for deviations from purely economic decision-making by incorporating social, spatial, and temporal dimensions in a single framework. The validation of complex socio-technical ABMs presents unique challenges. Hansen et al. [32] highlight that such models often focus on exploratory analyses due to data and system complexities. Ghorbani et al. [21] emphasize that heterogeneity in behaviour and spatial dynamics further complicates validation, while Rai and Robinson [37] advocate partial calibration against observed trends instead of full replication. These perspectives are particularly relevant for emerging technologies, such as residential DHNs, where historical data may not reflect current or future dynamics.

This approach has been applied to several areas of energy system transitions, including micro-cogeneration [38], electric vehicle adoption [39], decentralized energy frameworks [40], and energy feedback in buildings [34]. In the specific context of district heating, several recent studies have acknowledged similar validation challenges. Busch et al. [35] focus on exploring emergent dynamics and stakeholder interactions rather than historical validation. Nava-Guerrero et al. [25] employ hypothetical scenarios to explore heat transitions, while Pagani et al. [36] emphasize the particular challenges of validating spatially and temporally dynamic systems in DHN planning, therefore ABMs exploring complex socio-technical transitions can adopt a ‘realist’ approach that focuses on understanding underlying mechanisms and scenario exploration rather than precise forecasting.

Several studies have applied ABM to DHN adoption and deployment. Busch et al, [35] modelled the emergence of city-wide DHNs, highlighting how local champions and different stakeholder bodies can drive network expansion. Nava Guerrero et al. [25] explored how community-led initiatives and participatory governance influence sustainable heating transitions, emphasizing that stakeholder buy-in and cooperation are crucial. Cowley et al. [33] and Chapter 6 examined how increasing the number of connected users affects network efficiency and demand, implicitly recognising that changing household uptake can impact supply-side decisions. While these studies acknowledge a range of stakeholders—from policymakers and community groups to network operators and consumers—they primarily examine these roles at a particular stage or assume relatively stable conditions. As a result, current ABM-based DHN studies have not captured how residential adoption patterns and developer expansion decisions co-evolve. Although the importance of multiple stakeholder groups is clear, there has been no assessment of the time-dependent feedback between households and project developers specifically for district heating. This limitation leaves a key gap in understanding how evolving consumer preferences and strategic responses from developers shape the long-term trajectory of DHN growth.

However, existing literature often fails to capture the dynamic, iterative nature of the infrastructure expansion process by also assuming a discrete growth patterns [41], or predetermined expansion [33]. This limitation is particularly noteworthy as Kuntuarova et al. [42] highlight the need for modelling approaches that can represent the temporal evolution of district heating systems. In these earlier studies, network expansion is frequently represented as a one-time or static process without adjustment to changing conditions or infrastructure built in a previous time step [33] [36]. This limits their ability to reflect the phased or cascading expansion timeline of a real project. While integrating Geographical Information Systems (GIS) with ABM offers a common approach to identifying optimal routes or clusters [43], these existing approaches typically treat GIS inputs as fixed, applying them only once at the outset. For example, Pagani et al. [36] use GIS data to determine feasible expansion areas but do not update these spatial decisions as conditions change. Similarly, Unternährer et al. [43] employ GIS to cluster areas for geothermal integration but maintain a static spatial configuration over time. This static treatment does not capture how network layouts might adapt as socio-economic factors and policy contexts evolve. Chappin and Dijkema (2008) propose a more sophisticated framework that incorporates spatial-temporal dynamics and agent heterogeneity, addressing these gaps [44]. Their case studies, in the power sector and the global liquefied natural gas (LNG) market, underscore the importance of integrating strategic planning and supply-side decision-making into energy infrastructure transitions. This is an approach that is not apparent in DHN literature.

In addition to these considerations, incorporating insights from behavioural economics, such as social learning, peer influence, and the Theory of Planned Behaviour (TPB) [28] [45] provides a more comprehensive understanding of how, when, and why communities decide to adopt DHNs. This social dimension is increasingly recognized as crucial, with Schweiger et al. [46] highlighting that current district energy modelling approaches focus primarily on technical and physical aspects, inadequately capturing the consumer behaviour and social dynamics that significantly influence adoption patterns. Models that integrate both consumer and project developer decision-making offer valuable perspectives on multi-stakeholder dynamics [31] [35] [44] [47].

This study focuses exclusively on DHNs supported by Heat Network Zoning, to explore adoption dynamics and network expansion. It does not incorporate competing low-carbon technologies, such as air-source heat pumps or hydrogen systems. The method introduces a spatial-temporal ABM that integrates dynamic network evolution, multi-stakeholder dynamics on both the supply and demand sides, spatial modelling with GIS data, and insights from behavioural economics and technology diffusion theories into a single framework. By accounting for real-world triggers that prompt decision-making, such as heating system failures on the demand side and network expansion decisions on the supply side [37] [48] [35], the model offers a practical representation of the objectives and behaviours of households and project developers in the DHN sector. This framework directly addresses several key research gaps identified in the literature review.

7.2.1 Research Gaps and Contributions

Building on the framework described above, this study addresses three critical gaps identified in recent literature:

- Dynamic Modelling of Residential-Developer Interactions: Existing literature acknowledges multiple stakeholder roles [45] [35] [49]. However, few studies have explicitly modelled the bi-directional interactions between residential adoption patterns and developer strategies, often relying on static or unidirectional assumptions. Recent advances in ABM, as highlighted by Shi et al. [50], using evolutionary game theory to model interactions and evolving behaviours under policy interventions, and Busch et al. [35], which models the emergence of city-wide heat networks, provide methodological inspiration for capturing these complex dynamics. This model builds on these methodologies, explicitly capturing mutual influences between evolving consumer preferences and strategic developer decisions, thereby providing a nuanced, realistic depiction of DHN growth trajectories.

- Integration of Social Dynamics in Adoption Modelling: While earlier studies established socio-economic influences on energy choices (e.g., Train [51]), limited literature explicitly integrates social learning, peer influence, and opinion dynamics into household adoption modelling for district heating. Recent work by Volpe et al. [52] demonstrates the capability of ABM in modelling building-to-building relationships within community frameworks, while Zeng et al. applies scenario-based policy exploration to understand how different policy portfolios influence technology adoption across scenarios. However, these approaches have not been fully applied to district heating networks. This study advances the existing understanding by explicitly integrating these social dynamics, identifying critical socio-economic characteristics such as age, education, and income, and examining their role in driving DHN adoption rates. The insights gained offer actionable guidance for policymakers seeking targeted interventions to accelerate residential DHN uptake [28] [31] [53].
- Iterative Simulation of Network Evolution: Existing literature often fails to capture the dynamic, iterative nature of the infrastructure expansion process by assuming discrete growth patterns [41], or predetermined expansion [33]. This limitation is particularly noteworthy as Kuntuarova et al. [42] highlight the need for modelling approaches that can represent the temporal evolution of district heating systems. In these earlier studies, network expansion is frequently represented as a one-time or static process without adjustment to changing conditions or infrastructure built in a previous time step [36]. This limits their ability to reflect the phased or cascading expansion timeline of a real project. Schweiger et al. [46] and Guelpa et al. [54] further emphasizes this gap, noting that current district energy modelling approaches focus primarily on technical and physical aspects, inadequately

capturing the social dynamics that significantly influence adoption patterns. Building upon these insights, our approach employs iterative, phased network growth integrated within an ABM framework. This enables simulation of spatial-temporal feedback loops and adaptive decision-making, providing a robust methodological advance in understanding the complex interplay between socio-economic, regulatory, and technological factors in district heating network expansion.

7.3 Methodology

An ABM was developed to capture the complex dynamics of DHN adoption and expansion, addressing critical gaps identified in the literature, with the following sections detailing the components of the model.

7.3.1 Model Framework

To ensure model reliability given the absence of suitable historical validation data, the model integrates multiple validation techniques consistent with ABM literature [32] [37] [38] [39] for example, technical parameters are benchmarked against engineering standards, and an established economic model used [33]. Household profiles are derived from census data and energy demand is calibrated using the Cambridge Housing Model [55]. Behavioural dynamics draw on established frameworks, including the DeGroot consensus and Hegselmann-Krause models [56] [57], with sensitivity analyses (Appendix Figures A2, A3) to examine the effect of the two main behavioural parameters that influence the household decision-making.

The ABM integrates both supply-side and demand-side dynamics, providing a comprehensive understanding of DHN development. Spatial data layers and GIS [58] are employed to capture local contexts in detail. The model also includes a dynamic gas tariff component and a project owner decision-making process, allowing it to reflect evolving market conditions and strategic planning considerations. While DHNs can utilise various low-carbon heat sources (e.g., waste heat, geothermal, biomass), this study focuses on network dynamics and adoption patterns rather than heat generation technologies. The model assumes sufficient heat supply is available at the required network temperature to meet demand, as supply-demand matching has been explored in previous work [33]. This simplification allows the focus on the key dynamics between residential adoption and network expansion decisions. Additionally, insights from behavioural economics and technology diffusion theories are incorporated to better understand household adoption patterns. Unlike earlier models that assume static, phased spatial and temporal growth, this framework simulates temporal dynamics by iteratively building the network over many expansions. In doing so, it enables the DHN to evolve organically as socio-economic, policy, and technical conditions change.

The two primary agent types are:

1. Household Agents: Represent individual households within each output area, capturing their socio-economic characteristics, heating system profiles, and decision-making processes regarding DHN adoption.
2. Project Developer Agents: Represent entities responsible for planning, implementing, and managing the DHN, including decisions on network expansion, financial viability, and strategic planning.

These agents interact within a spatially explicit environment influenced by census data, Energy Performance Certificate (EPC) information, and environmental factors (Figure 1).

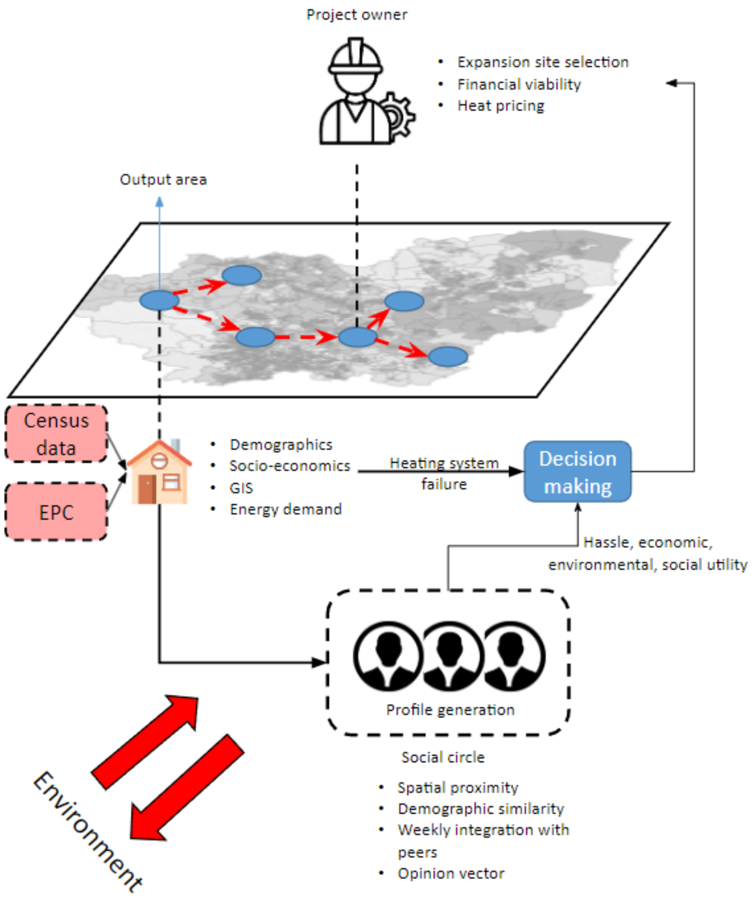

Figure 1: Framework of the ABM for DHN Adoption and Expansion

7.3.2 Household Agent Model

The household agent represents the diverse population of potential DHN adopters, the following section details profile generation, social learning dynamics, heating system lifecycle, and the decision-making process.

7.3.2.1 Profile Generation

Individual household profiles were generated using a stratified sampling approach based on output area census data, shown in Figure 2. It integrates city-wide census [59], EPC [60], and GIS data to create output area–specific databases. Key attributes include education, occupation, property type, tenure, economic activity, age, and heating system type. The household heating system types are categorised into four categories, district heating heat pumps, electric, and gas boiler, with additional systems (representing 1-3% of households per output area) aggregated into these main types. While the model tracks all heating system types in its calculations, results are presented in these aggregated categories. The focus is on transitioning gas-heated households and those without central heating to DHN, as these present the greatest carbon reduction opportunity. Households with existing low-carbon heating (heat pumps, electric, two or more types of renewable energy) excluded from transitions due to their existing low-carbon status.

During the iteration process, each assigned variable was removed from the database after each profile generation to ensure diversity and representation of that output area. When specific combinations were no longer available, the nearest available variables were assigned. This mostly reflected the socio-economic diversity while maintaining statistical integrity. Detailed equations are provided in the supplementary information, Appendix 7.8.4.1.

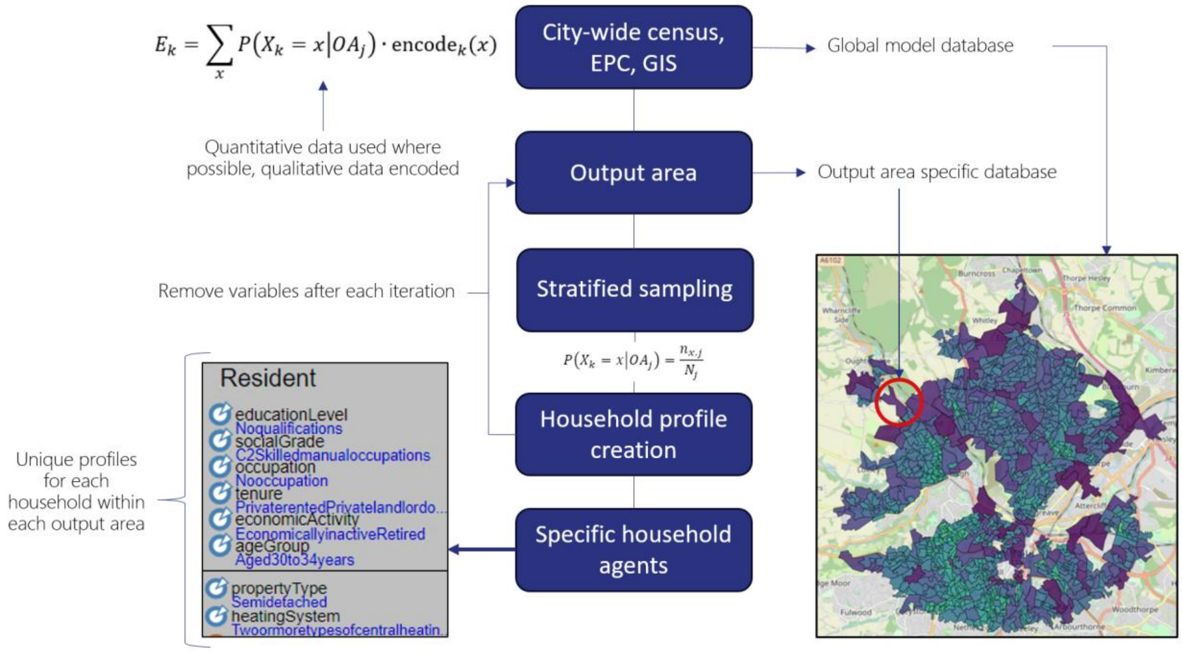

Figure 2: Profile Generation Process for Household Agents.

7.3.2.2 Social Learning

The social learning model simulates the influence of social dynamics on household decisions, utilizing elements from established theories such as the DeGroot consensus model and the Hegselmann-Krause model [56] [57], to capture how social and economic factors affect household opinion dynamics. Households' social circles are constructed based on spatial proximity and demographic similarity. The initial opinion of households on DHN adoption is determined by education and age, which are widely recognized as key socio-demographic factors influencing openness to sustainable energy technologies [11] [37]. Education serves as a proxy for environmental awareness, while age reflects generational attitudes toward innovation. Income and dwelling size, though influential, are incorporated later in the model through economic and hassle utility functions, which more accurately represent their impact on adoption decisions[32].

The initial opinion of a household on DHN adoption is modelled using a logistic function:

$$o_i(0) = \frac{1}{1 + e^{-(E_{a,i} \cdot E_{e,i})}} \quad \text{Eq. 1}$$

It defines the household's initial predisposition toward DHN adoption, while Equation 2 defines a time-varying economic influence factor used in subsequent decision updates. The influence factor $\delta_i(t)$ on household i's decision compares the delivery price of heat from the DHN to the annual cost of the households current heating system:

$$\delta_i(t) = \frac{u_{i,oa}(t)}{c_i^{heat}(t)} \quad \text{Eq. 2}$$

where $u_{i,oa}(t)$ is the delivery price per unit of heat in $\frac{£}{kWh}$ using the DHN, calculated by Equation A12 in Appendix 7.8.4.3. $c_i^{heat}(t)$ is the cost per unit of heat in $\frac{£}{kWh}$ using the households existing heating technology (e.g. gas boiler, electric, heat pump, oil, solid fuel, and households without central heating), details of these calculations provided in Appendix 7.8.1. This comparison allows households to make decisions based on readily available cost information, such as their heating bills, and the price set by the developer. The annualized cost basis ensures that household decisions reflect short-term economic considerations rather than lifetime averages, and the calculation is tailored to the specific heat demand of each household. If $u_{i,oa}(t) < c_i^{heat}(t)$, then $\delta_i(t) > 1$, indicating a positive influence toward adoption; otherwise, the influence is negative.

Over time, a household's opinion is influenced by interactions with both connected and unconnected peers, using a combination from the DeGroot consensus model and the Hegelsmann-Krause social learning model [56] [57], with an added consideration for savings experienced by connected peers. The opinion update for household i at time $t + 1$ is given by:

$$o_i(t+1) = o_i(t) + \lambda \cdot f_c\left(\bar{o}_{S_i}(t) - o_i(t)\right) \cdot I\left(\left|\left|\bar{o}_{S_i}(t) - o_i(t)\right|\right| \leq \epsilon\right) \quad \text{Eq. 3}$$

where λ is the learning rate, f_c is the influence factor, dependant on the peer's connection status and savings. $\bar{O}_{S_i}(t)$ is the average opinion of peers within influence circle S_i. I is the indicator function, equal to 1 if $\left|\bar{o}_{S_i}(t) - o_i(t)\right| \leq \epsilon$, and 0 otherwise, ϵ is the confidence bound within which the household considers other opinion relevant. The influence factor f_c differentiates peer types:

$$f_c = \begin{cases} \delta_i & \text{if interacting with a connected peer with positive savings} \\ -\delta_i & \text{if interacting with a connected peer with negative savings} \\ 1 & \text{otherwise} \end{cases}$$

Here, δ_i strengthens the influence of connected peers with positive savings leading to a positive opinion shift. For connected peers with negative savings, the influence is negative causing a negative opinion shift. Unconnected peers have a neutral influence.

Figure 3 illustrates the change in a household's opinion on DHN adoption after one interaction:

1. Initial State: The household's opinion, $o_i(t)$ is influenced by peers within its confidence interval, ϵ.
2. Opinion Update: Following interactions, the household's opinion shifts due to the influence of all peers, so does the confidence interval affecting future peer influence.

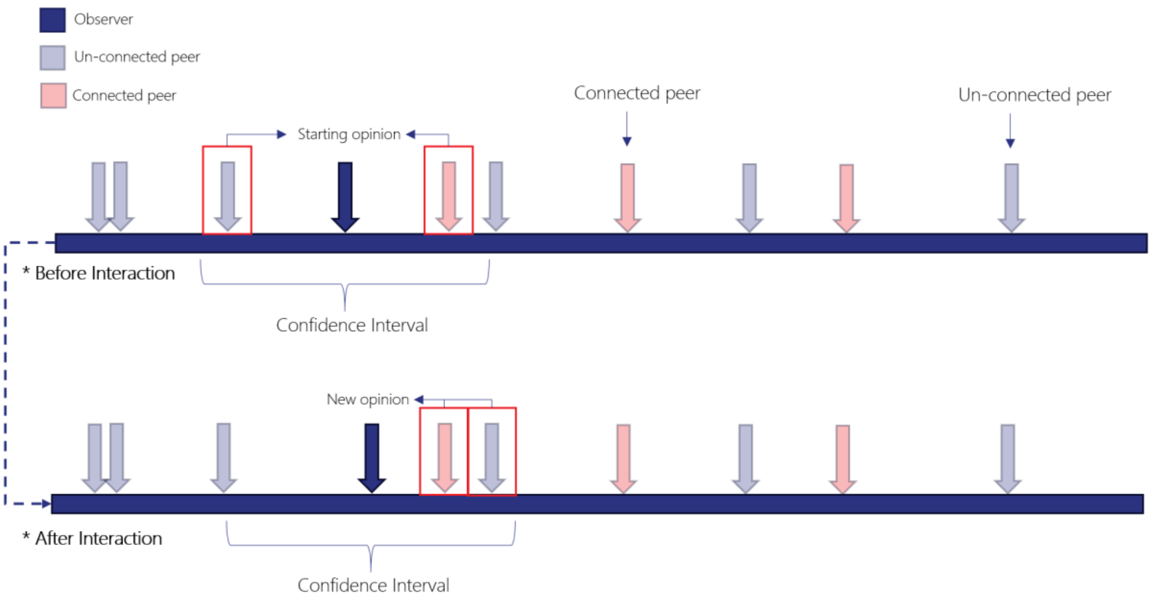

Figure 3: Social Learning and Opinion Dynamics in DHN Adoption

7.3.2.3 Heating System Lifecycle

The adoption of new heating technology is often prompted by the failure or imminent breakdown of existing systems. Each household is assigned an initial heating system age $a_i(0)$ drawn from a triangular distribution representing typical system ages in the area. The projected failure age f_i is determined based on a probability distribution reflecting real-world boiler lifespans. Additionally, each household has a random failure chance rf_i, using a Program Evaluation and Review Technique (PERT) distribution [61], capturing the uncertainty in heating system failures. Figure 4 illustrates the state transitions of the heating system lifecycle within the model.

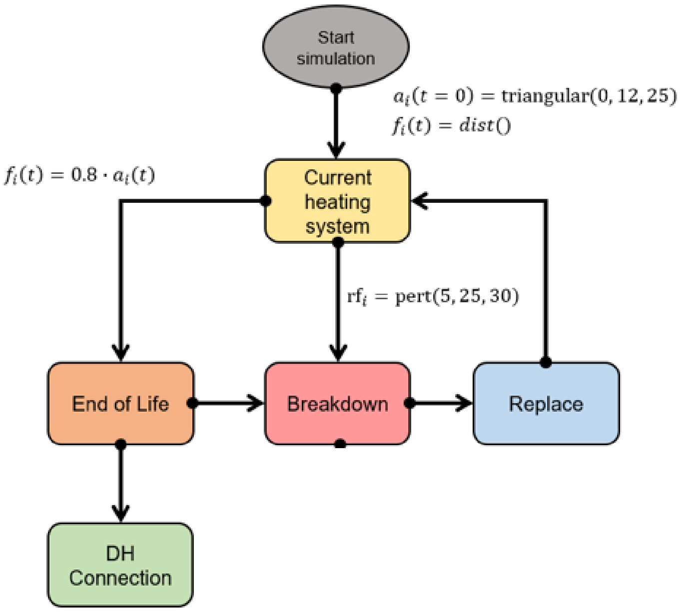

Figure 4: Heating system decision-making lifecycle.

This modelling approach captures the critical role of heating system lifecycles in influencing DHN adoption decisions [62] [37].

7.3.2.4 Decision-Making Process

The household decision-making process employs a multi-attribute utility framework, integrating economic, environmental, social, and hassle factors to evaluate the overall utility of adopting the DHN. This approach aligns with common practices in decision-making models for energy adoption [63] [32], providing a comprehensive assessment of the factors influencing household choices. At each time step t, the decision-making algorithm is triggered, allowing households to reassess their adoption decisions based on the most recent information and conditions. This iterative process reflects the dynamic nature of adoption behaviour and ensures that the model accurately captures the temporal evolution of household preferences and external influences.

At each timestep t, households calculate their utility for adopting the DHN based on four components, $U_{hassle,i}(t)$, $U_{economic,i}(\text{t})$, $U_{environmental,i}(t)$, and $U_{social,i}(t)$.

The total utility $U_{total,i}(t)$ for household i is computed as a weighted sum:

$$U_{total,i}(t) = \omega_{hassle} \cdot U_{hassle,}(t) + \omega_{economic} \cdot U_{economic,i}(t) + \omega_{environmental} \cdot U_{environmental,i}(t) + \omega_{social} \cdot U_{social,i}(t) \quad \text{Eq. 4}$$

where ω_{hassle}, $\omega_{economic}$, $\omega_{environmental}$, ω_{social} are weightings, representing the importance of each utility component. The utility terms are dimensionless.

The probability that household i will adopt the DHN at time t is calculated using a logistic function:

$$P_{connect,i}(t) = \frac{1}{1 + e^{-U_{total,i}(t)}} \quad \text{Eq. 5}$$

This ensures $P_{connect}$ remains within the probabilistic range [0, 1].

Hassle utility $U_{hassle,i}(t)$ quantifies the difficulty and inconvenience associated with adoption for each household i:

$$U_{hassle,i}(t) = 1 - \left(E_{p,i} \cdot E_{h,i}\right) \quad \text{Eq. 6}$$

Economic utility $U_{economic,i}(\mathrm{t})$ assesses the financial impact of adoption:

$$U_{economic,i}(\mathrm{t}) = E_{e,i} \cdot S_i(t) \cdot \left(1 - C_i(t)\right) \quad \text{Eq. 7}$$

where $E_{p,i}$, $E_{h,i}$ and $E_{e,i}$ represent the encoded values for the property type, heating system, and economic activity, respectively, $S_i(t)$ is the savings ratio at time t comparing DHN costs to the existing heating costs, $C_i(t)$ is the normalised cost differential for adoption:

$$C_i(t) = \frac{\gamma_i \cdot C_{DHN,i}}{\max_{i\epsilon I_{oa}}\left(s_i \cdot C_{DHN,i}\right)} \quad \text{Eq. 8}$$

where γ_i is the subsidy percentage, $C_{DHN,i}$ is the capital cost, I_{oa} is the set of households in output area oa, s_i is any subsidy for capital cost applied.

The savings ratio $S_{i,t}$ is calculated as:

$$S_i(t) = p_i(t) \cdot d_i + (e_i \cdot c_i(t) \cdot d_i) - (u_{i,oa}(t) \cdot d_i) \quad \text{Eq. 9}$$

where $p_i(t)$ is the price per unit of energy in $\frac{£}{kWh}$, d_i is annual energy demand in MWh, e_i is the emission factor in $\frac{kg}{kWh}$, $c_i(t)$ is the carbon cost in $\frac{£}{kg}$, $u_{i,oa}$ is the delivery heat price of the network in $\frac{£}{kWh}$.

Environmental utility $U_{environmental,i}(t)$ evaluates $\mathrm{CO_2}$ emissions reduction benefits:

$$U_{environmental,i}(t) = \left(E_{p,i} \cdot E_{h,i}\right) + \frac{d_i \cdot e_i - d_i \cdot e_{DHN}}{\max_{i\epsilon I_{oa}}(d_i \cdot e_i - d_i \cdot e_{DHN})} \quad \text{Eq. 10}$$

where e_{DHN} is the DHN emission factor in $\frac{kg}{kWh}$.

Social utility $U_{social,i}(t)$ reflects age and opinion influence:

$$U_{social,i}(t) = E_{a,i} \cdot o_i(t) \quad \text{Eq. 11}$$

where $E_{a,i}$ is the encoded age value and $o_i(t)$ is the opinion of the household at time t.

Installation downtime impacts adoption decisions. Acceptable downtime $D_{\text{acceptable}}(O)$ is:

$$D_{\text{acceptable}}(O) = \text{Triangular}\left(0, 90, T_{peak}(O)\right) \quad \text{Eq. 12}$$

with:

$$T_{peak}(O) = \begin{cases} 70, & \text{if } O = \text{Landlord} \\ 50, & \text{if } O = \text{Owner} - \text{occupied} \end{cases}$$

Actual installation downtime D_{actual} considers improvements over time:

$$D_{\text{actual}} = \text{Triangular}(7 \cdot F_{time}, (90 + 10 \cdot U_{hassle}) \cdot F_{time}, (30 + 10 \cdot U_{hassle}) \cdot F_{time}) \quad \text{Eq. 13}$$

where:

$$F_{time} = \max(0.5, e^{-\gamma \cdot t}) \quad \text{Eq. 14}$$

And γ represents the rate of installation quality improvement.

7.3.3 Project Developer

The Project Owner agent assesses financial viability, technical feasibility, and household engagement for DHN expansion over time.

The initial site selection sets the trajectory for future network growth. The initial expansion O_o is determined either based on strategic criteria or fixed at a specific location:

$$O_o = OA_{optimal}(t) \quad \text{Eq. 15}$$

where $OA_{optimal}$ represents the output area based on optimal conditions for initial DHN deployment.

Subsequent expansions are required to be adjacent to existing network segments, guaranteeing that each new expansion is directly connected to an existing segment:

$$O_t = OA_j | \exists OA_i \in O_{t-1}, OA_j \in Adj(OA_i) \text{ and } I_{built}(OA_i) = 1 \quad \text{Eq. 16}$$

where $Adj(OA_i)$ represents the set of output areas adjacent to OA_i, and $I_{built}(OA_i) = 1$ indicates that infrastructure exists.Within this expansion framework, the project developer must evaluate and constrain household connections, thus, household i is eligible to connect to the DHN if the following conditions are met:

The household has a high opinion of the DHN ($o_i \geq 0.75$), or all the following conditions are satisfied:

1. The household's heating system is not already compatible ($E_{h_i} \neq 0$)
2. The property type is suitable for connection ($E_{p_i} \neq 0$)
3. The household's probability of connecting exceeds the threshold ($P_{connect,i}(t) \geq x$)
4. There is a positive emissions reduction benefit ($d_i \cdot e_i - d_i \cdot e_{DHN} > 0$)
5. There is a perceived acceptable Installation time by the household
6. Heating system has broken down or is in end of life

Eligibility of household i for connection is determined by:

$$C_i = (I_{built} = 1) \wedge \left[(o_i \geq 0.75) \vee \left(E_{h_i} \neq 0 \wedge E_{p_i} \neq 0 \wedge \left(P_{connect,i}(t) \geq x\right) \wedge (d_i \cdot e_i - d_i \cdot e_{DHN} > 0)\right)\right] \quad \text{Eq. 17}$$

where $I_{built} = 1$ indicates DHN infrastructure in the households output area.

Project owners integrate heating system lifecycles into expansion decisions through simulated information flow from homeowners to installers to developers. This approach enables strategic targeting of areas with imminent heating system replacements and favourable community sentiment. The evaluation process incorporates technical feasibility, economic viability, and social factors, resulting in a composite score for each potential expansion area. The optimal expansion area is selected based on this assessment. Detailed equations are provided in the supplementary information, Appendix 7.8.4.2.

7.3.4 Economic, Environmental and Market Dynamics

- All technical parameters informing the economic evaluation—including network pressure losses, pumping energy consumption, and thermal losses—are calculated using the validated methodology from Cowley et al. [33] , where further details and full mathematical formulations can be found. This previous work provides the basis of calculation for the economic assessment in which: Pressure losses and pumping energy requirements are determined using an established hydraulic model (e.g., Darcy-Weisbach).

- Thermal losses are computed with a one-dimensional heat transfer model that accounts for pipe geometry, insulation properties, ground conditions, and fluid thermodynamics.
- Temperature dynamics within the network are represented using a water-front simulation approach, which models the finite speed of heat carrier fluid movement through the network.

Building on this foundation, we simulate evolving market and environmental conditions as follows. Initially, the baseline gas consumption across output areas is calculated:

$$D_{gas,initial} = \sum_{i \in H_{oa,b}(t=0)} d_{oa,i} \quad \text{Eq. 18}$$

where $H_{oa,b}(t = 0)$ is the set of households using gas boilers in output area oa at $t = 0$, and $d_{oa,i}$ is the annual heating demand of household i.

As the DHN expands, the demand for natural gas decreases. The current gas consumption at time t is:

$$D_{gas}(t) = \sum_{i \in H_{oa,b}(t)} d_{oa,i} \quad \text{Eq. 19}$$

The updated gas price is then determined by:

$$\text{gasPrice}_{kWh}(t) = \text{gasPrice}_{kWh}(0) \cdot \left(\frac{D_{gas,initial}}{D_{gas}(t)} \right)^{\beta} \quad \text{Eq. 20}$$

where $gasPrice_{kWh}(0)$ is the initial gas price in $\frac{£}{kWh}$ at $t = 0$, and β is the elasticity parameter.

Annual CO_2 emissions for each household i are calculated as:

$$E_i = d_i \cdot e_i \quad \text{Eq. 21}$$

where d_i is annual heat demand, and e_i is the emission factor in $\frac{kgCO_2}{kWh}$ for the household's current heating system.

For households connected to the DHN:

$$E_{DHN,i} = d_i \cdot e_{DHN} \quad \text{Eq. 22}$$

where e_{DHN} is the emission factor for the DHN in $\frac{\text{kg}}{\text{kWh}}$.

The total emissions reduction achieved by the DHN at time t is:

$$\Delta E(t) = \sum_{i \in H_{DHN}(t)} E_i - E_{DHN_i} \qquad \text{Eq. 23}$$

where $H_{DHN}(t)$ is the set of households connected to the DHN at time t.

7.4 Case Study

7.4.1 Context and Background

The Blackburn Meadows District Heat Network (BMDHN) in Sheffield, UK, is an existing network that currently supplies heat to commercial and public sector buildings in the region. The area is characterised by its heat density, diverse socio-economic characteristics, and proximity to the existing network, making it an ideal location for investigating the potential for residential expansion.

7.4.2 Data Collection and Processing

The data collection phase used open-source census data from the Nomis database, which covers the entire UK [59]. The analysis targeted the smallest geographic resolution, termed the "output area,"; a UK definition, which typically encompasses approximately 100 households. This dataset included essential demographic and socio-economic variables such as age, property type, heating system, education, occupation, tenure, economic activity, and household numbers.

Boundary polygons for each output area were obtained, and their areas were calculated. This process included identifying adjacent and intersecting boundaries to understand the spatial connectivity between output areas. The geographic midpoint (latitude and longitude) and adjacent areas of each output area were determined to facilitate the routing.

Energy Performance Certificates (EPCs) [60] were collected for each output area and The Cambridge Archetypes Model [55] was applied to the EPC data to generate demand estimates. Where the number of EPC certificates was less than the actual number of houses a scaling factor was applied to adjust the estimated demand to match the actual number of houses in each output area according to the census.

7.5 Results

This section presents the results of the ABM applied to the BMDHN case study, simulating expansion from 2023 to 2050. The model reveals complex dynamics of district heating adoption, network growth, and associated techno-economic and environmental impacts. Multiple simulations were conducted with consistent parameters to account for inherent variability.

7.5.1 Network Expansion and Adoption Rates

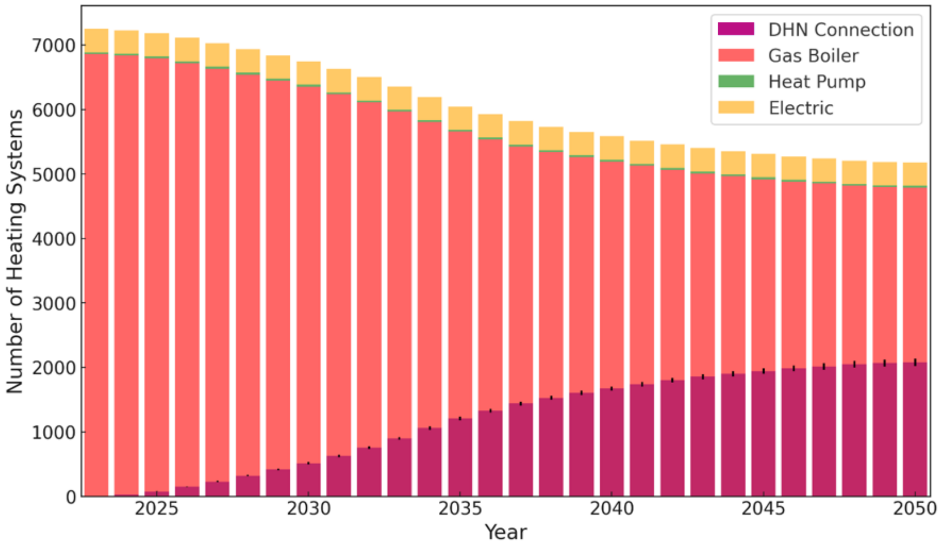

Figure 5: Heating System Transition and District Heating Network Uptake (2023–2050).

Figure 5 illustrates multiple realizations of the stochastic model, showing the transition from gas boilers to DHN connections. The results indicate a steady increase in connections, reaching an average of $2{,}083 \pm 155$ connected households by 2050, representing $30.4\% \pm 2\%$ of the total households in the area. Conversely, the average number of households using gas boilers decreases from 6,860 in 2023 to $4{,}777 \pm 155$ in 2050, highlighting the gradual replacement of gas boilers with connections. The proportion of households using electric heating and heat pumps remains constant throughout the period, as the expansion was outside the scope of this work.

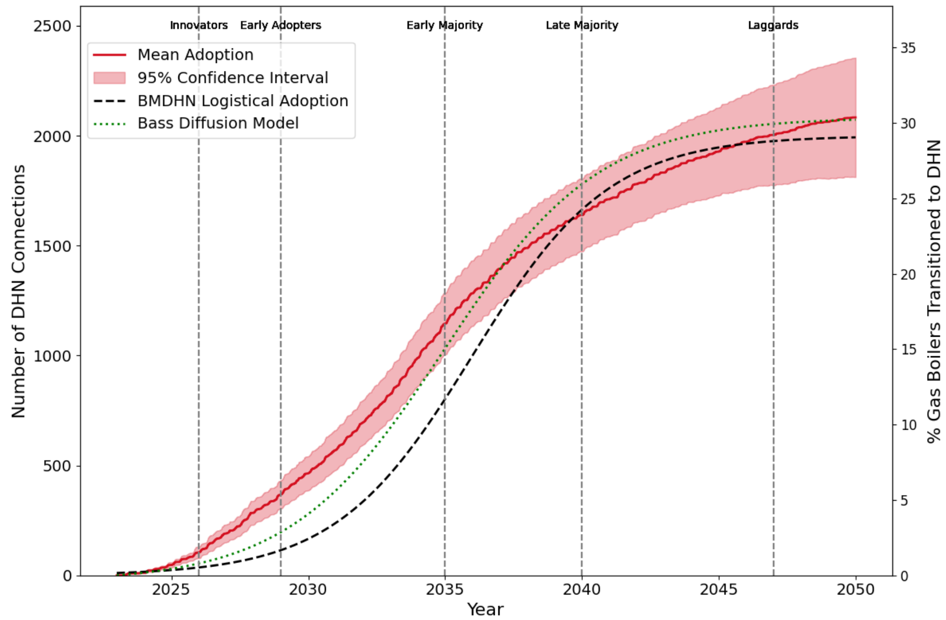

Figure 6: Adoption Distribution Including the Rogers, 1962 Diffusion of Innovations Theory [64] *versus Logistic and Bass Diffusion Models from 2023–2050.*

Figure 6 compares the predictions of adoption from the stochastic ABM with two established growth models: the logistic model [65] and the Bass diffusion model [66]. The stochastic ABM incorporates multiple simulations with consistent parameters, embedding stochastic elements in household decision-making, social dynamics, and heating system lifecycles to capture inherent variability in adoption patterns; the logistic model, defined by the equation $y = \frac{2000}{1+e^{(-0.4(x-13))}}$, which assumes a predetermined target of 2,000 connections (BMDHN target), a symmetrical adoption curve, and a midpoint at 13 years (2036); and the Bass diffusion model, expressed as $\frac{dN}{dt} = p(m - N) + \frac{q}{m} \cdot N(m - N)$, where p (innovation coefficient) = 0.005, q (imitation coefficient) = 0.35, and m (market potential) = 2,083 (average of ABM model), considering adoption influenced by innovation and imitation effects within a constant market potential. Notably, the increased variability observed in the later stages of adoption of the stochastic model underscores the unpredictable influence of socio-economic and behavioral factors over time.

All three models exhibit S-shaped adoption curves. The stochastic ABM predicts the highest final mean adoption of 2,083 connections (30.4% of potential), with a standard deviation of 138.56 connections, corresponding to a 95% confidence interval of 1,812-2,355. The logistical and Bass diffusion models project similar final adoptions of 1,993

(29.0%) and 2,068 (30.1%) connections, respectively. At the midpoint of the projection period, the stochastic model estimates 1,283 connections, while the logistic and Bass models predict 1,000 and 1,215 connections, respectively. Various adoption phases based on Rogers [64] characterisation of adopters are shown in Table 1.

The stochastic ABM predicts earlier adoption in the initial phases, but a longer overall adoption period compared to the other models. For innovators, the ABM forecasts adoption by January 2025 (± 1.3 months), significantly earlier than both the logistic (November 2027) and Bass (January 2027) models. This trend continues through the early adopters and early majority phases. The late majority phase in the ABM model occurs later than in the other models, starting in June 2041 (± 16.4 months), compared to February 2040 for the logistic model and August 2039 for the Bass model. For laggards, the ABM predicts adoption starting from July 2048 (± 14.0 months), considerably later than the logistic (March 2044) and Bass (December 2043) models.

A notable feature of the ABM results is the increasing variability in adoption timing as the process progresses. The uncertainty ranges from ± 1.3 months for innovators to ± 14.0 months for laggards, reflecting the cumulative effect of stochastic factors in the model. This contrasts with the deterministic nature of the logistic and Bass models, which don't account for such variability. The ABM's longer adoption period and increased variability in later stages suggest that it captures more of the complexity and unpredictability of real-world adoption processes, especially in the later stages where social, economic, and technological factors may have more diverse influences on adoption decisions.

Table 1: Uptake dates for Adopter Categories

Adoption Category	Stochastic Model	Logistical Model	Bass Model
Innovators	January 2025 ± 1.3 months	November 2027	January 2027
Early Adopters	August 2028 ± 5.3 months	December 2031	July 2030
Early Majority	May 2034 ± 6.6 months	January 2036	January 2035
Late Majority	June 2041 ± 16.4 months	February 2040	August 2039
Laggards	July 2048 ± 14.0 months	March 2044	December 2043

7.5.1.1 Spatial Dynamics of Network Growth

Figure 7 illustrates the temporal network changes, spatial layouts, and cumulative income for each output area based on the first simulation run. A pattern of expansion in the

Blackburn Meadows area from 2023 to 2050 is observed. Areas are prioritized based on heat demand density, socio-economic factors, and projected economic returns, while maintaining geographical continuity of the network.

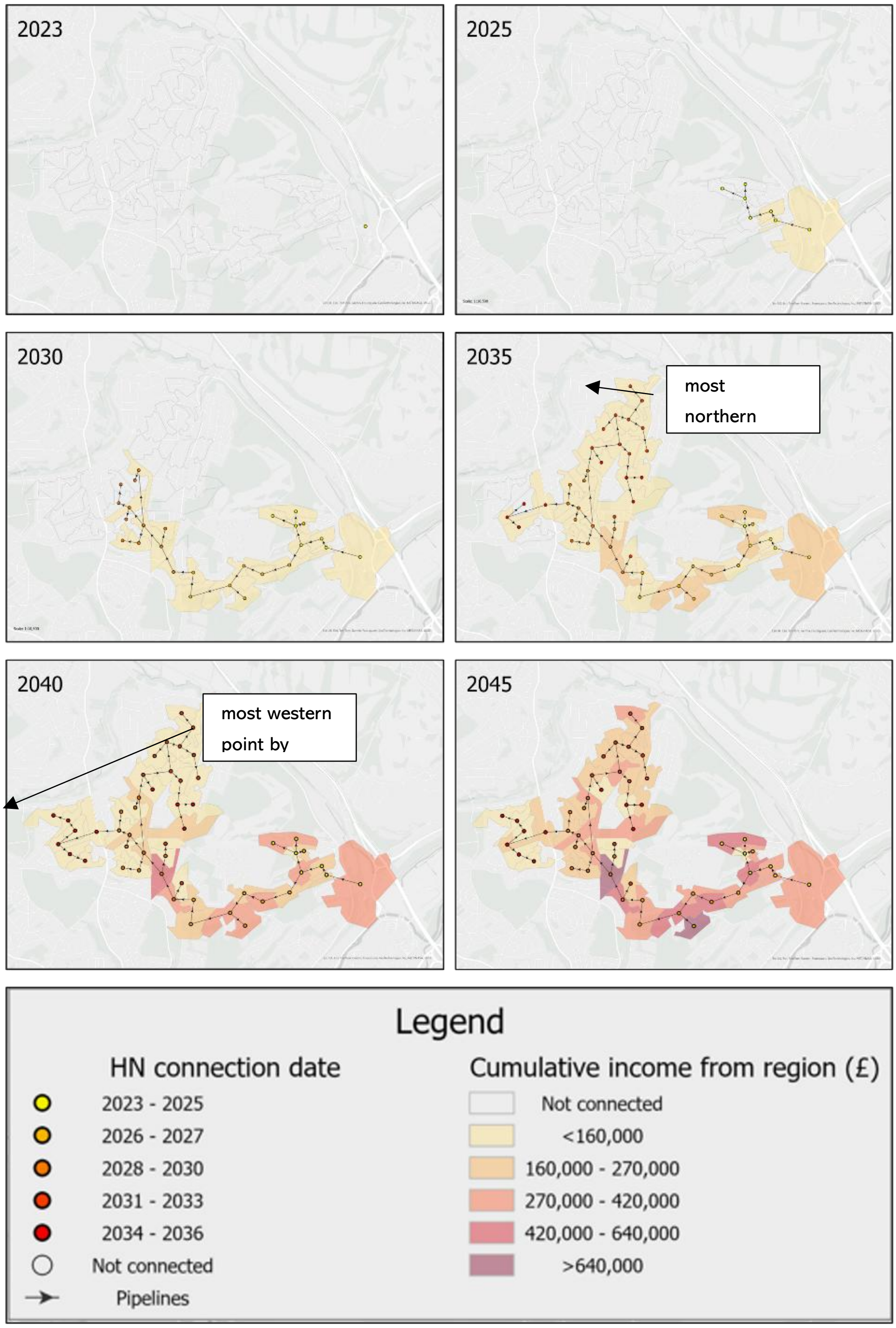

Figure 7: Network layouts, expansion dates, and cumulative income for BMDHN from 2023-2045.

The network expansion begins in 2023 in the southeastern part of the area, constrained by the proximity to the existing Blackburn Meadows plant. Between 2023 and 2025, the network expands primarily northward.

From 2026 and 2030, significant eastward growth occurs, with branches extending towards central and northern regions. This phase rapidly connects nearby nodes in areas with high heat demand density, establishing the core structure of the network by linking 23 nodes across diverse demographics.

Between 2031 and 2050, the network undergoes its final expansion phases, characterised by densification in the northern regions and extension toward the west. By 2036, the network organically reaches its geographical limits—no constraints were imposed on the network size—after which expansion focuses on increasing connection density within the established area.

The expansion pattern correlates with cumulative income data: early-connected southeastern areas show high cumulative income (over £400,000 by 2050), while later western connections yield lower returns (less than £300,000 by 2050). Two key expansion points are marked on Figure 7: the northernmost point reached by 2032 and the westernmost point by 2036.

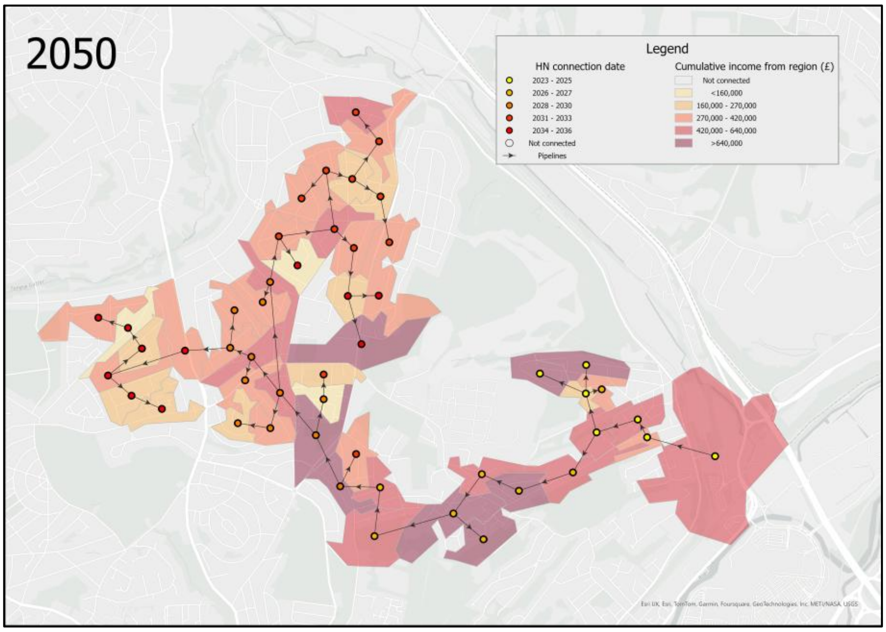

Figure 8: Network layout, expansion dates, and cumulative income for BMDHN in 2050.

Figure 8 presents the final projected layout of the BMDHN as of 2050. The simulation results in a network comprising 50 nodes and 49 connections, reflecting the spatial and socio-economic constraints of the study area. The key anchor nodes are situated in high-income areas, indicating that socio-economic status significantly influences network development and prioritization.

The temporal progression of the network is evident in the final layout. Early expansions from 2024 form the core structure, with subsequent additions filling gaps by 2036. This phased development demonstrates expansion into areas of highest demand and economic viability at each stage.

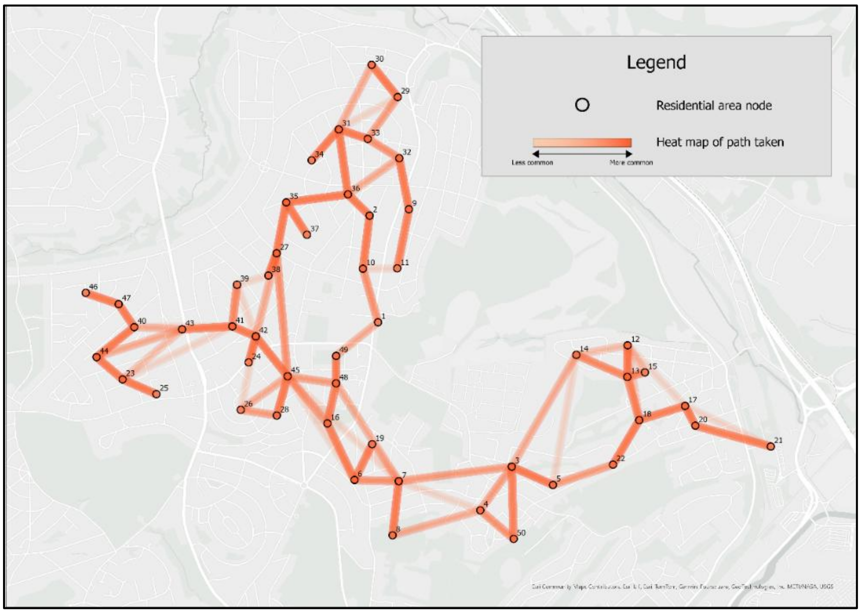

Figure 9: Heat map of final designs and alternative pathways.

Figure 9 illustrates the variation in network layouts across simulation runs, representing spatial and temporal changes. All simulations converge on a network of 50 nodes and 49 connections (as detailed in Table 1), suggesting a robust underlying structure driven by consistent spatial and socio-economic constraints. On average, each node maintains the same connections in 68% of simulations. Variability among nodes is observed, with 18% of nodes (9 out of 50) exhibiting perfect connection consistency and 20% (10 nodes) showing low consistency (less than 50%).

A temporal analysis of node additions reveals consistent growth patterns, with nodes added between 2024 and 2036. The build year of 76% of nodes (38 out of 50) remains unchanged across simulations, indicating high temporal stability in the network's expansion timeline. An average build year range of 0.24 years underscores this stability.

Table 2 summarizes key metrics of the network's temporal evolution and the degree of stochasticity observed across simulation runs. The top degree nodes—nodes 12, 44, and

17—are identified as critical hubs within the network due to their high number of connections. An average connection consistency of 0.68 indicates substantial agreement across simulations regarding network structure, while revealing notable variability in specific areas.

Table 2 -Temporal Evolution and Stochasticity in Network Expansion (2023-2050)

Metric	**Value**
Total Nodes	50
Total Arcs	49
Yearly Growth (Expansions)	2-4 (0.24 years avg)
Top Degree Nodes	12, 44, 17
Average Connection Consistency	0.68
Nodes with Consistent Build Year	38 (76%)
Nodes with Perfect Connection Consistency	9 (18%)
Nodes with Low Connection Consistency	10 (20%)

7.5.2 Socio-Economic Profiles of Adopter Categories

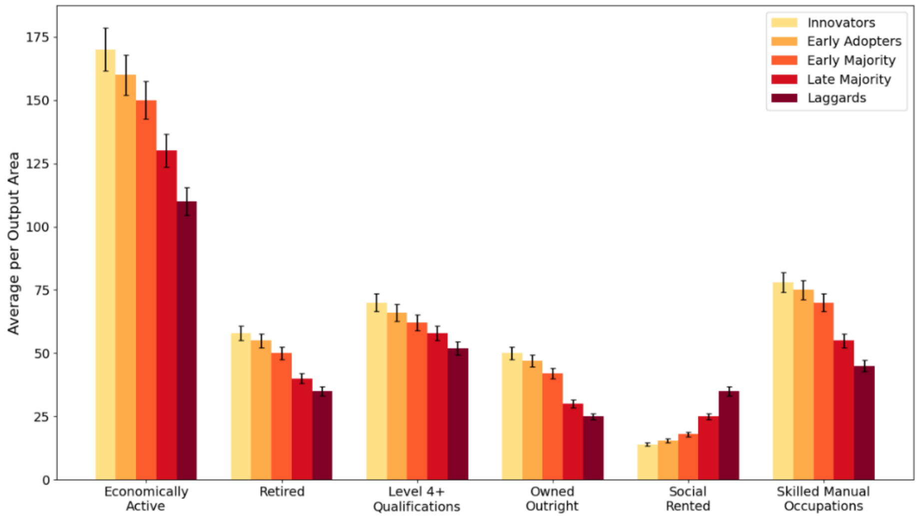

Figure 10: Adopter Categories and Key Socio-Economic Indicators

The socio-economic profiles of adopter categories were analysed to understand factors influencing the diffusion of adopters within the study area. Figure 10 illustrates the categories defined by Rogers' [64] diffusion of innovations theory—Innovators, Early Adopters, Early Majority, Late Majority, and Laggards—along with key socio-economic characteristics prominent in each group's adoption patterns. The profiles and error bars represent averages and variances across simulations, respectively.

Although the model was initialized and pre-parametrised with socio-economic data, the interplay between these factors and stochastic elements within the simulation yielded several notable insights. A clear correlation was observed between economic activity levels and adoption timing.

Innovators and Early Adopters predominantly originated from areas with higher economic activity, averaging 170 ± 8.5 and 160 ± 8.0 economically active individuals per output area, respectively. In contrast, Laggards were associated with significantly lower economic activity levels, averaging 110 ± 5.5 per output area. Property ownership significantly influenced adoption rates. Innovators exhibited the highest property ownership at $50\% \pm 2.5\%$, while Laggards had the lowest at $25\% \pm 1.25\%$, indicating a higher propensity for homeowners to adopt DHNs. Conversely, social housing presented a barrier to adoption. Innovators had a lower proportion of social renters at $14\% \pm 0.7\%$, compared to $35\% \pm 1.75\%$ among Laggards. Education levels correlated with earlier adoption, aligning with expectations that higher educational attainment is associated with earlier technology adoption. An unexpected finding was the high proportion of skilled manual workers among early adopters—78 ± 3.9 for Innovators compared to 45 ± 2.25 for Laggards.

7.5.3 Techno-economic Outcomes and Consumer Benefits

This section analyses the techno-economic performance of BMDHN and the projected heating cost savings for consumers by 2050, based on multiple model realizations. The evaluation is conducted from both the project developer's perspective and the consumer's perspective.

7.5.3.1 Project Developer Perspective

Table 3: Key Techno-Economic Indicators for BMDHN Expansion (2023-2050)

Category	Metric	Value	Unit

Financial Performance	Revenue	23.33 ± 1.52	million £
	Profit	5.47 ± 0.36	million £
	Profit Margin	30.51 ± 2.13	%
	Return on Investment (ROI)	130.12 ± 1.95	%
Costs	Installed CAPEX	5.47 ± 0.36	million £
	OPEX	10.74 ± 0.72	million £/year
	OPEX to Revenue Ratio	46.04 ± 0.48	%
Network Characteristics	Linear Heat Density	16,370 ± 524	kWh/m
	Heat Losses (estimated)	9.77	%
Demand	Total Demand	355.91 ± 23.73	GWh
	Demand Per Year	23.45 ± 1.48	GWh/year
	CAPEX per Connection	2,627 ± 37	£/connection
Per House Metrics	Revenue per Connection	11,201 ± 144	£/connection
	Average Demand per Connected House	11,259 ± 133	kWh/year/house

Table 3 summarizes the key performance indicators (KPIs) for the BMDHN expansion from 2023 to 2050, presenting mean values with their associated standard deviations to show the variability across the simulation runs.

The financial performance demonstrates robust economic viability. The average total revenue is £23.33 ± 1.52 million, with a profit of £5.47 ± 0.36 million. A profit margin of 30.51 ± 2.13% and a return on investment (ROI) of 130.12 ± 1.95%. Operational efficiency is reflected in the OPEX to Revenue Ratio of 46.04 ± 0.48%. The CAPEX per connection (£2,627 ± 37) was relatively low compared to the revenue per connection (£11,201 ± 144). Other key technical indicators include a high linear heat density of 16,370 ± 524 kWh/m, an average demand per connected house is 11,259 ± 133 kWh/year/house, and a heat price is approximately £0.10 per kWh. Finally, it's important to note that the constant heat loss of 9.77% across simulations is a model assumption and may not fully capture real-world variabilities. In practice, heat losses can vary due to factors such as pipe insulation quality, network configuration, and operating temperatures.

7.5.3.2 Consumer Perspective

Table 4: Projected Annual Heating costs for Consumers in 2050.

Heating System	2050 Cost (no inflation)	2050 Projected Cost
Heat Network	£404	£1,378
Standard Gas Boiler	£695	£2,370
Heat Network with Discounts*	£304	£1,037
Savings with Heat Network	£291	£992
Savings with Discounts	£391	£1,333

*Discounts include Warm Home Discount (£40) and Green Homes Grant (£60) equivalent.

Projected annual heating costs for consumers in 2050 are presented in Table 4, comparing DHN costs with those of standard gas boilers, both with and without applied discounts. The analysis considers two scenarios: one assuming no inflation and another incorporating a 5% annual inflation rate compounded over 27 years.

Without accounting for inflation, households could save £291 annually compared to using a standard gas boiler by 2050, a 41.9% reduction in heating costs. With discounts applied, savings increase to £391, resulting in a 56.3% reduction. When considering a 5% annual inflation rate compounded over 27 years, the savings are more pronounced. By 2050, a DHN connected household could save £992 per year compared to a gas boiler, and £1,333 with discounts applied. These results demonstrate the potential long-term economic benefits of DHN adoption for consumers, with savings becoming more pronounced when accounting for inflation over time. The model suggests that even small initial price differences can lead to substantial cumulative savings by 2050.

7.5.4 Environmental Impact and Emission Reduction

Figure 11 presents the projected CO_2 emission reductions from the BMDHN expansion from 2023 to 2050, compared with two benchmark heat decarbonisation pathways used for comparison: Error margins are included to account for uncertainties in long-term projections.

In the BMDHN model, CO_2 reductions increase substantially over time, rising from 2.85 ktCO_2 in 2023 to 890.16 ktCO_2 by 2050, a 24.3% marginal reduction relative to the initial emissions from gas boilers. Standard deviation widens from 0.41 ktCO_2 to 64.94 ktCO_2, reflecting increasing uncertainty in long-term forecasting. For comparative context, Figure 11 plots the BMDHN CO_2 reduction trajectory against two benchmark heat decarbonisation pathways applied to the same baseline emissions. These pathways are used as illustrative comparison curves rather than directly comparable local adoption targets [67]. On this basis, the BMDHN trajectory remains above both benchmark curves across the period.

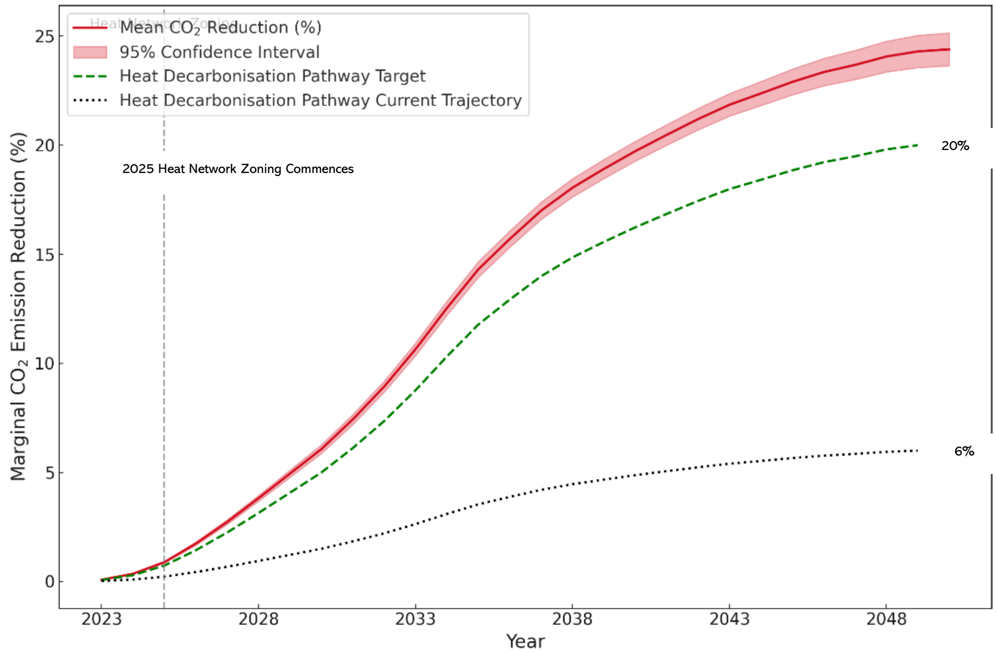

Figure 11: Projected CO_2 reductions from BMDHN compared with benchmark heat decarbonisation pathways used for comparison (2023–2050)

7.6 Discussion

The ABM of connection adoption and expansion of the DHN in Blackburn Meadows reveals complex dynamics at the intersection of technology diffusion, socio-economic factors, and policy implications. This discussion synthesizes key findings and their broader implications for urban energy transitions.

7.6.1 Network Expansion and Adoption

The model projects a 30.4% DHN adoption rate by 2050. This outcome, achieved without explicit target constraints, suggests that substantial, though still incomplete, DHN adoption is possible in dense urban areas under the socio-technical conditions represented in the model. The accelerated early adoption observed in the ABM, compared to traditional diffusion models, can be attributed to the incorporation of social learning dynamics and household heterogeneity. This finding aligns with recent literature emphasizing the importance of social factors in technology adoption [31] [25]. The extended adoption period for laggards, consistent with Rogers' diffusion theory [64], highlights the challenges in achieving complete market penetration. This persistent resistance underscores the need for targeted policies to address late-stage adoption barriers, particularly as climate goals necessitate rapid decarbonisation.

7.6.2 Spatial and Socio-Economic Factors

Early expansion phases prioritize high-return areas, often described as ‘low-hanging fruit.’ This strategy, while economically efficient, raises concerns regarding equitable access. [68] [69]. Moreover, the identification of key network hubs (nodes 12, 44, and 17) reinforces the need to balance efficiency with broader social objectives. Socio-economic profiles of adopter categories revealed expected correlations between economic activity, property ownership, and early adoption. However, the high proportion of skilled manual workers among early adopters was unexpected. This finding suggests that practical knowledge of heating systems may be as influential as formal education in driving adoption, challenging assumptions about the primacy of educational attainment in technology diffusion [64]. The "split incentive" problem observed in social housing contexts echoes broader challenges in the energy efficiency sector [70] Addressing this barrier may require innovative policy instruments, such as on-bill financing or green leases, to align landlord and tenant interests in DHN adoption.

7.6.3 Techno-Economic Viability and Consumer Benefits

The model demonstrates robust economic viability for DHN expansion, with high ROI and operational efficiency aligning with industry benchmarks [71]. The projected linear heat density of 16,370 kWh/m significantly exceeds the typical urban profitability threshold of 9,000 kWh/m [16], indicating strong potential for sustainable DHN operations in dense urban areas. Consumer savings projections, ranging from 41.9% to 56.3% by 2050, present a compelling case for DHN adoption. These findings suggest that DHNs could play a crucial role in addressing energy affordability and price volatility, particularly in regions vulnerable to fuel poverty [72]. Other studies have reported substantial consumer savings through DHN adoption, supporting the results. For instance, the Department for Business, Energy & Industrial Strategy [13] indicates that consumers connected to heat networks can save up to 30% on heating bills compared to conventional systems.

7.6.4 Environmental Impact and Policy Implications

The model's projected 24.3% CO_2 reduction by 2050 lies above the benchmark heat decarbonisation pathways used for comparison in Figure 11 [67]. This outcome underscores the potential of DHNs as a key strategy in urban decarbonisation efforts. Extrapolating these results globally implies that widespread DHN adoption could contribute significantly to international climate objectives, potentially leading to gigatonne-scale CO_2 emissions reductions annually. The United Nations Environment Programme [73] supports this assertion, estimating that district energy systems, depending on their underlying generation mix, could reduce global CO_2 emissions by up to 1 gigatonne per year by 2050. However, the widening standard deviation in long-term CO_2 reduction forecasts (from 0.41 $ktCO_2$ in 2023 to 64.94 $ktCO_2$ in 2050) highlights the increasing uncertainty in extended projections, emphasizing the need for adaptive policy frameworks.

This inherent uncertainty highlights the value of exploratory modelling approaches. As Ghorbani et al. [21] argue, historical validation is particularly challenging for socio-technical transitions involving behavioural and spatial heterogeneity, especially in emerging markets like residential DHNs. The nature of current UK heat decarbonisation policies and recent regulation, such as Heat Network Zoning (post-2025), create conditions without historical precedent. Consequently, while retrospective validation may be incorporated as suitable data becomes available, the model's strength lies in its theoretical grounding and ability to simulate complex socio-technical interactions.

The ABM's projection, which lies above the benchmark pathways used for comparison, suggests that DHNs could make a substantial contribution to urban decarbonisation under favourable socio-technical conditions. While the model provides robust insights into DHN adoption, the widening confidence intervals in CO_2 reduction forecasts highlight the inherent uncertainty in long-term predictions and underscore the need for adaptive policy frameworks. This suggests an opportunity for policymakers to revisit and potentially elevate DHN deployment targets, incorporating supportive mechanisms that leverage the identified economic and environmental benefits.

7.6.5 Conclusion

This study presents a novel agent-based model (ABM) simulating district heating network (DHN) adoption in urban environments, using Blackburn Meadows as a case study. The ABM approach proved highly effective in capturing the complex interplay of socio-economic factors, spatial dynamics, and individual decision-making processes. The model projects a 30.4% adoption rate by 2050, exceeding current UK policy targets, while predicting consumer cost savings of 41.9-56.3% compared to conventional heating systems. Additionally, the simulation forecasts a 24.3% reduction in carbon dioxide emissions by 2050. The model also identifies critical socio-economic factors influencing adoption patterns, providing valuable insights for policy development.

These findings demonstrate the potential of DHNs as a viable urban heat decarbonisation strategy, while highlighting areas requiring policy attention. The insights derived from this study can inform policymakers, urban planners, and energy stakeholders in developing effective strategies for DHNs deployment. Future research should focus on integrating competing technologies, exploring policy scenarios, addressing adoption barriers and applying to a wider city region. This study shows that well-designed DHNs can exceed current policy expectations in achieving urban sustainability goals. The success of the ABM approach in this context emphasizes its value for simulating complex urban energy transitions and underscores the need for adaptive, targeted policies in transitioning to low-carbon urban heating systems.

7.6.6 Limitations and Future Research Directions

This study faces several important limitations that warrant consideration. First, the stochastic modelling approach over the extended time horizon (2023–2050) inherently involves significant uncertainties. As Figure 6, and Table 1 demonstrates through widening confidence intervals for adoption and timing, long-term forecasts become increasingly uncertain due to potential technological disruptions, economic shifts, and policy changes. Parameters treated as relatively stable may evolve in unpredictable ways, challenging the validity of long-term projections [74].

The authors acknowledge a key methodological challenge: the combination of stochastic modelling with a lengthy future projection period risks becoming obsolete as technologies and market conditions evolve. Ideally, the model would be validated using historical data (e.g., 2000-2023) to establish greater confidence in the forecasting methodology. However, this validation approach faces substantial practical constraints in the UK residential district heating context. The minimal historical market penetration of residential DHNs in the UK has resulted in severely limited data availability and insufficient empirical cases for meaningful retrospective validation. Moreover, policy innovations like Heat Network Zoning represent unprecedented regulatory developments with no historical equivalents, further complicating historical validation efforts.

Given these constraints, the results should be interpreted as exploratory scenarios rather than definitive predictions. This aligns with methodological guidance in recent district heating literature [42] and recognised challenges in empirically validating long-term agent-based models [75]. Future research should prioritise developing more robust validation methods, perhaps through indirect calibration approaches or by leveraging historical datasets from regions with more extensive DHN implementation histories.

The model also explicitly focuses on DHNs supported by Heat Network Zoning, excluding alternative low-carbon heating technologies such as air-source heat pumps or hydrogen-based systems. While this simplification enhances analytical clarity, it neglects competitive market dynamics that could significantly influence adoption patterns. The emergence of competing technologies could substantially alter the adoption landscape projected in the model. Future research directions should address these limitations through:

- Integration of competing low-carbon heating technologies to better reflect market dynamics and technology substitution effects
- Exploration of alternative policy scenarios to identify optimal intervention points for accelerating district heating adoption
- Investigation of the "split incentive" barrier, particularly in social housing contexts, to develop equitable district heating uptake strategies

- Development of robust empirical validation methods, including indirect calibration techniques and comparative studies across regions with richer historical data
- Shorter-term modelling horizons with more frequent recalibration to account for rapid technological and market changes

These suggested enhancements would strengthen the methodological foundation and practical applicability of future district heating adoption research.

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7.8 Appendix

This appendix provides comprehensive information on the agent-based model (ABM) used to simulate the adoption and expansion of district heating networks (DHNs). It includes model parameters, data sources, detailed equations, and the simulation process. This information is crucial for understanding the model's mechanics and ensuring reproducibility of the study's results. The appendix is organized into sections covering model parameters, data sources and processing, detailed equations, the simulation process, and sensitivity analyses.

7.8.1 Model Parameters

This section outlines the key parameters used in the ABM, including economic factors, household decision-making variables, and operational considerations.

7.8.1.1 Installation costs, energy prices, and COP

To reflect current market conditions, the following energy prices and efficiency parameters are used. Boiler installation costs are modelled as a uniform distribution between £2,500 and £3,500 [76], while DHN connection costs are represented by a uniform distribution between £1,500 and £2,500 [13]. Energy prices are set to reflect current market conditions [77]: electricity at £0.245 per kWh (for heat pumps, this is divided by an average COP of 3.5 [77] to give the effective heat cost), gas at £0.0494 per kWh, oil at £0.100 per kWh, and solid fuels at £0.070 per kWh.

7.8.1.2 Carbon price and intensity

Carbon intensity of heat production assumed to be 0184 kg CO_2 per kWh [78]. The carbon price follows a linear trajectory, starting at £14 per tonnes in 2023, increasing to £231 per tonne by 2050 [79].Household Decision-Making Parameters

7.8.1.3 Utility weights

In the household decision-making utility function, each factor is assigned a weight:

- Economic Utility Weight = 1
- Environmental Utility Weight = 1
- Social Utility Weight = 1
- Hassle Factor Weight = -1

These weights reflect equal importance of factors, with hassle being a deterrent.

7.8.1.4 Learning Parameters

Learning Rate of 0.25 was chosen to reflect the speed of opinion change based on peer interaction. Confidence Bound of 0.2 to represent the threshold within which households consider peer opinions influential. Decay Rate of 0.1 to reflect the decreasing hassle over time on installation [56] [57].

7.8.2 Operational Parameters

7.8.2.1 DHN Operational Expenditure

The daily operational expenditure for the DHN is calculated using:

$$Daily\ OPEX = \frac{30.1 \times (Connected\ Demand/1000)}{365} \qquad \text{Eq. A1}$$

Where connected demand is the yearly heat demand of connected house in kWh, and 30.1 is the annual operation cost per MWh [13].

7.8.2.2 Output Area costs

Heat density calculated:

$$Heat\ Density\ (HD) = \frac{Total\ Area}{Total\ Heat\ Demand} \quad \text{Eq. A2}$$

Cost impact:

$$Cost\ Impact = 1 - e^{-\frac{(HD-\mu)^2}{2\sigma^2}} \quad \text{Eq. A3}$$

Potential cost:

$$Potential\ Cost = C_{min} + (C_{max} - C_{min}) \cdot (1 - Cost\ Impact) \quad \text{Eq. A4}$$

Where C_{min} is £80 per MWh , C_{max} is £239 per MWh [13], mean heat density μ is 24.3 kWh/m^2, and standard deviation σ is approximated by $\frac{Max\ Density-\mu}{2}$ from UK urban heat density distributions [80].

7.8.3 Data Sources and Processing

7.8.3.1 Geographic Information System (GIS) Data

Output area boundaries of the study area were used for spatial modelling. Figure A1 shows a map of the study area with output areas and heat density.

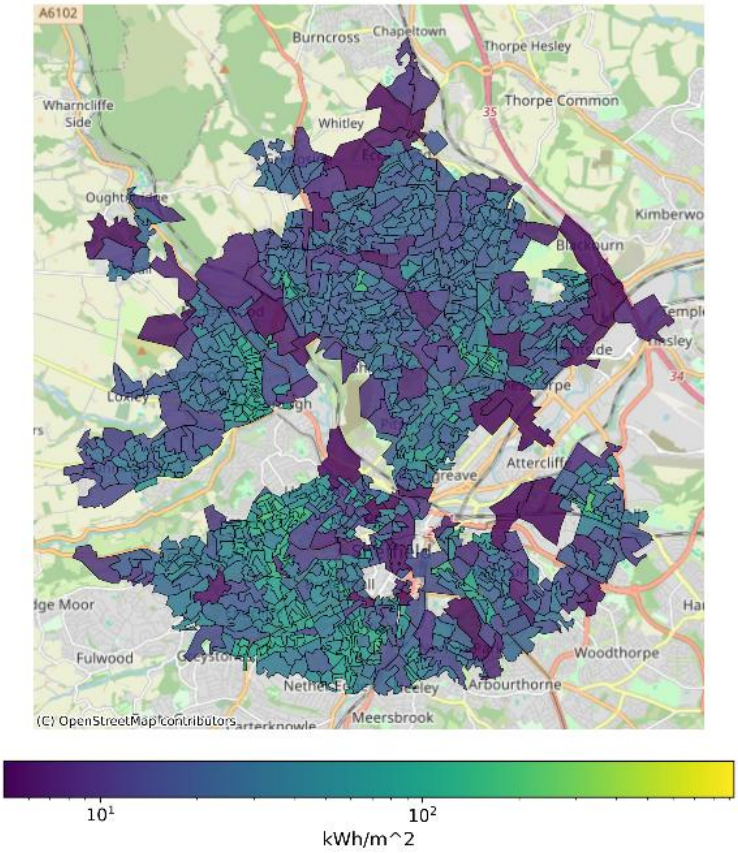

Figure A1: Map of study area showing output areas and heat density.

7.8.3.2 Household Characteristic Encoding

Household characteristics are encoded to quantify their influence on DHN adoption probabilities. Table A1 presents the encoding values for various household characteristics.

Table A1: Household Characteristic Encodings

Category	**Census Input**	**Encoding**
Property Type	Purpose-built flats/tenements	1.0
	Terraced houses	0.8
	Semi-detached houses	0.8
	Detached houses	0.6
	Converted/shared houses, commercial buildings, other	0.4
	Caravans/mobile structures	0.0
Heating System	District or communal heat networks only	1.0

	No central heating	0.7
	Mains gas only	0.6
	Heat Pump	0.0
	Electric	0.0
Tenure	Owned outright	1.0
	Owned with mortgage or loan	0.8
	Shared ownership	0.6
	Social rented (council/authority)	0.4
	Social rented (other)	0.4
	Private rented (landlord/agency)	0.2
	Private rented (other)	0.2
Economic Activity	Employed (full-time students and non-students)	0.7
	Unemployed (full-time students and non-students)	0.7
	Retired	0.4
	Looking after home/family, long-term sick/disabled, other	0.2
	Student (economically inactive)	0.1
	Economically inactive (unspecified)	0.3

7.8.3.3 Boiler Failure Probability Data

PERT distributions are used to simulate random failures and end-of-life states for boilers.

Table A2: Boiler Age Failure probability data

Boiler Age Range	**Number of Observation (%)**
1.0-6.0	0.0
6.0-10.0	22.0

10.0-15.0	57.0
15.0-20.0	67.0
20.0-25.0	100.0

7.8.4 Detailed Equations

7.8.4.1 Profile generation

Each household H_i, in Output Area OA_j is assigned characteristics based on stratified random sampling. The set of characteristics X_k (e.g., age property type, heating system, etc) is assigned according to the probability distribution observed in the census data, shown by:

$$P(X_k = x|OA_j) = \frac{n_{x,j}}{N_j} \quad \text{Eq. A5}$$

Where $n_{x,j}$ is the number of instances of characteristic x and N_j is the total number of households in the Output Area.

For each specific encode, the value is calculated as:

$$E_k = \sum_x P(X_k = x|OA_j) \cdot \text{encode}_k(x) \quad \text{Eq. A6}$$

Where E_k is the encoded value for the characteristic k, $\text{encode}_\text{k}(x)$ is just the function that converts the characteristic type k into a numerical value.

For characteristics with interdependences, such as occupation and economic activity, conditional probabilities are used:

$$P(O = o|EA = e) = \begin{cases} 1, & e \in E, o = \text{"No Occupation"} \\ \text{OccupationDist}(e)(o), & e \notin E \end{cases} \quad \text{Eq. A7}$$

Where e is the set of economically inactive variables E.

Social grade S is determined using a function G that maps combinations of tenure T, occupation O, and education D:

$$S = G(T, O, D) \begin{cases} AB \text{ if } O \in \{\text{Managers, Proffesionals}\} \text{ and } D \geq Level\ 4 \\ C1 \text{ if } O = \text{Administrative and } T \in \{\text{Owned outright}\} \\ \ldots \quad \text{other cases} \end{cases} \quad \text{Eq. A8}$$

This profile generation method ensures that the simulated population accurately reflects the socio-economic diversity of the study area, a critical factor in modelling DHN adoption dynamics [28, 29, 30].

7.8.4.2 Project Owner Financial Viability Assessment

To ensure financial sustainability prior to any expansion, the project owner assess current debt using Equation A9 [15]:

$$debtRatio(t) = \frac{CurrentDebt(t)}{AnnnualRevenue(t)} < debtCapacity \qquad \text{Eq. A9}$$

Where $CurrentDebt(t)$ denotes the net cumulative profit or loss in £ at time t, with losses represented as negative values and $AnnnualRevenue(t)$ is the total revenue in £ and time t. $debtCapcity$ is predefined ratio of investment to profit.

The return on investment (ROI) for a potential expansion area is calculated to ensure economic benefits justify the cost:

$$ROI_{oa}(t) = \frac{30 \cdot R_{oa}(t) - C_{oa}(t)}{C_{oa}(t)} \qquad \text{Eq. A10}$$

Where:

$$R_{oa}(t) = (\frac{\sum_{i \in H_{oa}(t)} d_{oa,i} \cdot P_{connect}(t)}{1000}) \cdot P_{MWh}$$

$$C_{oa}(t) = \left(\frac{\sum_{i \in H_{oa}(t)} d_{oa,i} \cdot P_{connect}(t)}{1000}\right) \cdot (C_{MWh} + (O_{MWh} \cdot T)$$

$R_{oa}(t)$ is the revenue potential from output area oa at time t, and $C_{oa}(t)$ includes the estimated capital and operational cost of expansion to output area oa at time t. O_{MWh} refers to the operational cost per MWh, and T represents the expected lifetime of the infrastructure.

Additionally, the method to determine the cost of installing DHN infrastructure per MWh, considering the heat density of the output area is calculated by:

$$C_{MWh} = MIN_{cost} + (MAX_{cost} - MIN_{cost}) \cdot (1 - Impact_{cost}) \qquad \text{Eq. A11}$$

Where:

$$Impact_{cost} = 1 - e^{-\frac{(HD_{oa}-\mu)^2}{2\sigma^2}}$$

HD_{oa} is the heat density of the households in the output area, μ and σ are the mean and standard deviation of heat density across the observed output areas. MIN_{cost} and MAX_{cost} set bounds for the interpolation based on infrastructure costs.

7.8.4.3 Heat Price Determination

The pricing model for heat sold to households is designed to ensure sustainability of the network while achieving necessary profit margins to allow for future expansions. The heat price, P_{MWh}, is determined by:

$$u_{i,oa}(t) = \frac{C_{oa}(t) + \gamma(C_{oa}(t))}{(\sum_{i \in H_{oa}(t)} d_{oa,i}) \cdot T} \cdot 1000 \qquad \text{Eq. A12}$$

Where γ is the required return on investment, $d_{oa,i}$ is the annual demand of household i in MWh, and T represents the expected lifetime of the infrastructure, and $C_{oa}(t)$ includes both capital and operational expansion costs.

7.8.4.4 Demographic and Technical Evaluation

The project owner evaluates the urgency and heat density of each output area to understand its readiness and need for DHN. The urgency score U_{oa} is calculated using:

$$U_{oa}(t) = \frac{EOL_{i,oa}(t)}{H_{oa}(t)} \qquad \text{Eq. A13}$$

Where $EOL_{i,oa}(t)$ is the number of heating systems near end of life at time t, and $H_{oa}(t)$ is the total household in the output area.

The heat density score is calculated by:

$$HD_{oa} = \frac{HD_{oa}}{\max\limits_{oa \epsilon OA} (HD_{oa})} \qquad \text{Eq. A14}$$

Where $\max\limits_{oa \epsilon I_j}(HD_{oa,j})$ is used to normalise the heat density against the maximum observed in the set of potential expansion areas.

The final selection of the best candidate area for expansion, considering financial viability and technical readiness is calculated by:

$$X = ROI_{oa}(t) + U_{oa}(t) + HD_{oa} \qquad \text{Eq. A15}$$

Areas must:

- Not have DHN infrastructure already built.
- Be adjacent to existing network areas.

7.8.4.5 Linear Heat density

Linear heat density is a key metric for assessing the efficiency of the DHN:

$$\text{Linear Heat Density} = \frac{\text{Connected Demand}}{1.5 \cdot \sqrt{\text{Connected Area}}} \quad \text{Eq. A16}$$

7.8.5 Model Integration and Simulation Process

Table A3: Simulation Process

Simulation Process
Initialization: 1. Generate household profiles. 2. Initialize DHN infrastructure and market conditions. **Time Step Iteration (Daily from 2023 to 2050):** a. Update Household Heating Systems: 1. Simulate aging and failure of heating systems. 2. Identify households nearing end-of-life for their current systems. b. Calculate Utilities and Adoption Probabilities: 1. Compute hassle, economic, environmental, and social utilities. 2. Determine the probability of DHN adoption for each eligible household. c. Simulate Household Decisions: 1. Households decide whether to connect to the DHN based on calculated probabilities, and only if infrastructure is available. d. Update Project Owner's Financial Status: 1. Update revenues, costs, and profits based on new connections and operational expenses. e. Evaluate Potential Expansion Areas: 1. Assess areas for expansion using financial, technical, and socio-economic criteria. f. Implement DHN Expansions: 1. Expand the network to new areas meeting the selection criteria. g. Update Energy Prices and Calculate Emissions: 1. Adjust gas prices based on changing demand. 2. Calculate CO_2 emissions for the current time step. h. Update Social Learning Model: 1. Update household opinions based on interactions with peers and connected households.

Result Collection and Analysis:

1. Aggregate data on adoption rates, network expansion, financial performance, and emissions reductions.

7.8.6 Sensitivity Analysis

Figure A2 shows the sensitivity check on hassle utility weightings, while Figure A3 presents the sensitivity check on social utility weightings.

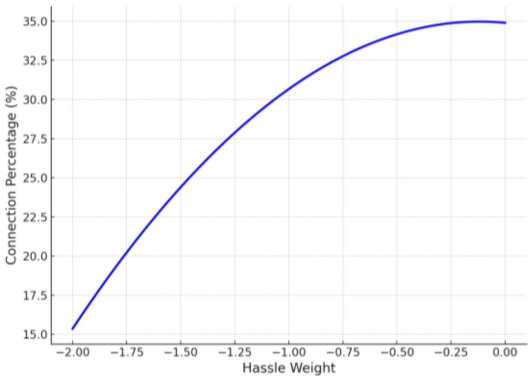

Figure A2: Sensitivity check on hassle utility weightings.

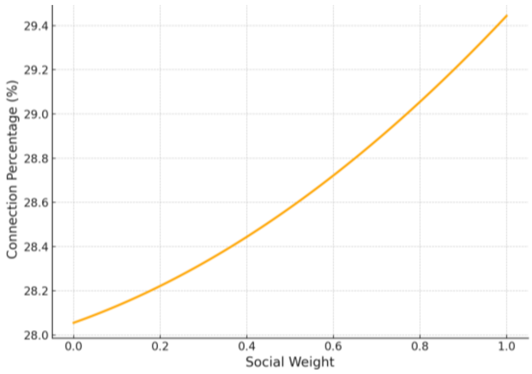

Figure A3: Sensitivity check on hassle utility weightings.

Figures A2 and A3 illustrate the model's sensitivity to hassle and social utility weightings, respectively. Figure A2 shows that as the hassle weight increases from -2.00 to 0.00, connection percentage rises from 15% to 35% in an S-shaped curve, with the most significant impact between -1.25 and -0.50. This suggests that reducing perceived hassle could dramatically increase adoption rates. Figure A3 demonstrates a nearly linear positive relationship between social weight (0.0 to 1.0) and connection percentage (26% to 29%). While social factors positively influence adoption, their impact is less pronounced compared to hassle factors. These analyses highlight the importance of minimizing perceived hassle in DHN adoption strategies, while also acknowledging the role of social influences.

Chapter 8

Heat Zoning Aligns Profit and Equity in District Heat Networks

8.1 Abstract

The expansion of District Heat Networks (DHNs) is critical for decarbonising heat, yet deployment stalls in liberalised markets due to a disconnect between investment strategy and social dynamics. This study employs a socio-technical agent-based model to simulate competing governance strategies, from purely profit-driven to socially-focused. The analysis reveals that single-objective strategies lead to failure: the profit-driven approach results in 'infrastructure redlining', while the social-maximising approach creates financially fragile 'equity traps'. Sustainable, city-scale expansion is only achieved through a balanced strategy that creates a socio-economic bridge between diverse urban districts. Crucially, the model shows that coordinated policy, such as heat network zoning, is the catalyst that aligns financial incentives with public good, and that its absence imposes severe, geographically determined costs on households. This work concludes that a strategic, place-based framework is essential to transform DHNs into an effective instrument for a Just Transition.

8.1.1 Keywords

District heat networks; Agent-based modelling; Socio-technical transitions; Energy Policy; Just Transition

8.1.2 Nomenclature and terminology

Symbol	Description	Units
$R_{cov}(t)$	Market coverage ratio at time t	–
$B_i(t)$	Connection state of area i at time t $(1 = \text{connected}, 0 = \text{unconnected})$	–

$G_{assign}(g,t)$	Assignment state of generator g at time t $(1 = \text{assigned}, 0 = \text{unassigned})$	–
γ	Fraction of capital cost covered by grants	–
$B_{spent}(y)$	Operator's cumulative CAPEX spend in year y	£
y_{last_reset}	Last year when B_{spent} was reset	year
d_{ij}	Euclidean distance between centroids of areas i and j	m
d_{max}^{adj}	Maximum effective adjacency distance for output areas	m
θ_i	Local willingness-to-connect factor for area i	–
A	Set of all modelled output areas	–
$A_{unc}(t)$	Set of unconnected output areas at time t	–
$A_{conn}(t)$	Set of connected output areas at time t	–
$A_n(t)$	Set of areas served by network n at time t	–
G	Set of all potential generator agents	–
$N(t)$	Set of all active Heat Network Agents at time t	–
B_{max}	Annual capital budget cap	£
$B_{rem}(t_m)$	Remaining budget at time t	£
B_{cov}^{min}	Minimum coverage ratio threshold	–
S_{min}	Minimum strategic score threshold	–
$D_i^{peak}(t)$	Peak thermal demand of area i at time t	kW

D_i^{ann}	Total potential annual heat demand of area i (households+anchors)	kWh/yr
$D_i^{actual,conn,ann}(t)$	Actual annual connected demand in area i at year t	kWh/yr
$D_i^{con}(t)$	Cumulative annual demand connected in area i at time t	kWh/yr
D_i^{dens}	Heat demand density of area i	kWh/m^2/yr
$D_i^{hh,pot,ann}$	Total potential annual household demand in area i	kWh/yr
$D_i^{achor,ann}$	Total annual anchor demand in area i	kWh/yr
$D_i^{exp,conn,ann}$	Expected annual connectable demand in area i	kWh/yr
$D_i^{avg,inst}$	Average instantaneous potential demand in area i	kW
k_i^{peak}	Peak-to-average factor for area i	–
$A_n(t)$	Set of areas connected to network n at time t	–
C_g^{max}	Maximum capacity of generator g	kW
C_g^{rem}	Remaining capacity of generator g at time t	kW
$CAPEX_g^{£/kW}$	Generator capital cost per kW	£/kW
η_g	End-to-end efficiency of generator g	–
$E_g^{ann,deliv}(y)$	Annual heat delivered by generator g in year y	kWh/yr
$E_g^{ann,input}(y)$	Annual input energy consumed by generator g in year y	kWh/yr
$O_g^{var,perkWh}$	Generator variable OPEX per unit heat delivered	£/kWh

$O_g^{var,ann}(y)$	Annual variable OPEX of generator g	£/yr
$O_g^{fixed,ann}$	Annual fixed OPEX of generator g	£/yr
$O_g^{vann}(y)$	Total OPEX of generator g in year y	£/yr
$C_n^{rem}(t)$	Remaining capacity of network n at time t	kW
$R_n^{ann}(y)$	Annual revenue of network n in year y	£/yr
$O_n^{ann}(y)$	Annual OPEX of network n in year y	£/yr
$C_n^{real}(y)$	Cumulative realized CAPEX of network n by year y	£
$C_n^{CumRev}(y)$	Cumulative revenue of network n by year y	£
$C_n^{CumOPEX}(y)$	Cumulative OPEX of network n by year y	£
$C_n^{CumProfit}(y)$	Cumulative profit of network n by year y	£
$ROI_n(y)$	Return on investment of network n in year y	–
PB_n	Payback period of network n	yr
$D_n^{inst}(t)$	Instantaneous demand on network n at time t	kW
$D_n^{peak}(t)$	Peak demand on network n at time t	kW
$f_{ij}(t)$	Served fraction of area i's peak by source j at time t	–
C_i^{cap}	Baseline pipe CAPEX to serve area i at peak	£
c_i	Density-adjusted unit cost for area i	£/kW

φ_{opex}	Annual pipe OPEX fraction	yr^{-1}
φ_{infra}	Infrastructure OPEX fraction	yr^{-1}
P_{mkt}	Average heat tariff price	£/MWh
P_{rev}	Revenue adjustment factor	–
$C_{ij}^{pipe}(t)$	Pipe CAPEX component for project (i,j)	£
$C_{ij}^{gen}(t)$	Generator CAPEX component for project (i,j)	£
$C_{ij}(t)$	Total CAPEX for project (i,j)	£
$\Delta_{ij}(t)$	Annual net cash flow for project (i,j)	£
$NPV_{ij}(t)$	Net Present Value of project (i,j)	£
IRR_{ij}	Internal Rate of Return of project (i,j)	yr^{-1}
ε	Convergence tolerance for IRR solver	–
N_{max}	Maximum iterations for IRR solver	–
$PB_{ij}(t)$	Simple payback period for project (i,j)	yr
PB_{max}	Maximum payback threshold	yr
$LCOH_{ij}(t)$	Levelized Cost of Heat for project (i,j)	£/MWh
$w_k(t)$	Weight for criterion k in multi-criteria scoring	–
ε_j	Random jitter for project (i,j)	–
δ	Range of random jitter	–
$S_{ij}(t)$	Multi-criteria score for project (i,j)	–
G_{adj}	Spatial adjacency graph of output areas	–

V	Vertex set of adjacency graph (output areas)	–
E	Edge set of adjacency graph (adjacent area pairs)	–
P^*	Shortest path to nearest unserved anchor	–
$h(t)$	Index along shortest path P^* at cycle t	–
L	Length (hops) of shortest path P^*	–
$C_{tot,conn}^{ann}(t)$	Total connected demand across all networks at year t	kWh/yr
$s_n(t)$	Market share of network n at year t	–
$HHI(t)$	Herfindahl–Hirschman Index at year t	–

Abbreviation	Full Form
ABM	Agent-Based Model / Agent-Based Modelling
BEIS	Department for Business, Energy & Industrial Strategy
BFS	Breadth-First Search
CAPEX	Capital Expenditure
CHP	Combined Heat and Power
COP	Coefficient of Performance
DESNZ	Department for Energy Security & Net Zero
DHN	District Heating Network
EPC	Energy Performance Certificate
GIS	Geographic Information System
HHI	Herfindahl-Hirschman Index
HMT	Her Majesty's Treasury (UK)

IEA	International Energy Agency
IRR	Internal Rate of Return
KPI	Key Performance Indicator
LCOH	Levelized Cost of Heat
NPV	Net Present Value
OA	Output Area (spatial unit in the model)
OFAT	One-Factor-At-a-Time
ONS	Office for National Statistics
OPEX	Operational Expenditure

8.2 Introduction

Achieving national net-zero targets requires the decarbonisation of heat, a complex challenge defined by the conflicting objectives of its diverse stakeholders [1] [2]. This complexity arises from balancing the profit motives of commercial investors against the public service mandates of policymakers and the cost sensitivities of consumers [3]. District heating networks (DHNs) are a proven solution for this purpose, yet their deployment reveals a sharp contrast across Europe. Coordinated, municipally led heat planning in nations like Denmark, for example, has resulted in connecting over 60% of households [4] [5]. This success highlights the deployment gap in nations with more fragmented, liberalised governance structures, such as the United Kingdom, where progress remains significantly behind stated policy ambitions and technical potential [6] [7].

This disparity suggests the barriers are not primarily technical but institutional, stemming from the UK's fragmented, liberalised energy market of competing interests, a model distinct from the coordinated public planning models that have proven successful in Europe [8]. Responsibilities are split among planners, utilities, and developers, whose frequently conflicting incentives often favour short-term, competitive project funding cycles. This approach undermines long-term investor confidence and DHN expansion, a weakness observed in the UK's history of abruptly cancelled support programs [9].

The result is not merely stalled progress but deepening social inequity. A market-led rollout risks creating a phenomenon akin to infrastructure 'redlining' where less profitable (often low-income) areas are left unserved [10]. Ensuring an equitable outcome is a core challenge of the 'just transition', which seeks to integrate climate, energy, and social justice objectives so that no group is left behind [11].

The challenge of coordinating DHN deployment is now at a critical juncture, as governments in many nations with historically liberalised energy markets are introducing significant policy interventions to accelerate progress. These policies, such as the introduction of mandatory heat network zoning [12] or area-based energy masterplans [13], attempt to de-risk private investment by borrowing principles from successful, centrally-planned models. However, the effectiveness of these top-down policies depends on how they interact with the complex, bottom-up dynamics of local stakeholder behaviour and existing spatial constraints [3]. Navigating this policy transition is critical in the next decade, before phase-out mandates for fossil-fuel boilers lock households into potentially suboptimal individual heating solutions. Assessment frameworks must therefore evolve to evaluate how these new policy configurations will interact dynamically with local stakeholder behaviour, as well as with technical and spatial constraints.

This institutional fragmentation is mirrored by a methodological one. The literature is broadly split between techno-economic models that treat network expansion as a deterministic engineering problem [14] [15] and qualitative studies that, while capturing social complexities, cannot quantify their systemic impact on network design or spatial equity [16] [8] [17]. The former often ignore critical behavioural barriers such as the landlord-tenant split-incentive or the role of community trust [18] [19], while the latter cannot easily model how these factors create path dependency or lead to financially unviable 'equity traps'. Neither approach, therefore, can fully investigate the feedback loops between policy, stakeholder behaviour, and engineering economics, a gap that Agent-based Modelling (ABM) is well-suited to address [20].

This analytical challenge manifests as the classic 'chicken-and-egg' dilemma of DHN deployment: large-scale investment requires demand security, while demand depends on infrastructure being present [21] [22]. The recent introduction of regulatory interventions like mandatory heat network zoning marks a fundamental policy shift designed to break this impasse [12] [18]. However, by forcing a decision on governance philosophies by pitting the strategy of a profit-maximising developer against that of a social-welfare-oriented utility, this new policy landscape makes it more urgent than ever to understand how competing strategies will drive spatially-explicit growth and equity outcomes under these new rules [20] [23]. Existing ABM studies, however, have not yet systematically tested these competing governance philosophies within this new policy context [24] [25].

To address this methodological gap, this study introduces a socio-technical framework that explicitly connects governance structures to long-term deployment outcomes. The model's key contribution is to operationalise abstract concepts from transition theory such as path dependency and stakeholder feedback loops within a spatially-explicit simulation. This approach allows for the quantification of emergent, city-scale consequences as they unfold over decades, from investment viability to social equity. It thereby provides a robust method for assessing how different operator strategies create patterns of infrastructure inequality, and for testing how policy levers like zoning can steer development towards more a sustainable and Just Transition.

8.3 Methodology

This section outlines the model's conceptual framework and operational logic. The complete mathematical implementation, including the step-by-step equations for all agents, financial metrics (NPV, IRR, LCOH), and the GIS-based initialisation procedure, is detailed in Appendices A, B, and C.

This study uses a spatially explicit ABM to investigate how an operator's strategic orientation shapes the viability, market structure, and emergent topology of DHNs over a 25-year simulation period (2025–2050). The model's architecture simulates the interactions among four core agent types within a framework reflecting a developer's decision-making process. The simulation operates in daily time steps to capture fine-grained social dynamics, while investment decisions occur on a monthly cycle and financial performance is reviewed annually. This multi-layered temporal structure creates a dynamic socio-technical feedback loop between household adoption and developer strategy while maintaining computational efficiency.

Figure 1 summarises the model architecture. Inputs (census, EPC, GIS, and energy demand data) and policy levers (capital budget, GHNF subsidy, heat zoning, hassle, heat price, and IRR hurdle) feed two coupled modules. The Operator Agent runs a monthly investment cycle that screens, scores, and selects candidate projects according to the strategy parameter λ, building networks on an adjacency graph of small-area units. Household Agents run a daily adoption model that updates willingness-to-connect in response to affordability, hassle, and peer-effect dynamics. The evolving network state updates costs and peer-effect dynamics, closing the feedback loop and producing system-level KPIs.

The simulation partitions the city into neighbourhood-scale small-area units (census micro-units) of about 100 households to capture intra-urban variation in density, deprivation, and tenure that shape peer-effect dynamics and affordability. Household Agents reside within these units and compute a dynamic 'willingness-to-connect' using a social learning algorithm adapted from Cowley et al. [26], integrating household affordability, evolving peer-effect dynamics, and policy subsidies. For the UK case study, the model instantiates these units as Census Output Areas, the smallest stable reporting geography, typically 100 to 125 households. Small-area units aggregate household signals and local costs that the Operator Agent uses in monthly investment decisions.

The Operator Agent evaluates the household demand landscape through its specified investment strategy and allocates an annual capital budget to expand the network. These decisions instantiate Heat Network Agents and Generator Agents and produce path-dependent growth that updates connection costs and peer-effect dynamics for subsequent cycles (Figure 1).

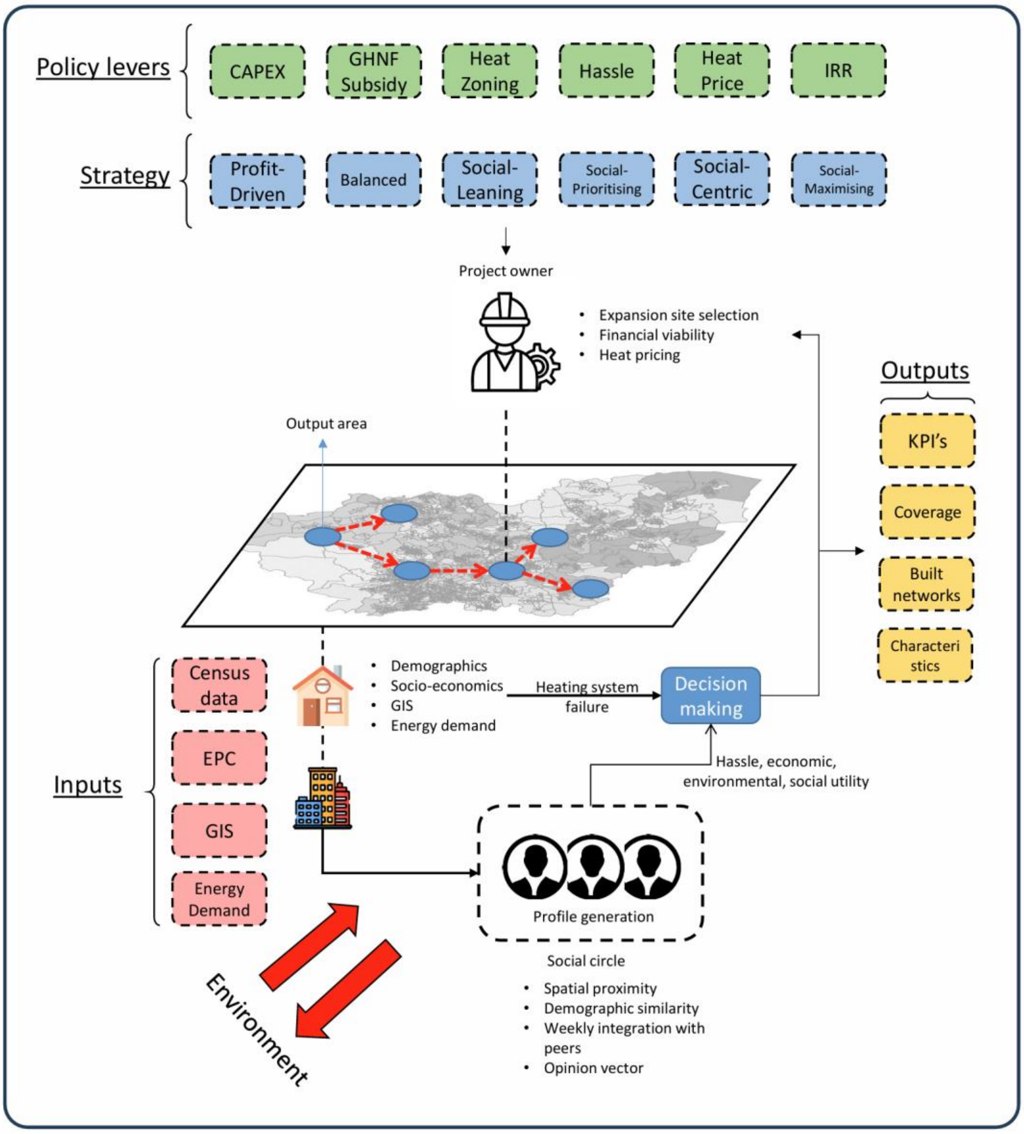

Figure 1: *Agent-based model overview. Inputs (census, EPC, GIS, energy demand) and policy levers (capital budget, subsidy, heat zoning, hassle, heat price, IRR hurdle) feed two modules: the Operator Agent's monthly investment cycle and the Households Agents' daily adoption model. The operator screens, scores, and selects projects according to strategy λ (Profit-Driven to Social-Maximising), building networks on an adjacency graph of small-area units (UK: Output Areas). Household willingness-to-connect evolves with affordability, hassle, and peer-effect dynamics. Feedback between network state and demand closes the loop. Outputs include coverage, financial performance, built networks, and their characteristics.*

To test competing approaches, the Operator Agent's strategy is controlled by a single parameter, λ (lambda), which adjusts the weighting in its investment algorithm between commercial and social objectives. We evaluate six discrete strategies across a spectrum from λ=0 (Profit-Driven) to λ=5 (Social-Maximising), creating a specific and replicable experimental framework. Under the Profit-Driven (λ=0) strategy, the agent exclusively prioritises network extensions with the highest projected Internal Rate of Return (IRR), whereas the Social-Maximising (λ=5) strategy prioritises connecting areas with the highest density of social housing and fuel-poor households. By simulating the outcomes for these extremes, as well as for balanced strategies (e.g., λ=2, Social-Leaning), this study aims to investigate the emergent effects on delivering sustainable and equitable heat networks.

8.3.1 Model Scope and Assumptions

The model's scope relies on several core assumptions that isolate the impact of operator strategy from other market variables. The simulation models a single Operator Agent, representing a monopolistic entity whose strategic priority, controlled by λ remains constant throughout each simulation run. This design isolates the effect of a given strategy by excluding confounding variables such as market competition or adaptive learning by the operator.

All potential network extensions are subjected to a strict financial viability screen. This screen assumes perfect foresight of cash flows over a 30-year project lifespan with a fixed discount rate (r). A project is discarded if it fails to meet specified minimum thresholds for Net Present Value ($NPV > NPV_{min}$), Internal Rate of Return ($IRR > IRR_{min}$), and maximum payback period ($PB < PB_{max}$). Furthermore, a project's Levelised Cost of Heat ($LCOH$) must not exceed the prevailing market price after accounting for capital expenditure subsidy from the Green Heat Network Fund (GHNF) (γ). To prevent stranded assets, the model implements a network adjacency rule: new 'seed' networks are only permitted if at least one adjacent Output Area is also independently viable for a future connection. Once an area is connected, it is assumed to remain so permanently, a rule that contributes to path-dependent outcomes and potential infrastructure lock-in. Finally, the analysis simplifies real-world complexity by excluding logistical disruption costs associated with construction.

8.3.2 Model Initialisation and Spatial Context

The simulation runs from 2025 to 2050, beginning from a 'greenfield' state at $t = 0$ where no DHN infrastructure exists. All key state variables are initialised to zero: the connection state for all areas is zero $B_i(0) = 0$, the set of active networks is empty $N(0) = \emptyset$, and the overall market coverage is zero $R_{cov}(0) = 0$. The model's spatial environment is structured by an undirected adjacency graph, $G_{adj} = (V, E)$, which is constructed from

GIS and census data. In this graph, the nodes (V) represent the individual Output Areas. A connecting edge (E) exists between two nodes only if the corresponding areas share a common boundary and the distance between their centroids is less than a maximum threshold, d_{max}^{adj}. This pre-computed graph governs all subsequent spatial processes in the simulation, from identifying adjacent candidates for network extensions to applying distance penalties in the project scoring algorithm.

8.3.3 Agent Specifications: The Operator

The investment strategy of the Operator Agent is key to the dynamics of the system. This agent is modelled as a rational coordinator, responsible for orchestrating the strategic expansion of the DHN. On each monthly decision-making cycle, it systematically generates, evaluates, and selects network expansion projects, operating within a fixed annual capital budget. The decision-making process is designed to be holistic, moving from an initial screening of all possible projects to a rigorous financial viability assessment and finally to a competitive selection based on a multi-criteria score. This score explicitly incorporates the λ strategy, balancing commercial returns against social and technical objectives. The agent's core decision-making logic is summarised in Table 1.

Table 1: Algorithm for DHN investment and Expansion Cycle.

Step	**Action**
1. Budget Reset	At the start of each year, reset the annual capital expenditure (CAPEX) budget.
2. Generate Candidates	Identify all potential expansion projects by finding unconnected areas adjacent to existing networks or suitable for seeding a new network.
3. Evaluate & Screen	For each candidate project, perform a full financial viability assessment (NPV, IRR, LCOH, Payback) as defined in the previous section. Discard any project that fails this screen
4. Score Projects	For all financially viable projects, calculate the final multi-criteria score based on the λ-strategy (weighting economic, social, and technical factors).
5. Select Best Project	Rank projects by their final score and select the top-ranked candidate.

6. Enforce Growth Rules	Apply rules to promote network diversity and prevent oversized, inefficient networks. If the selected project is a new "seed," verify that viable expansion pathways exist to nearby anchor loads.
7. Finalise & Implement	If a valid project is selected, commit the CAPEX, update the network state, and assign capacity for the next time step. If no project meets the minimum score threshold (S_{min}) or if the budget is exceeded, no expansion occurs.

The main step in this process is the multi-criteria scoring, where the operator's strategic orientation is applied. After passing the financial viability screen, each candidate project is ranked according to an overall score, S_{ij}, calculated as follows:

$$S_{ij}(t_m) = \sum_{k \in \{econ, equity, dtst, anchor, density\}}^{n} \omega_k s_{ij}^k - \omega_{size} s_{ij}^{size} + \epsilon_j \quad \text{Eq. 1}$$

where s_{ij}^k represents the normalised score for each of the k individual criteria (economic attractiveness, social equity, heat density, anchor-load distance penalty, and network size penalty), and ω_k are the weights for each criterion. Crucially, these weights are a function of the operator's λ strategy, shifting from prioritising economic criteria (e.g., ω_{econ}) under Profit-Driven strategy to social criteria (e.g., ω_{equity}) under Social-Maximising one. The term ϵ_j is a small random component used to resolve ties between identically scored projects.

8.3.4 Supporting Agents and Model Components

The Operator Agent's decisions are enacted through a set of supporting agents and components that represent the physical, spatial, and social dimensions of the system.

The physical assets are represented by Heat Network and Generator Agents. Each Generator Agent is defined by technology-specific parameters, including its maximum capacity C_g^{max}, operational efficiency η_g, and cost structures for both capital and operational expenditure. The Heat Network Agents function as administrative entities for each individual DHN. They aggregate system performance by tracking key financial metrics over time, including annual revenue, expenditures, and return on investment. The expenditure calculations incorporate both the variable operating costs from their associated generators and fixed annual maintenance costs calculated as a fraction of the initial infrastructure investment.

These physical assets serve a landscape defined by Output Area Agents, the core spatial units of the model. Each Output Area aggregates the heat demand from all households and local anchor loads within its census-defined boundary. The area's properties, particularly its local heat demand density D_i^{dens}, are a direct input into a dynamic pipe CAPEX sub-model. This sub-model calculates the specific installation cost C_i^{cap} for that area, reflecting the economic principle that denser areas allow for more cost-effective pipe configurations.

The demand within each Output Area is not static; it evolves based on the collective behaviour of Household Agents. At this most granular level, individual households determine their likelihood of connecting to the network according to the framework of Cowley et al. [26]. This framework simulates how decisions are influenced by personal economics (e.g., connection costs and tariffs), social networks (e.g., peer adoption rates), and policy incentives such as subsidies. The primary output of this sub-model is the dynamic 'willingness-to-connect' metric (θ_i) for each Output Area. This metric directly feeds back into the financial viability calculations for all potential network expansion projects, thus closing the socio-technical loop.

8.3.5 Key Performance Indicators (KPIs)

To provide a holistic evaluation and comparison of the outcomes from different operator strategies (λ), the model calculates several Key Performance Indicators (KPIs) at the system level: the primary measure of deployment success is Network Coverage (R_{cov}), calculated as the fraction of total heat demand connected to a DHN by the end of the simulation. To assess the emergent market structure, the Herfindahl-Hirschman Index (HHI) is used to measure market concentration. The overall financial health of the system is monitored through aggregate economic metrics, including ROI and Payback Period for each network. The simulation's functionality is underpinned by several key sub-models. A dynamic pipe-sizing model ensures technical feasibility by calculating required standard pipe diameters based on peak thermal loads. Critically, to prevent new networks from becoming stranded assets, an anchor-path search heuristic is employed. If a new "seed" network is established in an area without a major anchor load, this algorithm uses a Breadth-First Search (BFS) to identify and guide expansion along the most efficient path to a nearby unserved anchor.

8.4 Case Study

This study uses Sheffield, UK, as its case study region. The city was selected for its diverse urban morphology, well-defined socio-economic geography, and its role as a participant in the UK Government's Heat Network Zoning pilot programme [12]. The model boundary encompasses the city's 1,746 Output Areas (221,462 households), representing a total annual heat demand of approximately 1,200 GWh [27] [28] [29].

The analysis evaluates network expansion under two regulatory frameworks: a baseline market-driven scenario and a Heat Network Zoning scenario. The zoning scenario simulates current UK policy proposals, which mandate connection for specific building types within designated zones [13].

The model is parameterised using UK public sector evaluation standards [30] [31] and local data for heat demand, anchor loads, and generation sources. The final baseline parameters, presented in Table 1, were established following a preliminary sensitivity analysis. The complete specification of all data sources, asset characterisation, and the calibration process is detailed in Appendix D.

Table 1: Core Simulation Parameters for Operator & Household Agents.

Parameter	Symbol	Value	Units	Source/Info
Financial Parameters				
Discount rate	r	3.5	%	HM Treasury [31]
IRR threshold*	IRR_{min}	4-16	%	GHNF [30]
Grant factor (baseline)*	γ	0-80	%	GHNF [30]
Market heat price*	P_{mkt}	35-105	£/MWh	Ofgem [32]
Annual CAPEX budget*	B_{max}	2-60	£M	Operator financial constraint
Strategy Weighting				
Operator strategy parameter	λ	{0, 1, 2, 3, 4, 5}	-	Defines one of six discrete scenarios
Economic weight	w_{econ}	1	-	Balanced approach

Social equity weight	w_{equity}	1	-	Social-leaning emphasis
Project scoring function	Score	Formula		See Appendix B.1 for full formulation
Household Behaviour				
Hassle weight (household)*	H	0-2.5	-	Represents non-financial barriers to connection, from Cowley et al. [26].
Technical				
Simulation period	-	2025-2050	years	Policy timeframe
Spatial coverage	-	1,746	Output Areas	Census 2021 [27]
Total households	-	221,462	-	Census 2021 [27]

*Parameter was varied across a plausible range to test the model's sensitivity and robustness.

Using the calibrated baseline parameters from Table 1, the analysis evaluates six distinct operator strategies. These correspond to a spectrum of behaviours created by adjusting the λ parameter which corresponds to the following labels: Profit-Driven (λ=0); Balanced (λ=1); Social-Leaning (λ=2); Social-Prioritising (λ=3); Social-Centric (λ=4); Social-Maximising (λ=5). This experimental design isolates how operator motivation shapes socio-technical outcomes.

The outcomes of the six strategic scenarios are assessed across three core dimensions: performance, equity, and sustainability. Performance is quantified using technical and economic metrics, including total network coverage, cumulative profit, and the number of connected households and market concentration (HHI). Equity is evaluated spatially by correlating infrastructure deployment with the Index of Multiple Deprivation (IMD) [33], allowing for analysis of how benefits are distributed across socio-economic gradients. Sustainability is measured temporally, tracking the velocity and continuity of network expansion over the simulation period to distinguish between continuous growth and premature stagnation. The robustness of these findings is confirmed by the preliminary sensitivity analysis (Appendix A), which demonstrates the stability of the results across a wide range of input parameters.

To quantify the household-level economic consequences of different decarbonisation pathways, an opportunity cost analysis was performed (see Figure 10). This analysis models a policy-mandated scenario where households transition from natural gas to either a district heat network or an individual air-source heat pump (ASHP). The core technical and economic assumptions for this comparison are detailed in Table 2. To reflect the challenge of retrofitting in dense urban areas, a spatially differentiated cost for heat pumps is included based on evidence of increasing installation complexity in urban archetypes [34].

Table 2: Key technical and economic assumptions for the household-level opportunity cost analysis.

Parameter	Value	Units	Source/Info
Heat Network Pathway			
DHN connection cost	£5,000	per household	UK GOV [35]
DHN heat price	£75	per MWh	Ofgem [32]
Heat Pump Pathway			
Electricity price	£200	per MWh	NESO [36]
Heat pump base cost*	£12,000	per household	The Sixth Carbon Budget [37]
Rural areas	£10,800*	per household	-10% baseline
Rural towns	£11,400*	per household	-5% baseline
Suburban (baseline)	£12,000*	per household	Base case
Urban areas	£14,400*	per household	+20% baseline
Urban core	£16,800*	per household	+40% baseline
Common System Parameters			
Heat pump COP	3.5	-	IEA [38]
Annual household demand	12	MWh	DESNEZ [39]
Economic lifetime	25	years	HM Treasury [31]

*The heat pump base cost uses a conservative 2020s-era figure rather than a projected future cost.

8.5 Results

This section presents the primary findings from the 25-year (2025-2050) simulation. The findings are presented in four parts. First, the model's baseline output is compared to existing Heat Zoning plans [13], and its temporal dynamics are established. Second, we analyse the core findings, detailing how operator strategy and policy interact to determine overall network performance. Third, the focus shifts to the socio-economic outcomes, examining the equity of network distribution and household access. Finally, we conclude by presenting the direct economic consequences for households and identifying the most influential policy levers.

8.5.1 Establishing a Baseline and Temporal Dynamics

Figure 2 presents the spatial output of the 25-year baseline simulation, overlaid on Sheffield's policy-designated heat network zones. The map displays the simulated infrastructure (main pipelines and anchor connections), active heat producers, and connected anchor loads. The pink shaded areas represent the portions of designated zones served by the network developed in the simulation.

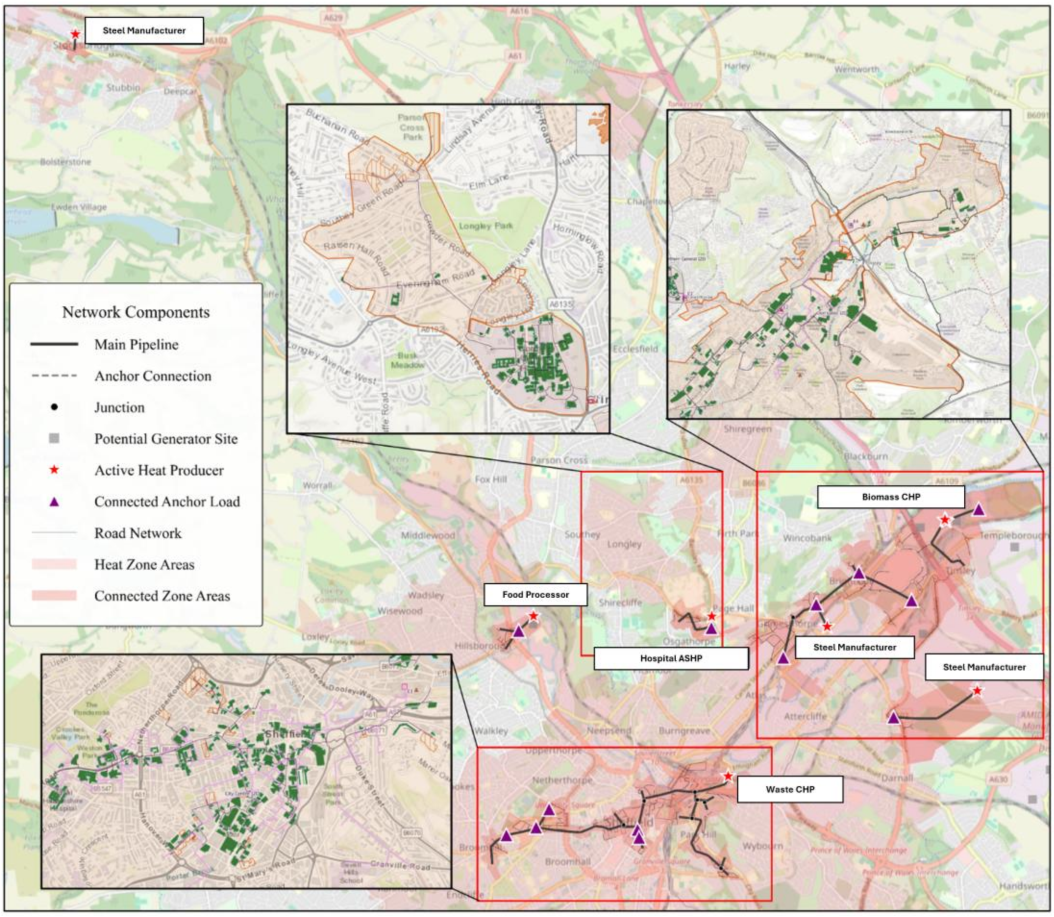

Figure 2: Validation of Model Outputs Against Policy-Designated Heat Network Zones

The baseline simulation produced seven distinct networks that connect 13 major anchor loads. Quantitatively, these networks achieved a coverage of 12% (±1.4%) of the total designated zone area and achieves a final household connection rate of 24.5% (±4.82%) within directly served areas. The individual networks varied significantly in scale, with final peak demands from 0.39 MW to 17.5 MW and a mean linear heat density of 15.8 MWh/km/year (±2.9 MWh/km). Spatially, the networks exhibit three distinct morphologies visible in Figure 2. First, linear corridors emerge along major industrial routes, as seen in the main map's Attercliffe area connecting steel manufacturers. Second, radial networks grow outward from large institutional anchors like hospital ASHP into surrounding residential areas. Finally, dense mesh networks form in the urban core where building and demand density is highest.

Having established the baseline spatial patterns, the analysis next examines the system's temporal sensitivity to key parameters. Figure 3 reports the temporal sensitivity (coefficient of variation, CV) of network expansion and customer adoption as three parameters are varied while all others are held at baseline. Clear divergences between the supply side (network expansion) and demand side (customer adoption) are observable.

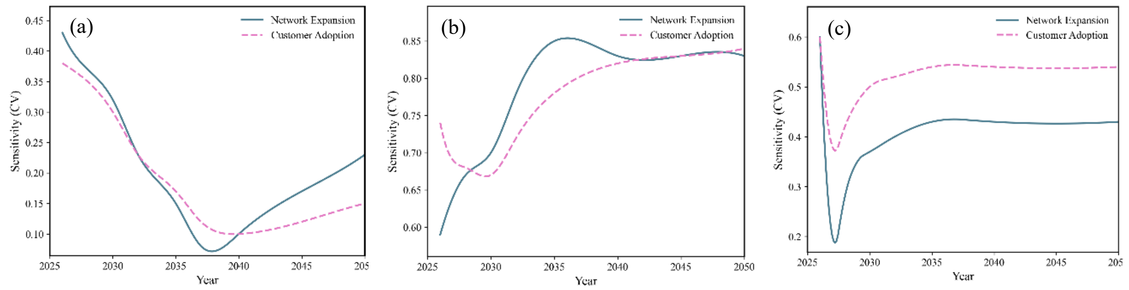

Figure 3. Temporal sensitivity (coefficient of variation, CV) of network expansion (solid) and customer adoption (dashed), 2025–2050. Each panel varies one parameter while all others remain at baseline: (a) annual CAPEX budget; (b) grant factor, the GHNF subsidy as a percentage of operator CAPEX; (c) non-financial hassle factor in the household adoption model (household-level disutility of connection/installation).

For the CAPEX budget (Figure 3a), sensitivity is initially high (CV ≈ 0.45) but drops sharply in the first decade to a minimum value (CV ≈ 0.07) before rising again slightly after 2040. The sensitivity pathways for the two metrics are initially tightly coupled but diverge after 2028, as network expansion sensitivity falls more sharply than that for customer adoption. The grant factor (Figure 3b) shows a different dynamic; sensitivity for network expansion is persistently high, remaining above a CV of 0.6 and stabilising around 0.85. The curves for the grant factor cross over around 2032, with customer adoption showing higher sensitivity before this point and network expansion showing higher sensitivity after. Finally, the hassle factor (Figure 3c) demonstrates a significant and persistent impact, with customer adoption displaying a consistently higher sensitivity (CV ≈ 0.52) than network expansion, creating a stable gap between the two metrics throughout the simulation.

8.5.2 Strategic Performance and the Role of Policy

Following the analysis of temporal sensitivities, the investigation turns to how operator strategy affects system performance. Figure 4a and Figure 4b present normalised performance metrics across six strategies (from λ=0-5), under two regulatory frameworks: a baseline without heat network zoning (Figure 4a) and a zoning framework (Figure 4b). Performance is measured by four indicators: cumulative profit, total household connections, social housing connections, and linear heat density. All metrics are normalised to enable direct comparison. The vertical dashed line marks the convergence point where multiple indicators are locally maximised.

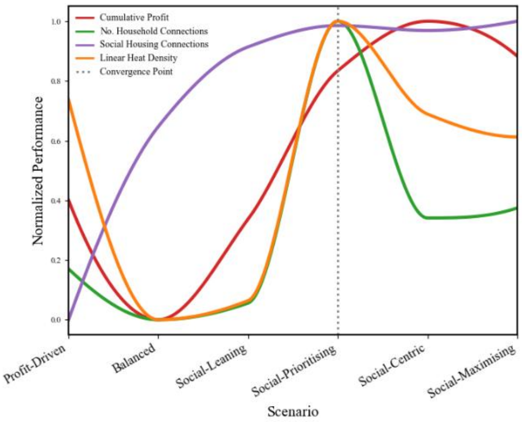

Figure 4a: Normalised performance metrics across operator strategies under the baseline regulatory framework.

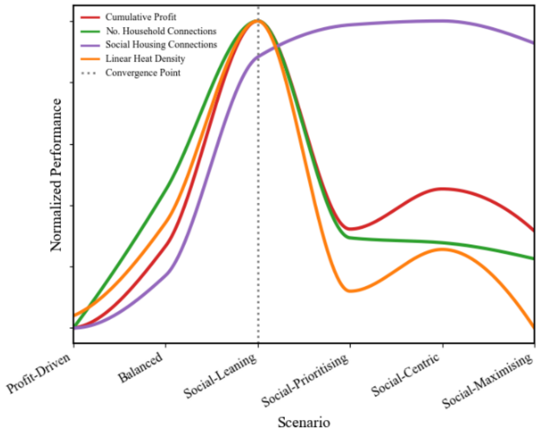

Figure 4b: Normalised performance metrics across operator strategies under heat network zoning.

In the baseline scenario without zoning (Figure 4a), the Profit-Driven (λ=0) strategy yields a moderate normalised profit (≈0.4) but fails to connect a significant number of households (≈0.2) and almost no social housing. The subsequent Balanced (λ=1) strategy results in a collapse of all metrics. Following this collapse between λ=1 and λ=3, both household connections (green line) and linear heat density (orange line) rise steeply from near-zero to their peak. The Social Housing Connections metric (purple line) follows this trajectory, reaching its maximum normalised performance (1.0) at the Social-Prioritising (λ=3) strategy. However, a critical divergence emerges at this point. While connections and density have peaked, cumulative profit (red line) continues to rise, peaking later at the Social-Centric strategy (λ=4). This reveals a direct trade-off, as maximising profit comes at the expense of household connections, which decline sharply after λ=3.

The introduction of heat network zoning (Figure 4b) fundamentally reshapes these trade-offs. The optimal convergence point for all metrics shifts decisively leftward to the Social-Leaning strategy (λ=2), which achieves near-maximal performance across all indicators simultaneously. This policy intervention effectively eliminates the trade-off seen in the baseline scenario. Beyond this new peak, performance for profit, connections, and density drops sharply, while social housing connections remain high, creating a robust performance plateau for that specific metric across the social-leaning to social-centric strategies.

To understand the mechanisms driving the performance differences seen in Figure 4, Figure 5 illustrates the spatial-temporal evolution of the networks under three representative strategies: Profit-Driven (λ=0), Social-Leaning (λ=2), and Social-Maximising (λ=5). The colours depict the construction period of each network segment, from Years 1-5 (blue) to Years 21-25 (green), showing the final 25-year state of the infrastructure.

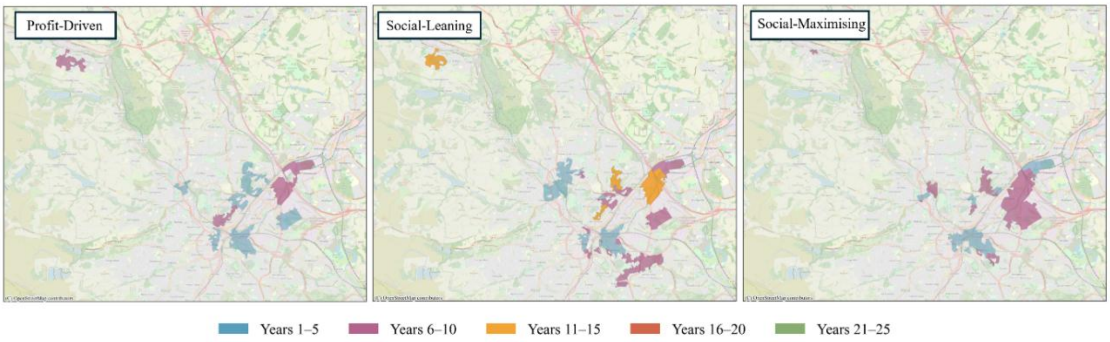

Figure 5: Temporal-Spatial Evolution of Network Infrastructure Under Different Operator Strategies

The results reveal two distinct development pathways: early stagnation and sustainable growth. Both the Profit-Driven and Social-Maximising strategies lead to stagnation, with no network construction occurring after Year 10 (an absence of orange, red, or green areas). The Profit-Driven strategy establishes a few small, scattered networks that fail to expand. In contrast, the Social-Maximising strategy shows intense, large-scale expansion in Years 6-10 (purple) before growth ceases completely.

Only the Social-Leaning strategy demonstrates a sustainable growth trajectory. Its expansion is continuous through multiple time periods, with significant buildouts in Years 1-5 (blue), 6-10 (purple), and 11-15 (orange). This persistent, phased expansion allows it to create larger, more integrated networks that connect a more diverse range of areas over the full simulation period.

These spatial patterns are confirmed by the underlying expansion velocity data. Both the Profit-Driven and Social-Maximising strategies show zero expansion velocity after Year 10. The Social-Leaning strategy, however, maintains a positive expansion rate throughout the first 15-20 years of the simulation, enabling its long-term success.

These temporal expansion patterns translate into distinct density-profit relationships that quantify the performance differences observed in Figure 4.

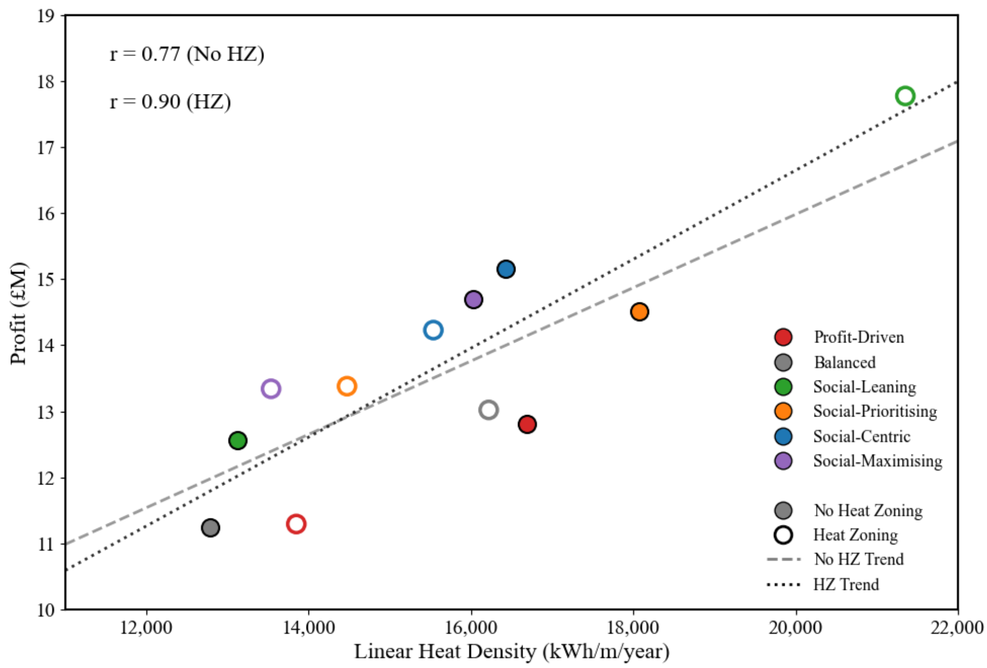

Figure 6: The Relationship Between Linear Heat Density and Financial Performance

Figure 6 presents the relationship between linear heat density (kWh/m/year) and cumulative profit (£M) across all operator strategies, comparing outcomes with and without heat zoning. Filled circles represent the baseline scenarios, while hollow circles indicate scenarios where zoning is active. Each colour corresponds to a specific operator strategy.

Without heat zoning (filled circles), a strong positive correlation exists between linear heat density and profit (r = 0.77). Notably, the Social-Centric (λ=4) strategy achieves the highest profit (£15.16M) despite not having the highest density, confirming the trade-off between maximising profit and maximising connections. The purely Profit-Driven strategy is a clear outlier, achieving only moderate density and profit as it fails to build scale.

Under the heat zoning policy (hollow circles), the relationship between density and profit becomes significantly stronger and more consistent (r = 0.90). In this scenario, the Social-Leaning (λ=2) strategy becomes the unambiguous leader, delivering both the highest density (21,352 kWh/m/year) and the highest profit (£17.78M).

The impact of the policy is most clearly seen in the upward shift of the trend line. Zoning allows for higher profits to be achieved at equivalent levels of network density, a benefit most pronounced for the intermediate strategies (λ=1 through λ=3). The policy has a counter-intuitive negative effect on the Profit-Driven strategy, which sees a slight decrease in both density and profit. The Social-Maximising strategy, meanwhile, shows almost no change, suggesting it is unaffected by the policy incentives.

8.5.3 Equity in Network Distribution and Household Access

Having established the quantitative performance differences, the analysis next examines how these translate into spatial equity outcomes across the city's socio-economic gradients.

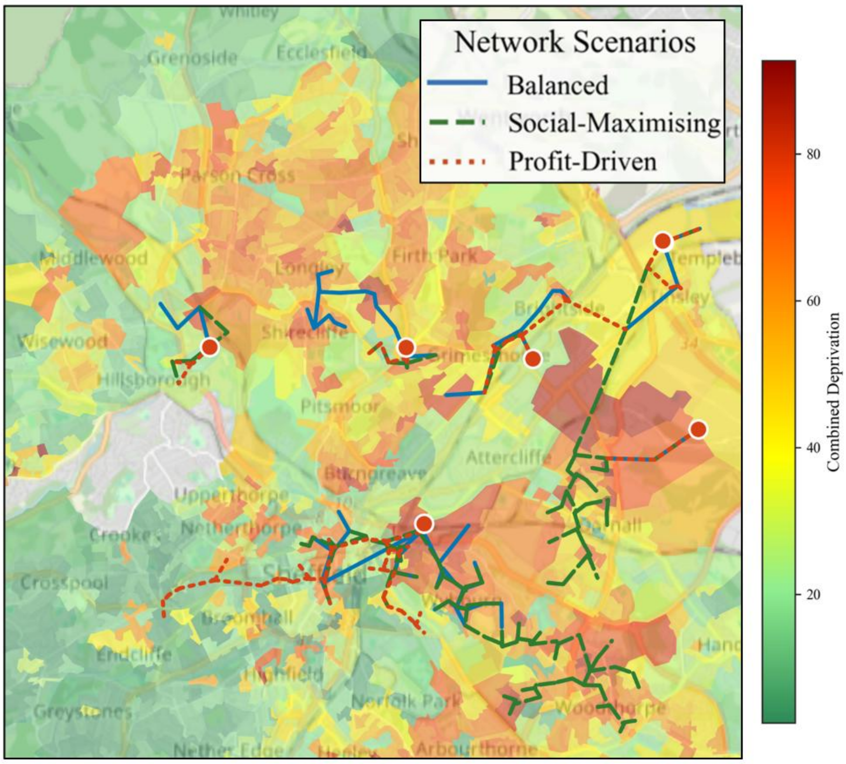

Figure 7: Spatial Distribution of Network Infrastructure Across Socio-economic Gradients

Figure 7 shows the projection of the network routes from three representative strategies on a representation of area-level deprivation, where dark red indicates higher deprivation and green indicates lower deprivation. Clearly distinct spatial patterns for the Balanced (λ=1, blue solid line), Social-Maximising (λ=5, green dashed line), and Profit-Driven (λ=0, red dotted line) strategies can be observed.

The Profit-Driven strategy concentrates its infrastructure in the central and western portions of the study area, predominantly routing through areas with lower deprivation. The network routes circumvent the high-deprivation areas in the eastern sections, with the notable exception of one eastern zone, likely targeted due to a high-value anchor load. This results in fragmented networks that largely exclude high-need communities.

Conversely, the Social-Maximising strategy focuses its deployment almost exclusively in the high-deprivation eastern sections. It forms two large, continuous networks that are geographically concentrated in these zones and fails to build significant infrastructure elsewhere, effectively isolating the networks from the rest of the city.

The Balanced strategy results in a portfolio of smaller, geographically distinct networks. Unlike the other strategies, this approach is unique in distributing infrastructure across the full socio-economic spectrum. This is clearly demonstrated in the western area, where the Balanced strategy serves both a more deprived and a less deprived zone, based on the area-level deprivation index derived from census data, while the Profit-Driven strategy builds a similar network that exclusively serves the less deprived zone. By establishing separate networks across all community types, it avoids both the targeted exclusion and the regional isolation of the other strategies.

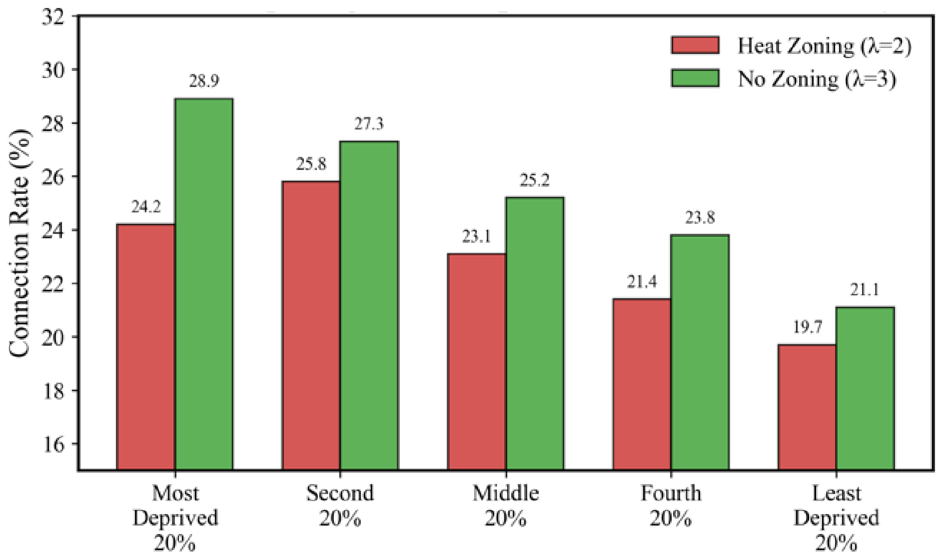

Figure 8: Household Connection Rates by Deprivation Quintile.

To understand the socio-economic breakdown of these outcomes, Figure 8 compares household connection rates across five socio-economic quintiles for the two optimal strategies: Social-Leaning with Heat Zoning (λ=2, red) and Social-Prioritising without Zoning (λ=3, green). The two scenarios reveal different responses across the deprivation gradient. In the 'No Zoning' scenario (green bars), the relationship is clear: the connection rate is highest in the most deprived quintile (28.9%) and consistently decreases with affluence, down to a low of 21.1% in the least deprived quintile. However, the 'Heat Zoning' scenario (red bars) shows the peak connection rate (25.8%) occurs in the second most deprived quintile, which is higher than the rate in the most deprived quintile

(24.2%). From the second quintile onwards, the rate then declines. A second key finding remains that the 'No Zoning' strategy still produces higher absolute connection rates in every quintile compared to the 'Heat Zoning' strategy.

Building on the general deprivation patterns from Figure 8, the analysis next focuses on connection rates among specific vulnerable population groups to assess service equity.

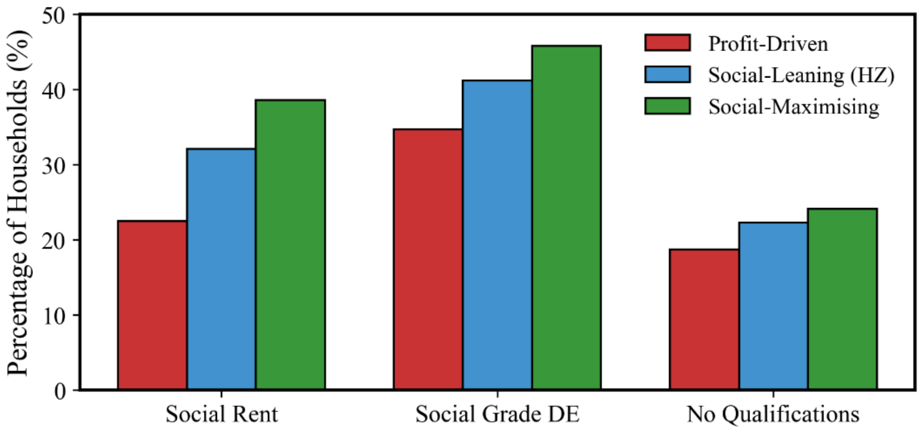

Figure 9: Connection Rates Among Vulnerable Groups by Operator Strategy

Figure 9 shows the connection rates within three vulnerable population groups—social renters, households in social grades D and E, and households with no formal qualifications across the three representative strategies. A clear and consistent ranking emerges across all three groups: the Profit-Driven strategy produces the lowest connection rate, Social-Leaning (with HZ) achieves a significantly higher intermediate rate, and Social-Maximising delivers the highest rate. For social renters, for instance, the connection rates are 22.5%, 32.1%, and 38.6% respectively.

However, this rate-based assessment must be combined with the spatial extent findings from Figure 5. While the Social-Maximising strategy achieves the highest connection rate within its limited service area, its early stagnation means the total network is small. In contrast, the Social-Leaning strategy applies its moderate connection rate across a much larger and continuously growing network. As a result, the Social-Leaning strategy connects a greater total number of vulnerable households over the 25-year period than either of the two extreme strategies.

8.5.4 Economic Outcomes and the Impact of Policy Parameters

For individual households, we now quantify the financial impact of network availability under a mandated transition from gas heating, revealing how emergent network topology creates significant, geographically contingent variations in household costs.

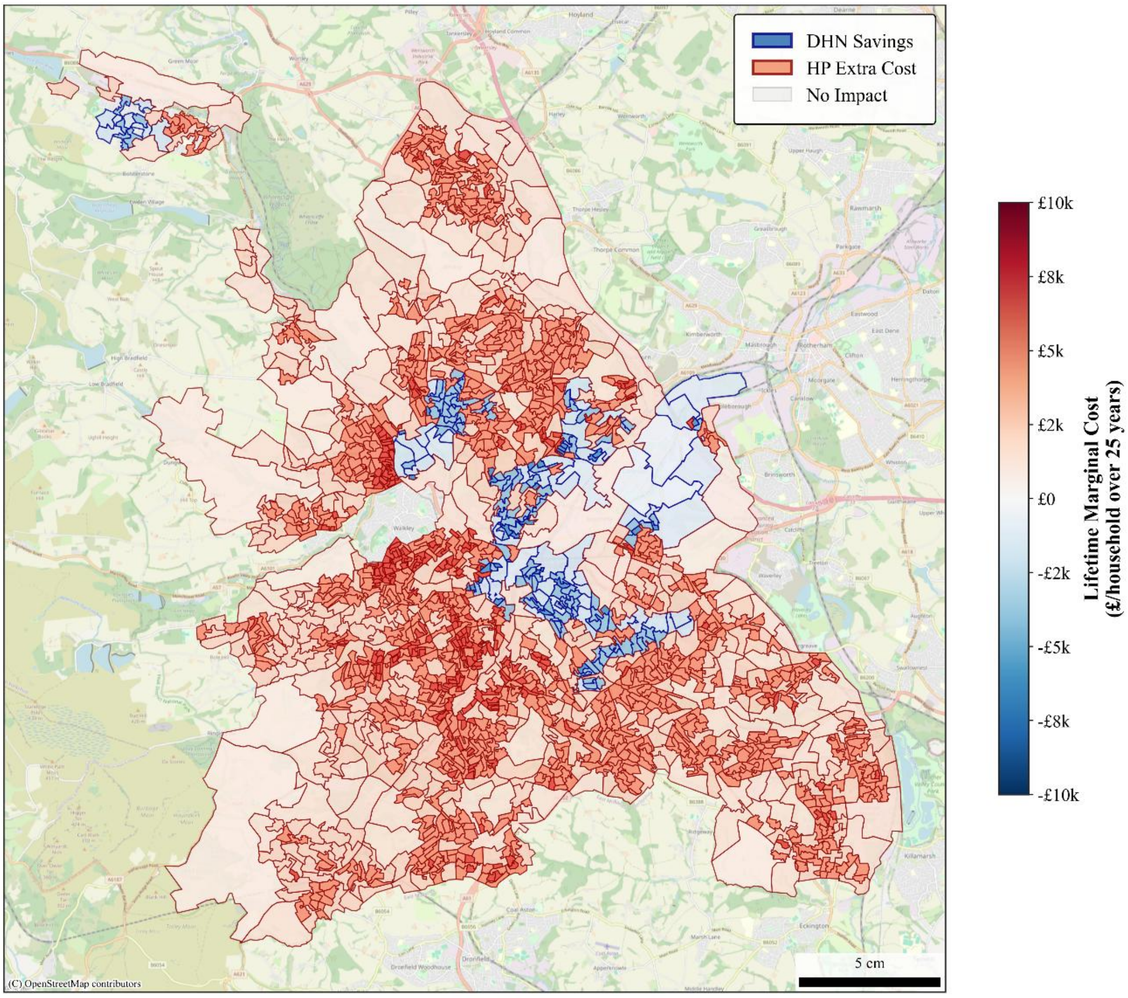

Figure 10: Illustrative Household Economic Impact of DHN Access Over a 25-Year Lifetime

This effect is visualised in Figure 10, which presents a spatial analysis of the per-household economic impact over a 25-year lifetime. The analysis assumes a mandatory switch from gas boilers to either a heat pump (HP) or a district heat network (DHN). The map displays the marginal lifetime cost of choosing an HP over a DHN, revealing the significant financial benefit of network access.

In areas with planned DHN infrastructure (blue zones), the map shows the direct lifetime savings for a household. According to the model output, these savings range from £443 to £6,443 per household over the 25-year period. The largest savings are concentrated in the dense urban core, where the spatially differentiated installation costs of heat pumps are highest.

Conversely, in areas without DHN access (red zones), the map illustrates the opportunity cost, or financial penalty, imposed on households. This penalty mirrors the savings range, costing households between £443 and £6,443 extra in lifetime costs compared to a peer in an identical building who was able to connect to a DHN. The economic burden of the heat transition falls most heavily on those in the urban core who are geographically excluded from district heating networks.

Finally, a final sensitivity test was conducted to quantify which input parameters are the most influential drivers of the model's outcomes. Figure 11 presents this analysis as a tornado plot, showing the percentage change from the baseline for five key performance indicators (KPIs); all corresponding sensitivities values for this analysis are detailed in Appendix A (Figures A1-A2).

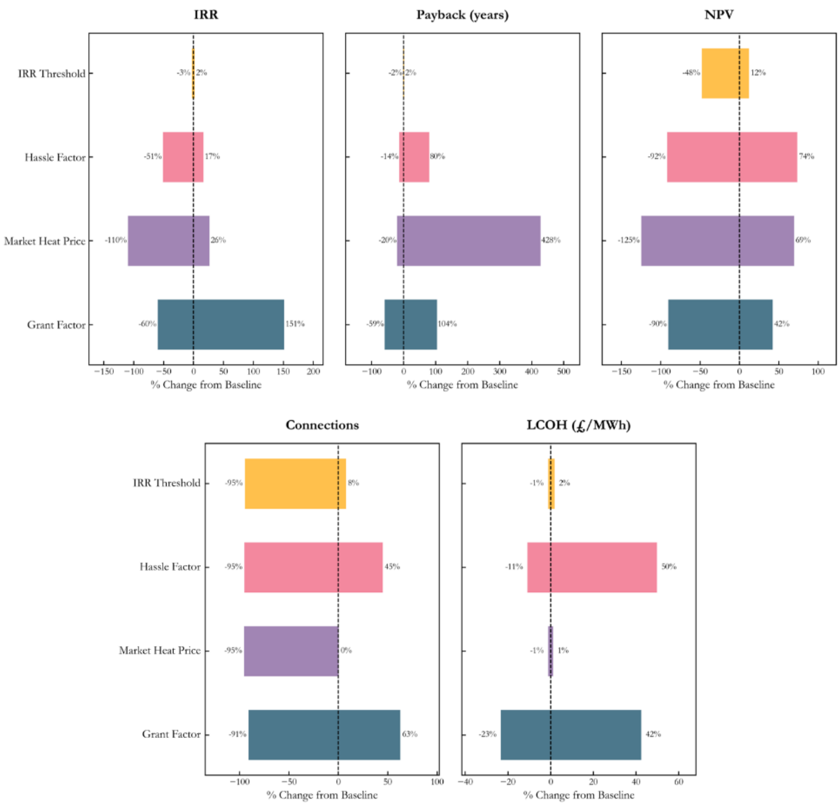

Figure 11: Policy Parameter Impacts on Key Performance Indicators

The Grant Factor emerges as the most influential parameter across all KPIs. Varying the grant has a profound impact on project viability, improving IRR by up to 151%, reducing payback periods by 104%, and increasing NPV by 142%. The underlying data confirms that grant funding below 40% of capital costs makes projects unviable, establishing a minimum public investment threshold.

The Market Heat Price shows the second-strongest influence, with a notable asymmetric effect on the payback period, which can increase by over 400% with higher prices. The results define a critical price corridor of £60-£80/MWh; below this range, networks are unprofitable, while above it, household connection rates fall significantly.

The non-financial Hassle Factor demonstrates a consistently strong, negative impact, reducing IRR by 51% and decreasing the number of household connections by 46%. The IRR Threshold, by contrast, shows only a modest impact on the final outcomes, suggesting that most financially viable projects in the simulation cluster within a narrow range of returns.

8.6 Discussion

The shortcomings modelled in this study offer a compelling explanation for the slow and inequitable deployment of DHNs in contexts like the United Kingdom. The findings demonstrate that strategies guided by a singular focus on either pure profit or pure social welfare can lead to suboptimal outcomes that lock urban energy systems into paths of stagnation. By simulating these distinct archetypes, the research offers a quantitative illustration of the mechanisms of underperformance. This suggests the challenges in many liberalised energy markets may be rooted as much in institutional and methodological frameworks as in fundamental technical constraints.

A purely market-led strategy (λ=0), which emulates the institutional logic of a fragmented commercial market, produces systemic "infrastructure redlining," where less profitable, often low-income, areas are left unserved [10]. The model demonstrates how this strategy, by narrowly optimising for profit, leads to an emergent behaviour where deprived areas are consistently bypassed. In this way, deprivation becomes a de facto proxy for financial risk, and the system fails to capitalise on the high connection willingness within these communities. This outcome reveals a critical disconnect, showing that conventional techno-economic models, relied upon for policy appraisal, can fail to identify significant market opportunities and misrepresent the needs of stakeholders who stand to benefit most. The strategy not only reinforces urban inequality [8] [9] but also leads to the system missing significant market opportunities, resulting in a stunted network.

Conversely, a strategy guided by social welfare (λ=5) creates a different, yet equally problematic, outcome: the "equity trap." By rapidly connecting households in deprived areas without integrating financially robust commercial or industrial loads, the operator builds a large but isolated and financially fragile network. This system, while well-intentioned, illustrates a path dependency toward a state of long-term financial vulnerability [25] [40]. It lacks the diverse revenue streams and internal cross-subsidies necessary to fund long-term operation, maintenance, and future expansion [41]. This finding offers a crucial, pragmatic lesson for Just Transition frameworks, reframing financial sustainability from a passive constraint into an active instrument of social policy. The model shows the most effective path to durable equity is counter-intuitive: the financial resilience of the wider system, built by co-targeting profitable zones, is precisely what enables the sustainable, cross-subsidised inclusion of vulnerable communities.

The limitations of these siloed approaches highlight the necessity of strategic coordination, providing empirical weight to the planning principles that underpin success in countries like Denmark [4] [5]. The model demonstrates that the central challenge is not an intractable trade-off between profit and social good but a contingent outcome of market and policy design. The introduction of heat network zoning helps to alleviate this conflict. It provides the certainty and scale needed to de-risk investment, thereby better aligning commercial incentives with social objectives. Under a zoning policy, the model indicates the most profitable strategy (λ=2) also delivers superior social outcomes in terms of household connections.

This policy-driven alignment creates a wide and robust "performance plateau," where a range of balanced socio-economic strategies can deliver successful city-wide deployment. This resilience is a key feature of coordinated planning [42] [4] [6], suggesting the role of policy is not to prescribe a single investment strategy but to create a stable environment where actors can collaboratively build integrated and financially sound systems. It is important to note, however, that while policy can create a favourable investment environment, it does not erase persistent social barriers; factors such as public trust, perceived disruption, and service quality remain critical hurdles that capital and coordination alone cannot overcome. Without such coordination, nations risk replicating the patterns of redlining and equity traps. This would not only jeopardise climate targets but also deepen the urban energy inequalities that strategic heat planning has the potential to correct.

8.7 Conclusion

This research concludes that the primary barrier to at-scale DHN deployment is not technical feasibility but the absence of a policy framework that aligns investment incentives with systemic efficiency. The findings demonstrate that strategic spatial planning is the key enabling mechanism. It creates a self-sustaining growth model that functions as a socio-economic bridge, leveraging commercially viable anchor loads to fund the subsequent inclusion of higher-need communities. By making efficient, density-oriented expansion the most profitable strategy, this coordinated approach actively penalises the inefficient 'cherry-picking' behaviour characteristic of fragmented markets. The central conclusion is that policy must be designed not merely to encourage investment, but to direct it, creating a market where the most profitable path is also the one that delivers the most equitable and technically sound city-wide system.

Achieving this equitable outcome, however, requires a reassessment of how social benefit is measured in infrastructure policy. The findings caution against the use of simplistic, rate-based metrics, which can be misleading. A strategy that achieves a high connection rate within a small, targeted community may appear successful, but this research shows such an approach can lead to overall network stagnation, ultimately serving far fewer vulnerable households in absolute terms. The conclusion is that sustainable, city-wide coverage is a more meaningful measure of social value than narrowly targeted connection rates. This leads to one of the most important propositions of this work: long-term financial sustainability should not be viewed as being in opposition to social equity, but rather as the precondition for achieving it at meaningful scale. In the model, financially fragile social-maximising networks can achieve high connection rates within a limited footprint, but then stagnate because they lack the revenue base needed for ongoing operation, maintenance, and phased expansion. By contrast, financially resilient networks use returns from dense and commercially robust areas to sustain the system and extend service to a greater absolute number of vulnerable households over time.

Translating this principle into practice demands that policy be material, timely, and sustained. The model points to three primary levers for steering deployment: capital grant support, market price regulation, and socio-technical engagement to overcome non-financial barriers. Crucially, the success of these levers is contingent upon meeting significant material thresholds; symbolic policies that fail to commit sufficient resources are unlikely to catalyse growth. The results indicate that capital grants are not merely accelerants but enabling conditions for deployment under current market conditions, as insufficient grant support renders projects financially unviable and prevents network growth from reaching scale. The analysis also reveals a window for action between 2025 and 2035, during which initial investments have a disproportionate, path-defining impact on a network's ultimate scale. This finding challenges the 'kick-starter' narrative of temporary support. Instead, the research concludes that consistent, long-term policy commitment is essential to maintain expansion momentum and build the investor confidence that has been historically undermined by stop-start funding cycles.

Yet even an optimal policy and investment strategy is insufficient without addressing persistent social barriers. The model reveals a critical asymmetry: while sensitivity to initial funding diminishes over time, sensitivity to non-financial 'hassle factors' remains high and constant throughout the network's lifecycle. This suggests that even when a project is financially viable for the operator, high levels of friction for the customer can derail deployment. The conclusion is that capital is a necessary but not sufficient condition for success. Lasting, city-scale deployment requires a continuous operational focus on the customer experience, on building trust, and on delivering high-quality service, as these deep-seated social challenges cannot be front-loaded or solved with financial incentives alone.

Ultimately, the consequence of failing to adopt such a multi-faceted, strategic approach extends beyond inefficient network growth to the creation of social and economic injustice. The analysis shows how technology-neutral decarbonisation mandates can produce severe, geographically determined inequities. In an uncoordinated environment, residents in areas 'redlined' by commercial operators risk being forced into high-cost 'distress purchases' of individual heating solutions. Conversely, proactive households who invest early in alternatives can see their personal expenditure become a stranded asset when a more efficient, collective solution eventually arrives. Both scenarios demonstrate that socially-blind policy can penalise citizens for their location, not their choices. This makes a powerful case for DHNs not as just another technical option, but as an essential instrument for delivering a Just Transition. The research concludes that strategic spatial planning is imperative to prevent the energy transition from deepening existing urban inequalities and to provide the coordinated framework necessary for a fair and economically rational decarbonisation for all.

8.8 Limitations and Future Directions

It is important to situate these findings within the context of the model's methodology. As an agent-based model, its strength lies in revealing the complex dynamics, feedback loops, and relative effectiveness of different strategies under controlled conditions, rather than generating definitive real-world forecasts. The economic comparison (Figure 10), for instance, assumes current cost trajectories for alternative technologies; a more rapid than expected decrease in heat pump installation costs could reduce the magnitude of the 'postcode lottery' penalty, though the underlying spatial inequality of access would likely persist. The analysis also uses a simplified economic comparison that does not account for dynamic factors such as fuel price volatility, future carbon pricing, inflation, or evolving technology costs.

Therefore, the analysis has focused on the differences between strategic scenarios and the sensitivity to key parameters, which represent robust findings. While the absolute numbers may change with external conditions, the fundamental conclusions that a balanced, policy-led strategy outperforms the extremes, that social barriers are persistent, and that a lack of strategic infrastructure planning creates severe spatial inequality are core dynamic behaviours of the system we have modelled. Future work could build on this foundation by incorporating more complex economic factors, modelling multiple competing operators, or exploring the impact of evolving consumer preferences over time.

8.9 References

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8.10 Appendix A: Model Assumptions and Limitations

This appendix details the foundational assumptions, limitations, and initial state of the Agent-Based Model.

8.10.1 Assumptions

- There is no network disconnection, once $B_i(t)$ becomes 1 for some area i, it remains 1 for all $t' > t$. We do not model strategic-level disconnections, though households may choose not to connect, captured by θ_i.
- The Operator Agent seeks to maximise a multi-criteria utility score under an annual budget cap B_{max}. We use standard viability metrics, Net-present value (NPV), Internal Rate of Return (IRR), Payback (PB), and levelized cost of heat (LCOH).
- All DHN expansion projects and generator investments are evaluated over the same fixed lifespan T(years).
- To avoid stranded assets, any "new-seed" project for area i must have at least one immediately adjacent area k with an $NPV > NPV_{min}$.

8.10.2 Limitations

- The model assumes a single, coordinating Operator Agent. In reality, DHN markets might involve multiple competing developers with different strategies.
- While the Operator uses a sophisticated process, it doesn't explicitly model learning or dynamic changes in its own strategic priorities over time in response to past successes/failures.
- The model doesn't include explicit disruption costs or complex logistical planning challenges.
- Policy instruments are set as exogenous scenario parameters rather than emerging endogenously from a policymaker agent.
- Financial evaluations assume perfect knowledge of cash flows over time, albeit based on current best estimates of demand and costs.

8.10.3 Model Initialisation and Spatial Setup

The simulation begins at time $t = 0$, with all system variables initialised as follows:

For each output area i in the set of all modelled output areas A, define a binary connection state:

$$B_i(t) = \begin{cases} 1, & \text{if area } i \text{ is connected to any DHN at time } t, \\ 0, & \text{otherwise.} \end{cases}$$

At $t = 0$, then:

$$B_i(0) = 0 \quad \forall i \in A$$

Let G be the set of all potential generator agents. Each generator $g \in G$ is initially unassigned:

$$G_{assign}(g, 0) = 0 \quad \forall g \in G,$$

Where

$$G_{assign}(g, t) = \begin{cases} 1, & \text{if generator } g \text{ is commissioned in some network by time } t, \\ 0, & \text{otherwise.} \end{cases}$$

Denote by $N(t)$ the set of all active Heat Network agents at time t. At Initialization:

$$N(0) = \emptyset$$

Define overall DHN market coverage (penetration) at time t by:

$$R_{cov}(t) = \frac{\sum_{i \epsilon A_{conn}(t)}[\theta_i D_i^{hh,ann}] + \sum_{i \epsilon A_{conn}(t)}\left[D_i^{acnhor,ann}\right] +}{\sum_{i \epsilon A}[\theta_i D_i^{hh,ann}] + \sum_{i \epsilon A(t)}\left[D_i^{anchor,ann}\right] +},$$

where

$$A_{conn}(t) = \{i \in A : B_i(t) = 1\},$$

θ_i is the local willingness-to-connect in area i, $D_i^{hh,ann}$ is the total potential annual household demand in area i, and $D_i^{acnhor,ann}$ is the total annual anchor demand in area i. At $A_{conn}(0) = \emptyset$, so:

$$R_{cov}(0) = 0.$$

Using Geographic Information System (GIS) data, we compute an undirected adjacency graph:

$$G_{adj} = (V, E),$$

where $V = A$ (nodes are output areas) and the edge $\{i, j\} \in E$ if areas i and j share a common boundary and the Euclidean distance between their centroids satisfies:

$d_{ij} \leq d_{max}^{adj}$,

here d_{max}^{adj} is the maximum connection distance for local "neighbourhood" expansions. Precomputing E allows rapid identification of spatially adjacent areas during candidate project generation.

8.11 Appendix B: Agent-Specific Formulations

This appendix provides the detailed mathematical formulations governing the behaviour and decision-making of each agent type in the model.

8.11.1 Operator Agent

The Operator Agent orchestrates the expansion of DHNs. Its primary functions include managing an annual investment budget, generating and evaluating candidate expansion projects, performing financial viability screening, applying a multi-criteria scoring mechanism to rank viable projects, and making budget-constrained investment decisions. Table B1 shows the mathematical formulation of the decision steps.

Table B1 – Expansion cycle.

1. **If** year ≠ last_reset (Eq. 3.1), **then**
   - $B_{spent} \leftarrow 0$
   - last_reset ← year
2. Build candidate set $C = \{\text{extension}, \text{new} - \text{seed}\}$ via Eq. 3.2
3. **For each** $(i, j) \in C$:

   a. Compute served fraction $f_{\ ij}$ (Eq. 3.2)

   b. Compute pipe C_{ij}^{pipe}, C_{ij}^{gen}, C_{ij}, O_{ij}, R_{ij} (Eqs. 3.3-X)

   c. **If** $NPV_{ij} \leq 0$ (eq. X), or $IRR_{ij} < IRR_{min}$ or $PB_{ij} \geq PB_{max}$ or $LCOH_{ij} > PB_{max}$, **discard**.

   d. Compute score S_{ij} (Eq. 3.7)
4. Let $C' = \{j \in C : C_{ij} \leq B_{max} - B_{spent}\}$.
5. **If** C' empty or $max_{\{j \epsilon C'\}} S_{ij} < S_{min}$, **exit** "no expansion."
6. Select $j^* = \arg\max_{j \epsilon C} S_{ij}$ (Eq. 3.8). Apply diversity fallback if j^*'s network is oversized.

The operator maintains an annual capital expenditure budget B_{max}. If $B_{spent}(y)$ is the operator's cumulative CAPEX spend in the calendar year y, then the is reset annually:

$$\text{if } y \neq y_{last\_reset} \quad : \quad B_{spent}(y) \leftarrow 0, \quad y_{last\_reset} \leftarrow y$$

the remaining budget at month t_m is:

$$B_{rem}(t_m) = B_{max} - B_{spent}(y)$$

The Operator identifies potential DHN expansion projects. Anchor loads (e.g., hospitals, schools) with high, stable heat demands are pre-identified and can act as strategic nuclei for network development, if:

$$A_{unc}(t_m) = \{i \in A : \ B_i(t_m) = 0\}$$

Is all unconnected areas. Let $N(t_m)$ be active networks; each network $n \in N(t_m)$ has remaining capacity $C_n^{rem}(t_m)$. Each unassigned generator g has maximum capacity C_g^{max} and remaining capacity:

$$C_n^{rem}(t_m) = \max\{C_g^{max} - D_{assigned,g}(t_m), 0\},$$

Where $D_{assigned,g}(t_m)$ is the total peak demand already served by g.

For each $i \in A_{unc}(t_m)$, two expansion types are proposed:

1. Network extension: for each existing network n such that i is spatially adjacent to at least one built area $j \in A_n(t_m)$, where:

$$A_n(t_m) = \{j \in A : \ B_j(t_m) = 1 \text{ and } j \text{ belongs to } n\}$$

And $C_n^{rem}(t_m) > 0$, propose a project (i, n) to extend network n to serve area i.

2. New network seed: for each unassigned generator g with $C_g^{rem}(t) > 0$ and $\text{dist}(g, i) \leq D_{max}$, propose a project (i, g) to establish a new network seeded by g initially serving area i. Denote the set of all candidate projects at time t_m by:

$$C(t_m) = \{(i, g)\}, \qquad j \in \{\text{network } n \text{ or generator } g\},$$

For each candidate (i, g), define the served fraction of area-peak demand as:

$$f_{ij}(t_m) = \min\left(1, \frac{C_j^{rem}(t_m)}{\frac{D_i^{peak}(t_m)}{\beta}}\right), \quad f_{ij} \in [0, 1],$$

where $D_i^{peak}(t_m)$ (kW) represents area i's peak thermal demand, and $\beta(-)$ is the thermal-to-electrical load conversion factor. $C_j^{rem}(t_m)$ (kW) is the remaining capacity of source j at t_m. If j is a network n, then $C_n^{rem}(t_m)$; if j is a generator g, then $C_g^{rem}(t_m)$.

In principle, if $f_{ij} < 1$), the project is only viable if area i contains a high-priority anchor load; otherwise, only $f_{ij} \geq 1$ is considered for pure-residential areas.

Each candidate $(i,j) \in C(t_m)$ compute CAPEX, OPEX and revenue scaled by f_{ij} and local willingness to connect θ_i, derived from the household adoption model [26]. Then the following CAPEX components are:

$$C_{ij}^{pipe}(t_m) = C_i^{cap} f_{ij}(t_m)\theta_i$$

Where C_i^{cap} (£) is the baseline cost to install piping for area i.

If $j = g$ or if a new capacity on network n is required:

$$C_{ij}^{gen}(t_m) = (\frac{D_i^{peak}(t_m)}{\beta}) f_{ij}(t_m)\theta_i C_j^{(\frac{gen}{kW})},$$

Where $C_j^{(\frac{gen}{kW})}$ (£/kW) is the specific capital cost of generator j.

If γ is the fraction of total capital cost covered by the Green Heat Network Fund. Then total project capex is:

$$C_{ij}(t_m) = (1-\gamma)(C_{ij}^{pipe}(t_m) + C_{ij}^{gen}(t_m))$$

OPEX has pipe-related and generator-related components, if φ_{opex} is the annual OPEX fraction of initial pipe CAPEX, then:

$$OPEX_{ij}^{pipe}(t_m) = C_{ij}^{pipe}(t_m)\varphi_{opex}$$

If D_i^{ann} (kWh/yr) be area i total potential annual heat demand, and if $O_j^{(\frac{gen}{kWh})}$ is the generator j variable OPEX per unit heat, then:

$$OPEX_{ij}^{gen}(t_m) = D_i^{ann} f_{ij}(t_m) O_j^{(\frac{gen}{kWh})}$$

Thus, the total annual OPEX is:

$$O_{ij}(t_m) = OPEX_{ij}^{pipe}(t_m) + OPEX_{ij}^{gen}(t_m)$$

If P_{mkt} [£/MWh] is the average tariff charged, and p_{rev} s the revenue adjustment factor, then annual revenue from project (i,j) is:

$$R_{ij}(t_m) = P_{mkt} D_i^{ann} f_{ij}(t_m) p_{rev}$$

Each candidate (i,j) must satisfy four criteria based on net annual cash flow:

$$\Delta_{ij}(t_m) = R_{ij}(t_m) - O_{ij}(t_m)$$

1. Net present Value (NPV): Over project lifetime T, using a discount rate r:

$$NPV_{ij}(t_m) = -C_{ij}(t_m) + \sum_{t=1}^{T} \frac{\Delta_{ij}(t_m)}{(1+r)^t} > NPV_{min}$$

Where NPV_{min} is the specified threshold.

2. Internal Rate of Return (IRR): The IRR is the discount rate at which the NPV of all cash flows equals zero. It must equal or exceed a minimum acceptable threshold IRR_{min}:

$$0 = -C_{ij}(t_m) + \sum_{t=1}^{T} \frac{\Delta_{ij}(t_m)}{(1+IRR_{ij})^t}, \quad IRR_{ij} \geq IRR_{min}$$

This is solved numerically using a bounded secant iteration method, with a convergence tolerance ε and maximum iterations $N_{max} = 100$.

3. Payback period (PB): This is the simple payback period, representing the time taken for cumulative net cash flows to recover the initial investment:

$$PB_{ij} = \begin{cases} \frac{C_{ij}(t_m)}{\Delta_{ij}(t_m)}, & \Delta_{ij} > 0, \\ \infty & \Delta_{ij} \leq 0. \end{cases} \quad PB_{ij} < PB_{max}$$

4. Levelized Cost of Heat (LCOH): This represents the average cost of producing and delivering heat over the project's lifetime per unit of heat delivered:

$$LCOH_{ij}(t_m) = \frac{\frac{C_{ij}(t_m)}{T} + O_{ij}(t_m)}{D_i^{ann} f_{ij}(t_m)} \times 10^3 \leq P_{mkt}$$

Here $D_i^{ann} f_{ij}(t_m)$ is the total heat delivered. Only projects satisfying all four criteria advance to the multi-criteria scoring.

The Operator Agent evaluates candidate expansion projects through a comprehensive scoring framework that operationalizes each λ strategy. Let $V(t_m) \subseteq C(t_m)$ be the subset of financially viable candidates. For each $(i,j) \in V(t_m)$, compute the individual criteria scores, then aggregate into overall score $S_{ij}(t_m)$.

1. Economic attractiveness: This score reflects the lifetime profit margin. It is derived from the profit margin p_{ij}, calculated by:

$$s_{ij}^{econ}(t_m) = \frac{1}{2}(\frac{2\ln(1+p_{ij})}{1+|2\ln(1+p_{ij})|} + 1), \qquad p_{ij} = \max(0, \frac{T\left(\triangle_{ij}(t_m)\right) - C_{ij}(t_m)}{C_{ij}(t_m)})$$

2. Social equity: This score prioritises areas with a higher proportion of social housing, H_i (%):

$$s_{ij}^{equity} = \frac{H_i}{100} \quad \in [0,1]$$

3. Distance penalty: This score penalises projects requiring longer pipe connections, the raw distance is first scaled and normalised:

$$d'_{ij} = \min[(\frac{d_{ij}}{D_{norm}})^2, 1], \qquad s_{ij}^{dist} = 1 - \frac{d'_{ij}}{1+d'_{ij}} \in [0,1]$$

4. Anchor-load bonus: This score gives preference to projects connecting areas with significant anchor loads. The bonus is a function of the total annual anchor load demand A_i (kWh/year) in area i:

$$s_{ij}^{anchor} = \frac{\min[a\,ln\left(1+\frac{A_i}{A_{norm}}\right), a]}{a} \in [0,1]$$

Where A_{norm} (kWh/yr) is the maximum expected anchor demand size, used for scaling, and a is a tuning parameter.

5. Heat-density Bonus: This score favours projects in areas with higher heat demand density D_i^{dens} (kWh/m^2/year):

$$s_{ij}^{density} = \frac{\min\left(D_i^{dens}, D_{max}\right)}{D_{max}} \in [0,1]$$

Where D_{max} (kWh/m^2/year) is the maximum density.

6. Network Size Penalty

If (i,j) is a network extension to existing network n_j of size $|A_{n_j}(t_m)|$, define:

$$n_j = |A_{n_j}(t_m), \quad K > 0$$

Then:

$$s_{ij}^{size} = \begin{cases} (\frac{n_j}{n_j + K})^2, & \text{if } (i,j) \text{ is an extension,} \\ 0, & \text{if } (i,j) \text{ is a new} - \text{seed network.} \end{cases}$$

Where K tunes the inflection point.

The overall project score aggregates individual criteria through λ-dependent weights, and a small random jitter $\varepsilon_j \sim U(-\delta, \delta)$ to breaks ties:

$$S_{ij}(t_m) = \sum_{k \in \{econ, equity, dist, anchor, density\}} w_k s_{ij}^k - w_{size} s_{ij}^{size} + \varepsilon_j, \quad S_{ij} \leftarrow max\big(0, S_{ij}\big)$$

Where weights w_k vary systematically across the λ=0 to λ=5 spectrum to represent different strategic priorities.

Let:

$$V(t_m) = \{(i,g) \in C(t_m) : \ C_{ij}(t_m) \le B_{rem}(t_m)\}$$

If $V(t_m) = \emptyset$ or $\max_{(i,g) \epsilon V} S_{ij}(t_m) < S_{min}$, then no expansions occur, otherwise select:

$$(i^*, j^*) = \arg\max_{j \epsilon C} S_{ij}\,(t_m)$$

Then implement project (i^*, j^*) and update:

$$B_{spent}(y) \leftarrow \ B_{spent}(y) + C_{i^* j^*}(t_m)$$

Then set $B_{i^*}(t_m + \Delta) = 1$ (connected) at next update Δ. If (i^*, j^*) is a network extension to existing network n, then assign area i^* to n:

$$A_n(t_m + \Delta) = A_n(t_m) \cup \{i^*\},$$

And subtract capacity:

$$C_g^{rem}(t_m + \Delta) = C_g^{rem}(t_m) - f_{i^* g}(t_m) \frac{D_{i^*}^{peak}(t_m)}{\beta},$$

And add n_{new} to $N(t_m + \Delta)$.

If (i^*, j^*) is a new-seed by generator g, then immediately check each adjacent unconnected area k with $\{(i^*, j^*)\} \in E$. Compute:

$$NPV_{ik}^{pipe} = -(1-\gamma) C_k^{cap} + \sum_{t=1}^{T} \frac{P_{mkt} D_k^{ann}}{(1+r)^t}$$

If $max_k\{NPV_{ik}^{pipe}\} \le 0$, then reject the new-seed (i^*, j^*) even if $S_{i^* j}$ was highest.

8.11.2 Heat Network Agent

Each Heat Network Agent n, represents an individual, operational DHN. It serves as an administrative entity within the model, primarily focused on managing its portfolio of connected Output Areas $A_k(t)$ and associated Generator Agents $G_k(t)$, and tracking its aggregate financial and operational performance over time.

When area i, joins network n at time t:

1. Update membership: $A_n(t) \leftarrow A_n(t^-) \cup \{i\}$, $G_n(t) \leftarrow G_n(t^-) \cup \{g\}$ (if $g \notin G_k$)
2. Identifies parent node by first defining the set of built adjacent areas: $N_i(t) = \{j \in A_n(t^-) \{i\} : \{i^*, j^*\} \in E\}$

The parent node is then selected as follows:

$$p_i = \begin{cases} argmin_{j \in N_i(t)} d_{ij}, & N_i(t) \neq \emptyset, \\ arg \min_{j \in A_k(t^-)} d_{ij}, & N_i(t) \neq \emptyset \text{ and } |A_n(t^-)| > 0, \\ g, & N_i(t) \neq \emptyset \text{ and } |A_n(t^-)| = 0 \end{cases}$$

Where d_{ij} denotes the Euclidean distance between centroids of areas i and j.

At each calendar year y, network n computes:

1. Annual revenue:

$$R_n^{ann}(y) = \sum_{i \in A_n(y)} (D_i^{con}(y) \times \frac{P_i}{1000})$$

Where D_i^{con} (kWh/yr) is the actual heat delivered in year y to area i (e.g., in kWh) and P_i (£/MWh) is the effective average tariff (£/MWh or £/kWh) charged to consumers in area i.

Annual operating expenditure:

$$O_n^{ann}(y) = \sum_{g \in G_n(y)} O_g^{ann}(y) + \varphi_{infra} C_n^{real}(y),$$

Where $O_g^{ann}(y)$ (£/yr) is generator g's total annual OPEX in year y, φ_{infra} is the infrastructure OPEX fraction, and $C_n^{real}(y)$ is the cumulative realised CAPE up to year y.

Cumulative updates:

$$C_n^{CumRev}(y) = C_n^{CumRev}(y-1) + R_n^{ann}(y),$$

$$C_n^{CumOPEX}(y) = C_n^{CumOPEX}(y-1) + O_n^{ann}(y),$$

$$C_n^{CumProfit}(y) = C_n^{CumProfit}(y-1) - \left(R_n^{ann}(y) - O_n^{ann}(y)\right).$$

With return on investment as:

$$ROI_n(y) = \frac{C_n^{CumProfit}(y)}{C_n^{real}(y)}, \quad C_n^{real}(y) > 0$$

And simple payback as:

$$PB_n = \begin{cases} \dfrac{C_n^{real}(y)}{R_n^{ann}(y) - O_n^{ann}(y)} & R_n^{ann}(y) > O_n^{ann}(y) \\ +\infty & otherwise \end{cases}$$

For network n at time t :

$$D_n^{inst}(t) = \sum_{i \in A_n(t)} D_i^{inst}(t),$$

where $D_i^{inst}(t)$ is the area i's instantaneous demand. And peak demand:

$$D_k^{peak}(t) = \sum_{i \in A_k} D_i^{peak}(t)$$

where D_i^{peak} (kW) is the design-peak demand of area i.

8.11.3 Generator Agent

Each generator $g \in G$ has technology-specific parameters (e.g., COP, efficiency, capital cost per KW, fixed OPEX, variable OPEX per kWh, maximum capacity C_g^{max}, at time t:

Capacity Utilisation and Remaining Capacity:

If generator g is assigned to heat network(s) $N_g(t)$, $D_n^{peak}(t)$ be the networks peak demand allocated to g, then:

$$u_g(t) = \begin{cases} \dfrac{D_n^{peak}(t)}{C_g^{max}}, & C_g^{max} > 0 \\ 0, & otherwise \end{cases}$$

$$C_g^{rem}(t) = \max\{C_g^{max} - D_n^{peak}(t), 0\}.$$

When a generator g is newly commissioned or more capacity is allocated requiring $\Delta D_k^{peak}(t)$ (kW), the incremental CAPEX is::

$$C_g^{cap} = \Delta D_n^{peak} \times CAPEX_g^{perkW}$$

Annual heat delivered is then:

$$E_g^{ann,deliv}(y) = \sum_{n \in N_g(y)} \sum_{i \in A_n(y)} D_k^{actual,conn,ann}(y)$$

Annual input energy if η_g is the end-to-end efficiency, then:

$$E_g^{ann,input}(y) = \frac{E_g^{ann,deliv}(y)}{\eta_g}$$

And the generators variable OPEX if $O_g^{var,perkWh}$ is per delivered-heat variable cost then:

$$O_g^{var,ann}(y) = E_g^{ann,deliv} \times O_g^{var,perkWh}$$

Then each generators fixed annual OPEX $O_g^{fixed,ann}(y)$, then total annual OPEX is:

$$O_g^{ann}(y) = O_g^{fixed,ann} + O_g^{var,ann}$$

8.12 Output Area Agent

Each area $i \in A$ aggregates underlying Household Agents and anchor loads. $Area_i$ is the land area of i in m^2, H_i is the set of household agents in area i, and $A_{anchors,i}$ he set of anchor loads in area i.

The total potential annual household demand is this:

$$D_i^{hh,pot,ann} = \sum_{h \in H_i} D_h^{ann}$$

The total annual anchor demand is:

$$D_i^{anchor,ann} = \sum_{a \in A_{anchors,i}} D_a^{ann}$$

The total potential annual demand:

$$D_i^{tot,pot,ann} = D_i^{hh,pot,ann} + D_i^{anchor,ann}$$

Local Willingness to connect, if $\theta_i \in [0,1]$ is the fraction of $D_i^{hh,pot,ann}$ expected to connect, then expected connected demand is:

$$D_i^{exp,conn,ann} = \theta_i D_i^{hh,pot,ann} + D_i^{anchor,ann}$$

Then the actual connected demand if $D_i^{actual,conn,ann}(t)$ is the realised total heat demand of household and anchors that will actually connect at year t, then the instantaneous demand needed at any time t is:

$$D_i^{inst}(t) = \sum_{h \in H_i : h \text{ connected at } t} \frac{D_h^{ann}}{8760} + \sum_{a \in A_{anchors,i} : a \text{ connected at } t} \frac{D_a^{ann}}{8760}$$

Then using peak-to-average factor k_i^{peak}, the average instantaneous peak demand is:

$$D_i^{avg,inst} = \frac{D_i^{tot,pot,ann}}{8760}, \quad D_i^{peak} = k_i^{peak} D_i^{avg,inst}$$

And heat demand density is:

$$D_i^{dens} = \frac{D_i^{tot,pot,ann}}{Area_i}$$

The baseline capital cost for laying new DHN distribution pipes to serve Output Area i is estimated as a function of its peak demand and local heat demand density. This reflects the principle that denser areas may allow for more cost-effective pipe configurations or shorter average connection lengths per unit of demand.

Using the areas heat density, $\Delta_i = D_i^{tot,pot,ann}/Area_i$, normalise:

$$\check{\Delta}_i = \frac{\min(\max(\Delta_i, D_{min}), D_{max}) - D_{min}}{D_{max} - D_{min}}, \quad \check{\Delta}_i \in [0,1]$$

The density-adjusted unit cost is then:

$$c_i = C_{max} - (C_{max} - C_{min})\check{\Delta}_i$$

Where C_{max}, C_{min} are the maximum and minimum possible unit costs for full pipe CAPEX to serve area i at peak is:

$$C_i^{cap} = D_i^{peak} c_i$$

And Infrastructure OPEX:

$$O_i^{infra} = \varphi_{infra} C_i^{cap}$$

Revenue potential:

$$R_i^{pot} = P_{mkt} D_i^{exp,conn,ann}$$

With heat price P_{mkt} (£/MWh).

The realized CAPEX:

As households connect, realised pipe investment evolves. If $D_i^{con}(t)$ is the cumulative annual demand connected at time t, then:

$$C_i^{cap,real}(t) = C_i^{cap} \times \min\left(1, \frac{D_i^{con}(t)}{D_i^{tot,pot,ann}}\right)$$

8.12.1 Household Agent

Each household $h \in H_i$ follows the social learning framework established in Cowley et al. [26]. Households assess lifetime connection costs versus perceived benefits (tariff savings, comfort improvements) while considering social network signals regarding neighbor satisfaction and adoption rates. Individual financial constraints and responsiveness to policy incentives (grants, carbon pricing) influence connection decisions through a probabilistic logistic function. The key output is the dynamic evolution of $D_i^{actual,conn,ann}(t)$ for each Output Area i, reflecting aggregate household choices under different operator strategies and regulatory contexts.

8.13 Appendix C: Key Performance Indicators (KPIs) and Sub-Models

This appendix details the metrics used to evaluate system-level performance and the key sub-models that enable core model functions.

8.13.1 Performance Metrics

Network Coverage:

Coverage ratio tracks market penetration at year t:

$$R_{cov}(t) = \frac{\sum_{i \epsilon A_{conn}} D_i^{exp,conn,ann}}{\sum_{i \epsilon A} D_i^{exp,conn,ann}}, \qquad A_{conn} = \{i: B_i = 1\}$$

Where $D_i^{exp,conn,ann} = \theta_i D_i^{hh,pot,ann} + D_i^{anchor,ann}$

Market Concentration

Total connected demand:

$$D_{tot,conn}^{ann}(t) = \sum_{n \in N(t)} \sum_{i \in A_n(t)} D_i^{actual,conn.ann}(t)$$

Therefore, n's market share:

$$s_n(t) = \frac{\sum_{i \in A_n(t)} D_i^{actual,conn.ann}(t)}{D_{tot,conn}^{ann}(t)}$$

The Herfindahl-Hirschman Index monitors network diversity:

$$HHI(t) = \sum_{n \in N(t)} [s_n(t)]^2$$

Using fraction share yield $HHI \in [0, 1]$.

8.13.2 Core Heuristics and Sub-Models

When a new network seed n_{new} at area $s \in A$ lacks an anchor, the Operator may connect to a nearby unserved anchor via a shortest-path on adjacency graph $G_{adj} = (A, E)$, adhering still to the financial criteria.

We define unserved anchor areas as:

$$A_{anc_{unconn}}(t) = \{i \in A : i \text{ has an anchor and } B_i(t) = 0$$

Next compute the shortest path using breadth-first search (BFS):

$$P^* = (v_0, v_1, \dots, v_L)$$

Such that $v_0 = s$, $v_L \in A_{anc_{unconn}}(t)$, and $\{v_{\ell-1}, v_\ell\} \in E$ for all $l = 1, \dots, L$, minimises L. Then let $h(t_m)$ is the index of target along P^* at time t_m. Initialize $h(t_0) = 1$. At each subsequent time step, if $v_{h(t_m)}$ is unconnected, propose $\left(v_{h(t_m)}, n_{new}\right)$. Upon connection, set $h(t_{m+1}) = h(t_m) + 1$. If $v_{h(t_m)}$ is already connected, just increment h. Continue until $h(t_m) = L$, meaning anchor v_L is connected.

Supply-Return ΔT:

$$\Delta T = \begin{cases} T_{sup}, & \text{if no generator or } T_{sup} > T_{return} + 1 \\ \max\{T_{sup} - T_{return}, 40\}, & \end{cases}$$

Segment Peak Load

For destination output area i:

$$Q_{peak} = D_i^{peak} + \sum_{a \in A_{anchor,i}} (\frac{D_a^{ann}}{8760}) \emptyset_{anchor}$$

Volumetric Flowrate:

$$\dot{V} = \frac{Q_{peak} \times 1000}{\rho c_p \Delta T}$$

Inner diameter:

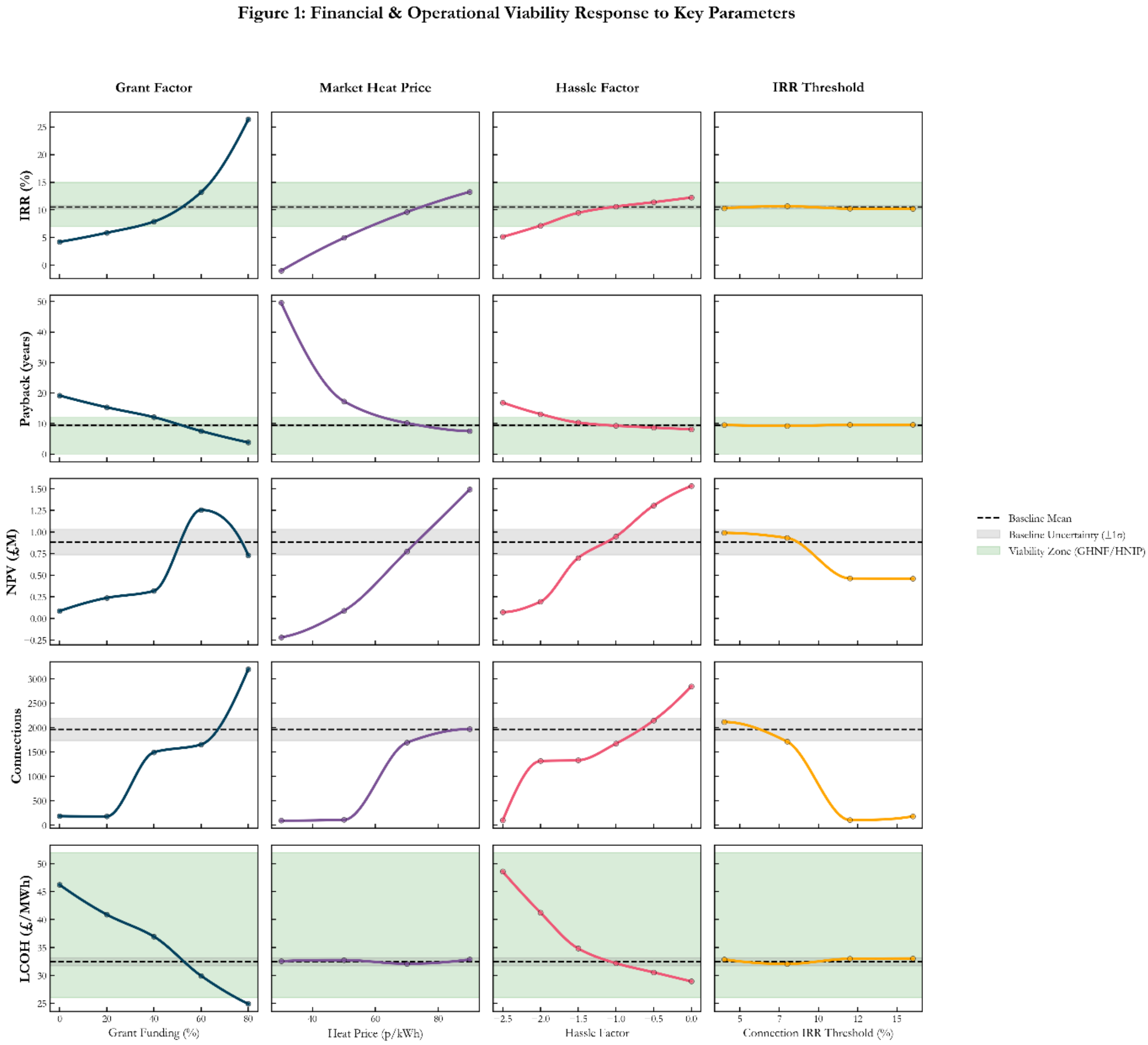
$$d_{inner} = \sqrt{\frac{4\dot{V}}{\pi v_{max}}}$$

Select Standard DN:

Choose the smallest DN in $\{25, 32, 40, \ldots, 500\}$.

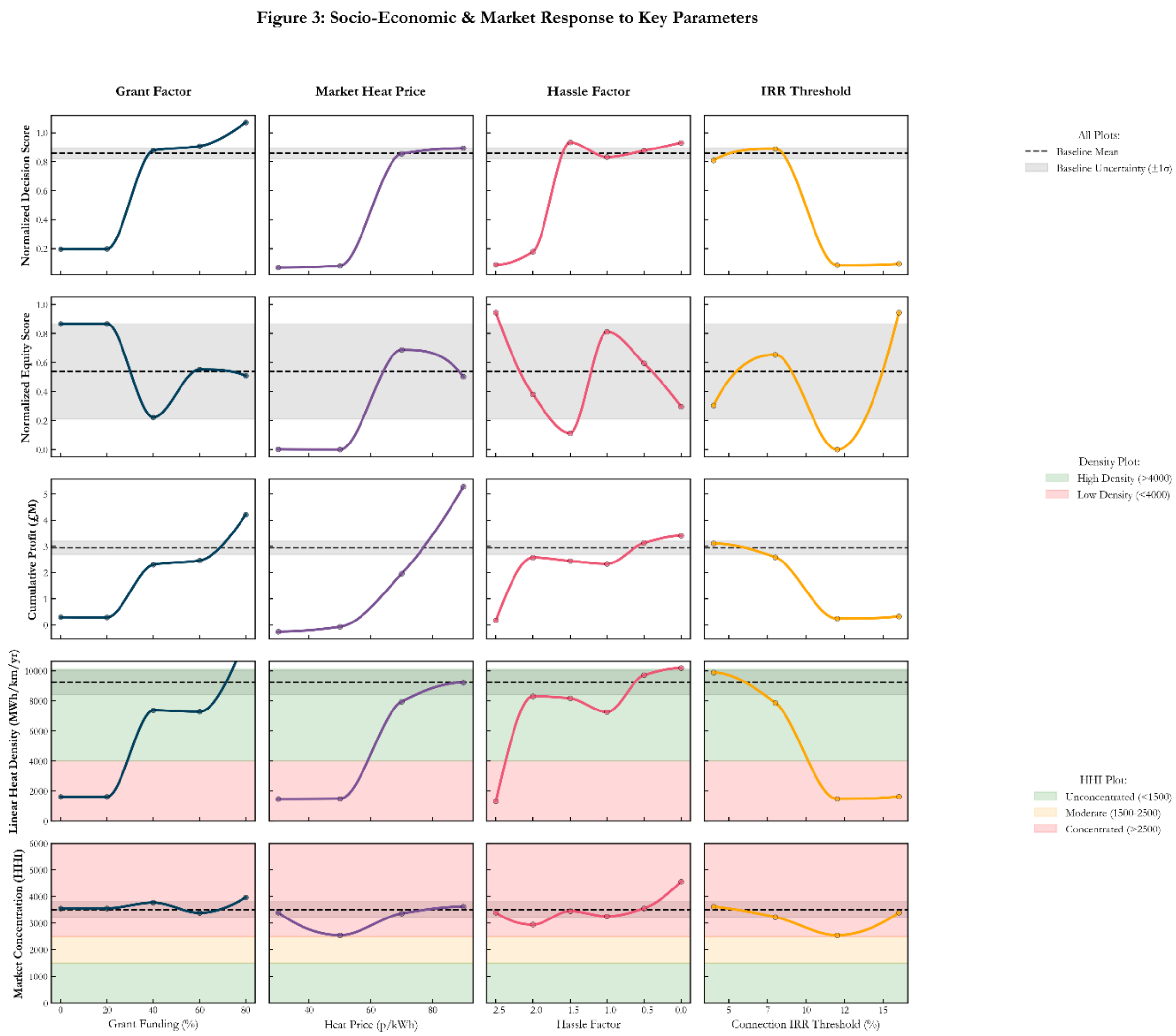
And total diameters:

$$d_{steel} = d_{inner} + 2t_{steel}, \quad d_{insul} = d_{steel} + 2t_{insul}, \quad d_{case} = d_{insul} + 2t_{case}$$



Appendix Figure A1: Financial & Operational Viability Response to Key Parameters

Appendix Figure A1 presents absolute values for financial and operational metrics across parameter variations, with green zones indicating optimal performance ranges and red zones representing non-viable conditions based on UK Green Heat Network Fund criteria and heat zoning policy thresholds. The viability zones (green shading) correspond to technical parameters established in UK policy guidance, with dashed lines indicating baseline mean values and uncertainty bands (±1σ) shown in grey.



Appendix Figure A2: Socio-Economic & Market Response to Key Parameters

Appendix Figure A2 shows absolute values for socio-economic and market metrics, with color-coded density classifications and viability thresholds derived from heat zoning policy technical standards. High density areas (>4000 kWh/m/year, green shading) and low density areas (<4000 kWh/m/year, pink shading) represent policy-defined thresholds for heat network suitability, while moderate density zones (1500-2500 kWh/m/year) indicate marginal viability conditions.

These detailed absolute values complement the percentage changes presented in Figure 10, providing quantitative benchmarks for policy implementation and model validation against UK regulatory frameworks.

8.14 Appendix D: Case Study Data Specification and Parameterisation

This appendix details the data sources and calibration process used to parameterise the model for the Sheffield case study.

8.14.1 Demand Characterisation

The total annual heat demand for the Sheffield metropolitan area (1,200 GWh) was spatially resolved at the Output Area (OA) level. The process integrated 2021 UK Census demographics [27] with building stock data from Energy Performance Certificates (EPCs) [28]. These inputs were processed using the Cambridge Archetypes model [29] to produce a granular, bottom-up heat map that accounts for variations in building type, age, and occupancy across the city.

8.14.2 Asset Identification and Specification

The simulation environment was populated with geolocated energy assets identified from multiple data sources.

- **Anchor Loads:** 22 major non-domestic anchor loads, spanning the institutional, commercial, and industrial sectors, were identified from Sheffield's heat network zoning report [13]. These provide stable initial demand points for network expansion.
- **Heat Generation Sources:** 22 potential heat generation sites were compiled from two primary datasets. Four key sites were identified in the Sheffield report [13], with the remaining 18 derived from the National Atmospheric Emissions Inventory (NAEI) point source dataset [43]. This combined portfolio offers a diverse range of potential heat sources, with thermal outputs ranging from 15°C (wastewater heat recovery) to 150°C (energy recovery facilities), allowing the model to select from different technologies based on cost and location.

The simulation environment was populated with geolocated energy assets identified from multiple data sources.

8.14.3 Financial Parameter Calibration

Before finalising the parameters for the primary analysis, a series of preliminary sensitivity analyses were conducted to calibrate the model and identify the parameters to which outcomes were most sensitive. This process ensured the baseline parameters (Table 1) represent a credible and robust operational environment for testing the strategic scenarios. The detailed methodology and results of this sensitivity analysis are presented in Appendix A.

The simulation environment is populated with assets identified from multiple data sources. The 22 major anchor loads, which span the institutional, commercial, and residential sectors, are drawn from Sheffield's heat zoning report [13]. The 22 potential heat generation sources are compiled from two primary datasets: four key sites are identified in the same Sheffield report [13], with the remaining 18 derived from the National Atmospheric Emissions Inventory (NAEI) point source dataset [43]. This combined generation portfolio offers a diverse range of thermal outputs, from 15°C (wastewater heat) to 150°C (energy recovery facilities). These assets are evaluated under two regulatory frameworks: a baseline market-driven scenario and a heat network zoning scenario. The zoning scenario simulates current UK policy proposals, enforcing mandatory connection for new developments (post-2025), existing communally heated buildings, and large non-domestic buildings (>1,000m²) within designated zones.

The model's financial parameterisation is aligned with UK public sector evaluation standards, principally the Green Heat Network Fund guidelines [30] and HM Treasury Green Book [31]. Before finalising the parameters for the primary analysis, a series of preliminary sensitivity analyses were conducted to calibrate the model. This process, the detailed results of which are presented in Appendix A, was used to identify the set of core parameters to which the model outcomes were most sensitive. This allowed for the definition of the final baseline parameters, detailed in Table 1, which represent a credible operational environment in which to test the primary strategic scenarios.