https://doi.org/10.71573/09pw7m27

Maximising heat recovery in the sewer network

Sepideh Zandhaghighi [1] https://orcid.org/0009-0001-7760-7041,
Mohamad Abdel-Aal [1, *] https://orcid.org/0000-0002-6726-5826, & *David Butler* [1]

[1]*University of Exeter, United Kingdom*
**Corresponding author email: M.Abdel-Aal@exeter.ac.uk*

Abstract
This research investigates the potential for enhancing urban decarbonisation through wastewater heat recovery systems, focusing on heat recovery optimisation and integration into urban infrastructure. Wastewater, as a continuous energy source, offers a stable source for heat recovery with minimal environmental impact. The research demonstrates the optimised recovery of heat from a sewer network with 41 pipes, the application of genetic algorithms for system configuration, and the optimal locations for installing heat exchangers.

Highlights
- Balancing high flow and high temperature finds the best heat recovery sites
- Using Genetic Algorithm to maximise heat recovery across a 41-pipe network
- Limiting heat recovery by environmental constraints to protect the biological process

Introduction
Wastewater heat recovery offers an ideal source for urban heating (Vavrin J. A, 2011). Harnessing waste heat reduces energy costs. In the UK, 16 billion litres of wastewater (7 - 25°C) are produced daily, equating to 20 TWh, enough to heat 1.6 million homes (Farman Ali S, Gillich A., 2021). Different heat recovery models for sewer networks help identify their advantages and drawbacks by analysing wastewater temperature, flow, and environmental factors. These models aim to predict recoverable thermal energy and assess system efficiency. Key considerations include wastewater temperature variability, heat transfer, and external factors like ambient temperature and sewer design. (Figueroa A, 2021). The TEMPEST Model (Durrenmatt DJ & Wanner O, 2014) simulates thermal-hydraulic dynamics, estimating steady-state conditions using time series data. Alternatively, a simplified model introduced by Abdel-Aal (Abdel-Aal M., et al., 2014) separates the heat transfer processes, accounting for interactions between wastewater, soil, and air. This approach estimates downstream temperatures by segmenting the sewer system and applying heat transfer calculations to each section. Both models emphasise the role of local factors like sewer depth and layout in optimising heat recovery efficiency. Optimisation plays a crucial role in wastewater heat recovery modelling, as it helps to determine the optimal location and timing for maximising heat extraction. By aligning heat recovery with peak wastewater temperatures and flow rates, optimisation enhances energy utilisation and reduces operational costs. Advanced, gradient-free optimisation algorithms like GAs have become prevalent over the last two decades, overcoming the limitations of traditional methods such as linear and dynamic programming. Traditional techniques often fail on large-scale, non-differentiable problems, frequently converging on local rather than global optima (Rao RV, et al., 2020; Yousefi M, et al., 2012). Optimising a single heat exchanger is challenging, as it involves a trial-and-error process to balance

competing objectives like energy savings and capital cost while adjusting numerous parameters to meet specific performance targets. However, this complexity is significantly amplified in a heat exchanger network. On top of the challenges for each unit, designers must also navigate a massive number of potential configurations, determining the optimal way to match and sequence the process streams. HEN synthesis optimises exchanger arrangements to maximise heat recovery, reduce energy input, and lower costs. Key factors include heat transfer area, flow patterns, pressure drops, material selection, and cost efficiency (Ravagnani M, et al., 2005). Optimising heat exchangers work together through thermal integration called process integration, which enhances heat recovery (Short M, et al., 2016). The primary application of a genetic algorithm (GA) is to solve the structural optimisation problem of the HEN. Combining heat transfer enhancement and integration has recently led to cost savings and improved energy efficiency, especially in retrofitted systems. GA is a robust, population-based method that explores the solution space effectively and is well-suited for this complexity, demonstrating a strong ability to search for and identify optimal solutions in thermal engineering applications, making them effective tools for designing and predicting the performance of the heat exchangers network (Venkata Rao R, et al., 2020; Yao J, 2018).
The process of optimising a sewer network for heat recovery is limited by a critical need: maintaining the effectiveness of the downstream wastewater treatment plant (WWTP). Specifically, the heat extraction must not negatively affect the temperature-sensitive biological process of ammonia nitrification. Consequently, the optimisation operates within thermal constraints dictated by the temperature requirements for this essential ammonia removal process (Wanner O, et al., 2005).

$$NH_3 + O_2 \rightarrow NO_2^- + 3\,H^+ + 2\,e^- \quad (1)$$
$$NO_2^- + HO_2 \rightarrow NO_3^- + 2\,H^+ + 2\,e^- \quad (2)$$

As detailed by regulatory bodies and scientific literature, insufficient ammonia removal leads to severe environmental consequences, including direct toxicity to aquatic life, eutrophication, the creation of hypoxic dead zones, and infrastructure corrosion within the treatment facility itself. Ensuring the influent to the WWTP remains above 9°C is therefore paramount for maintaining the performance of nitrifying bacteria and complying with stringent effluent quality standards (Adam MR, et al., 2005; Mugwili ME, et al., 2023; Zulkifli M, et al., 2022; Zangeneh A, et al., 2022).

Methodology

This study quantified and optimised the maximum potential for heat recovery from an urban sewer network in Antwerp by the Aquafin company (Aquafin, 2015). The network model is based on real-world data from the city's system. The system under investigation consists of a 41-pipe network with interconnected flow paths, and according to the sequence of pipes, there are 7 orders of pipes in the network. The network is categorised as follows:
First-order Pipes: A total of 17 pipes that directly receive wastewater from residential and commercial buildings.
Second-order and higher-order pipes: The remaining 24 pipes are fed by the confluence of upstream pipes rather than direct building discharge.
Heat recovery units (heat exchangers) were modelled as being installed at the midpoint of each pipe.

Operational and Environmental Constraints

This research aims to maximise the total heat energy recovered from a 41-pipe sewer network by optimising the outlet temperature of each pipe. The GA is used to adjust these 41 temperatures to find the combination that yields the highest net energy gain. A quasi-steady-state model simulates the network's thermal behavior over a year, using discrete time steps with pre-loaded data. The model integrates both dynamic and static data:
Dynamic Inputs (30-minute resolution): Hydraulic data (flow, depth, velocity), catchment inflows, and thermal data (soil and ambient air temperatures).

Static Parameters: Physical pipe characteristics and thermal properties.
Boundary Conditions: Initial wastewater temperatures are set for first-order pipes, with constant temperatures for inflows: Foul Water (10°C), Trade Effluent (11°C), and Surface Runoff (9°C).
A fundamental principle of the model is the conservation of heat. The heat balance equation is (Thulukkanam K, 2000):

$$Q_{in} + Q_{gen} = Q_{out} + Q_{stored} \tag{3}$$

For each time step, the GA determines the optimal set of outlet temperatures for all 41 pipes to maximise total heat recovery. The calculation process is sequential (as shown in Figure 1), following the direction of flow.
Calculating the Inlet Temperature (T_{in}):
The inlet temperature for any pipe is a flow-weighted average of its upstream sources. For a first-order pipe, the inlet temperature ($T_{in,i}$) is calculated from its direct subcatchment inflows (S_i):

$$T_{in,\,i} = \frac{\sum_{S_i}^{k} (T_{Sc,k}\, Q_{Sc,k})}{\sum_{S_i}^{k} (Q_{Sc,k})} \tag{4}$$

Where

- $T_{Sc,k}$ is the temperature of a direct subcatchment inflow k, °C.
- $Q_{Sc,k}$ is the flow rate of that subcatchment inflow k, m^3/s.

Second-order or higher pipe, the inlet temperature is a flow-weighted average of the outlet temperatures of its upstream pipes (U_i) and any subcatchment inflows (S_i):

$$T_{in,i} = \frac{\sum_{U_i}^{j} (T_{out,j}\, Q_{out,j}) + \sum_{S_i}^{k} (T_{Sc,k}\, Q_{Sc,k})}{\sum_{U_i}^{j} (Q_{out,j}) + \sum_{S_i}^{k} (Q_{Sc,k})} \tag{5}$$

Where:

- $T_{out,j}$ is the outlet temperature of an upstream pipe j, °C.
- $Q_{out,j}$ is the flow rate from that upstream pipe j, m^3/s.

Calculating the Natural Outlet Temperature (Natural T_{out}):
The model first calculates the natural temperature loss to the surrounding air and soil without any heat recovery (HR=0). The total heat loss is a sum of heat transfer to the soil and air (Thulukkanam K, 2000):

$$Total_{\ Heat\ Loss} = \mathrm{HR} + Heat_{Transfer\ to\ soil} + Heat_{\ Transfer\ to\ air} \tag{6}$$

$Total_{\ Heat\ Loss}$ in the equation is calculated by the temperature drop from the pipe upstream to the pipe downstream. For calculating the natural temperature loss, there is no HR, so: $Total_{\ Heat\ Loss} = Heat_{Transfer\ to\ soil} + Heat_{\ Transfer\ to\ air}$

For each pipe, the potential recoverable energy is calculated as:

$$Total_{\ Heat\ Loss} = \rho\ c_p\ Q\ (\ T_{UpStream} - T_{DownStream}\ ) \tag{7}$$

where Q is the flow rate (m^3/s), ρ is the density of water (Kg/m^3), C_p is the specific heat capacity (j/Kg ·°C), $T_{UpStream}$ and $T_{DownStream}$ (° C) are the upstream and downstream temperatures of the pipes.

The model assumes heat from wastewater is lost to the surroundings (to the air and soil):

$$Heat_{Transfer\ to\ air} = \frac{1}{R_{wa}} \left(T_{UpStream} - T_a \right) \tag{8}$$

$$Heat_{Transfer\ to\ soil} = \frac{1}{R_{ws}} \left(T_{UpStream} - T_s \right) \tag{9}$$

- T_a is the ambient air temperature inside the pipe, °C.

- T_s is the surrounding soil temperature,°C.
- R_{wa} is the thermal resistance between the water and the air in the pipe, °C/w.
- R_{ws} is the thermal resistance between the water and the soil, °C/w.

These resistances are dynamically recalculated at each time step, as they depend on the flow depth and velocity, which change over time. Then from equations (7), (8), and(9):

$$\rho\ c_p\ Q\ (\ T_{UpStream} - T_{DownStream}\ ) = \left(\frac{T_{UpStream} - T_a}{R_{wa}}\right) + \left(\frac{T_{UpStream} - T_s}{R_{ws}}\right) \quad (10)$$

To accurately calculate the wastewater's temperature drop, the pipe is divided into 100 smaller sections, a method called meshing. This approach is used because the rate of heat loss is not uniform; it's faster where the water is warmer near the inlet. The temperature drop is calculated for each small section, one by one, along the entire length of the pipe. This provides a highly accurate overall temperature drop and a detailed temperature profile along the pipe. For each small segment i, the heat loss to the environment is calculated as:

$$Heat\ loss\ _{segment} = \left(\frac{T_{w,i} - T_a}{R_{wa}}\right) + \left(\frac{T_{w,i} - T_s}{R_{ws}}\right) \quad (11)$$

- $T_{w,i}$ is the water temperature at the beginning of the current segment.

The $Heat\ loss\ _{segment}$ is then used to calculate the temperature at the end of the segment ($T_{w,i+1}$):

$$T_{w,i+1} = T_{w,i} - \frac{Heat\ loss\ _{segment}}{\rho C_p Q} \quad (12)$$

This calculation is repeated 100 times (Mesh=100) along the pipe's length. The final temperature after the last segment is the Natural T_{out}.

Calculating the Optimised Heat Recovery (HR):

The final step involves the GA. The GA's role is to propose a Target T_{out} for each pipe. The objective function then uses this target to determine the final calculated outlet temperature and the corresponding energy that can be recovered.

If the proposed Target T_{out} is lower than the Natural T_{out} (final $T_{w,i+1}$), it means the GA is suggesting a temperature that allows for heat extraction. In this case, energy can be recovered. The final outlet temperature of the pipe is set to this Target T_{out}, and the recoverable energy is calculated as:

$$HR = \rho\ c_p\ Q\ (\ \text{Natural}\ T_{out} - Target\ T_{out}\ ) \quad (13)$$

This process is sequential; First-order pipes are calculated, then second-order pipes, and so on. Calculation for a pipe depends on the final outlet temperature of the pipes immediately upstream of it. This entire process is repeated for every pipe in the network, in order, for every single function evaluation within the GA, until an optimal set of Target T_{out} values is found for that specific time step. The final temperature of the last pipe is simply the result of this calculation for that specific pipe index. The function iterates through all 41 pipes, calculating the energy for each and summing them to get the total network profit. The outlet temperatures calculated for upstream pipes are used as inputs for downstream pipes, ensuring the thermal cascade is respected within the optimisation. The final value returned by the objective function is the sum of the heat recovery from all pipes, where any pipe with a net loss is clamped to zero, so it does not negatively affect the total.

$$Total\ HR = \sum_{i=1}^{41} (\text{HR}) \quad (14)$$

The main goal is to maximise heat recovery from wastewater, but this must be balanced with crucial environmental and operational limits to protect the downstream WWTP. The optimisation process is governed by two key temperature constraints based on Aquafin's requirements: 1. Minimum Individual Pipe Temperature: The temperature in any single pipe cannot drop below 5°C. This acts as a safeguard to prevent near-freezing conditions that could damage infrastructure and disrupt the wastewater's biological stability. 2. Minimum Network Outlet Temperature: The final temperature of the wastewater entering the WWTP must be at least 9°C. This is critical for the survival and effectiveness of nitrifying bacteria, which are essential for removing ammonia. Failing to meet this threshold would lead to the discharge of ammonia-rich effluent, which is toxic to aquatic life, causes algal blooms, and can corrode treatment plant infrastructure.

Optimisation Technique: Genetic Algorithm (GA)

A Genetic Algorithm (GA) is used to optimise heat recovery for each 30-minute time step by defining a system-wide heat extraction strategy.

The GA Process:

Individual Solution: A solution is an individual vector containing 41 specific Target T_{out}, one for each pipe in the network.

Initialisation: The GA begins by creating an initial population of random temperature vectors (each vector contains 41 specific Target T_{out}), with each temperature falling within the allowed constraints. This ensures a diverse set of initial individuals (Katoch, Chauhan et al. 2021).

Fitness Evaluation: The fitness of each individual is determined by the total power (in Watts) it recovers from the entire network. The vector of 41 Target T_{out} is fed into a thermal model, which calculates the total recoverable heat. Individuals that yield more power are considered more successful (Xie, Sundén et al. 2008).

Reproduction: The fittest vectors are selected to create the next generation through crossover and mutation.

- Selection: A stochastic process called Roulette Wheel Selection is used, where vectors with higher fitness have a greater chance of being chosen for mating.
- Crossover: This process creates new child solutions by exchanging parts of the parent vectors. For instance, a new individual might combine the first 15 pipe temperatures from one parent with the remaining 26 from another. Uniform Crossover is the specific method used, which allows for any combination of the two parent vectors. The crossover probability in this model is set at 0.8 to broadly explore the solution space.
- Mutation: This introduces small, random changes to a temperature vector, such as altering a single pipe's Target T_{out} slightly (For example, from 9.5°C to 9.4°C). This helps to fine-tune solutions and prevent the algorithm from getting stuck. The mutation probability in this model is 0.3 (Mishra, Das et al. 2009, Guo, Liu et al. 2014). One-point mutation is the specific method used, where there is a small chance that a child's vector will be mutated at a single point (Xie, Sundén et al. 2008).

Convergence: A new population is formed by selecting the best individuals from both the parent and child generations. This iterative process repeats for 30 generations, and after several generations, it converges on a final, optimised vector of 41 Target T_{out}, which represents the best solution for maximising heat recovery while adhering to temperature constraints. The entire GA optimisation is re-run for each 30-minute time step, with updated dynamic network parameters to find the maximum possible heat recovery for that specific moment.

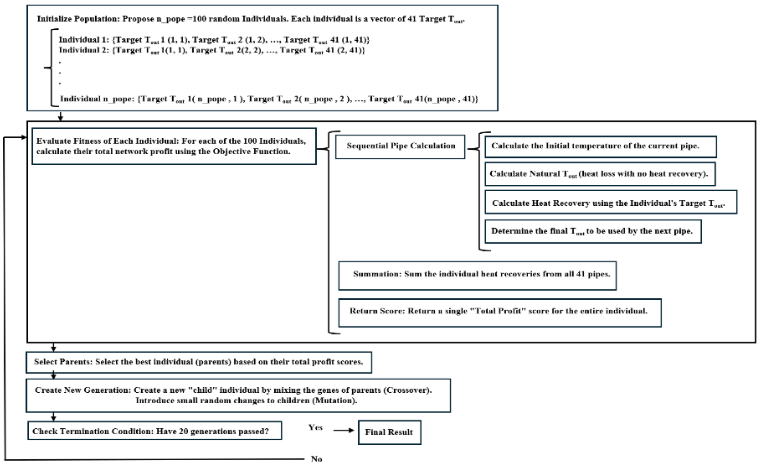

Figure 1. Optimisation flow chart for each time step

Results and discussion

Figure 2 illustrates the GA-optimised maximum thermal power recoverable from the 41-pipe network over 24 hours on January 10th. The analysis reveals that the system's thermal potential is primarily influenced by its hydraulic response to a significant discharge event.

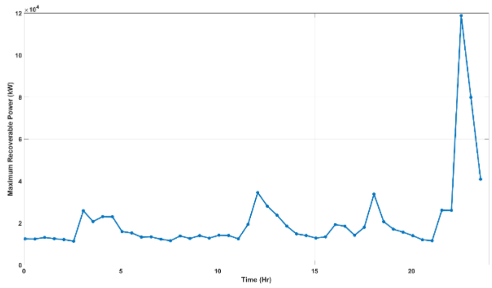

Figure 2. Maximum Recoverable Power Over Time (30-min intervals)

The network shows a typical diurnal pattern with a consistent baseline potential fluctuating above 1000 kW, with moderate peaks around 12:00 and 18:00 corresponding to domestic and industrial activity, such as midday consumption and evening peaks in household hot water usage for showering and cooking.

The defining feature of the graph is a sharp, anomalous spike at 22:30. At this point, the recoverable power surged briefly to nearly 120,000 kW (120 MW), an order of magnitude greater than the rest of the day. This massive thermal event was caused by a significant rainfall event or industrial discharge that dramatically increased the mass flow rate in the sewer network. The sharp peak in recoverable heat at 22:30 is most likely caused by an industrial or commercial discharge, not rainfall. While rainfall increases flow, it lowers the water temperature, which would not result in such a large heat spike. A more plausible explanation is a facility, such as a factory or commercial laundry, releasing a large volume of hot water at the end of a shift. This event would increase both the flow rate and the temperature of the wastewater simultaneously. Since recoverable heat is a product of these two factors, their combined increase creates a powerful multiplicative effect, leading to the dramatic spike shown in the graph.

The following figure (Figure 3) presents the 24-hour flow data, which clearly shows a direct correlation between the spike in total flow rate and the corresponding increase in recoverable power.

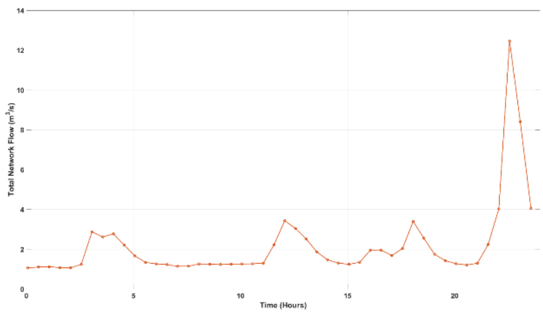

Figure 3. Total Combined Network Flow Rate Over Time

Figure 3, which shows the network's flow rate, provides the hydraulic context for the power profile in Figure 2. The hydrograph displays a base flow of approximately 1 m³/s, with superimposed peaks that directly correlate to the recoverable power. Moderate diurnal flow peaks (at 12:00 and 18:30) align with moderate power peaks.

Crucially, an extreme flow peak of approximately 12 m³/s at 22:30 aligns perfectly with the anomalous ~120 MW power spike. This perfect temporal alignment is conclusive evidence that the massive increase in recoverable power was driven by a hydraulic event. The governing equation for advective heat transport (Heat = $\rho c_p Q \Delta T$) is dominated by the flow rate term (Q). The tenfold increase in mass flow from the stormwater event caused a correspondingly massive increase in recoverable thermal energy, a factor that overwhelmed the lower temperature of the stormwater itself.

Figure 4 presents the total volumetric flow contribution (in m³) that passed through each of the 41 pipes over the entire 24-hour simulation. This provides a clear, integrated measure of the hydraulic load on each individual asset.

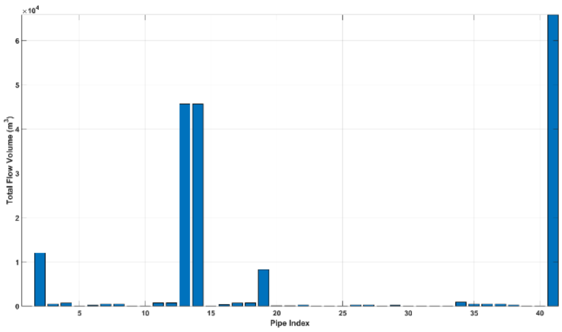

Figure 4. Total Flow Volume Contribution Per Pipe Over Simulated Period

The flow distribution in the network is highly concentrated, with a few pipes conveying most of the volume. As shown in Figure 4, Pipe 41 is the most dominant conduit, acting as the final outfall and carrying over 60,000 m³ per day. Pipes 13 and 14 are also major trunk sewers, each conveying approximately 45,000 m³ daily, while most other peripheral pipes have negligible flow.

This distribution reflects a classic hierarchical network structure. Low-flow, first-order pipes on the periphery collect wastewater, which then aggregates into high-flow, higher-order trunk sewers like 13, 14, and 41. This confirms that a pipe's hydraulic significance is a direct function of its downstream position and order within the system.

Figure 5 disaggregates the average recoverable power, presenting the contribution in (kW) and average target temperature (°C) from each of the 41 pipes over the entire 24-hour simulation period. The use of a logarithmic scale on the y-axis for average recoverable power is crucial, as it reveals a vast heterogeneity in the energy potential across the network, with contributions spanning at least five orders of magnitude.

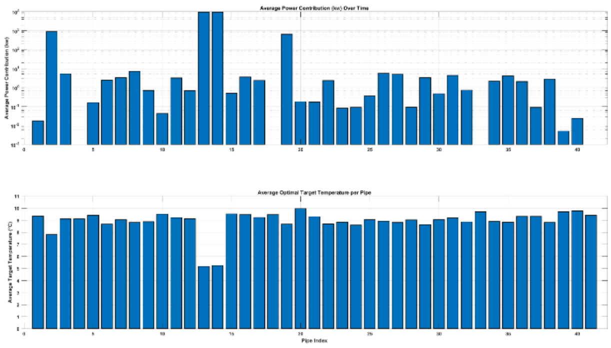

Figure 5. Average Power Contribution (kW) and Average Target Temperature (°C) Per Pipe Over Simulated Period

The distribution of average recoverable power across the network is highly hierarchical. A few primary contributors (pipes 2, 13, 14, 19) each yield over 1 MW, while many peripheral pipes are insignificant, contributing less than 1 kW. This is governed by the heat transfer equation, where recoverable energy depends on both the flow rate (Q) and the available temperature drop (ΔT). The high-potential pipes are major trunk sewers whose total power yield is dominated by massive, short-duration increases in flow during storm or discharge events. Conversely, low-potential pipes have consistently low flow rates, rendering them non-viable.

A comparison of the hydraulic load (Figure 4) with the thermal potential (Figure 5) reveals a crucial finding. Pipe 41, which carries the highest total flow volume, is not a top power contributor. The highest power comes from pipes 2, 13, 14, and 19.

This discrepancy is explained by the full power equation (Power = $\rho\, c_p\, Q\, \Delta T/t$), where the amount of recoverable power from a pipe depends on two key factors: the flow rate (how much water is flowing) and the temperature drop (how much the water can be cooled). The pipes that contribute the most energy are successful because they have the best of both worlds. They not only handle a very high flow rate, but the optimisation algorithm also intelligently assigns them a lower target temperature. This strategy creates a large temperature drop for heat extraction. It is this powerful combination of both high flow and a large, optimised temperature drop that explains their exceptional performance.

Pipe 41 (Highest Flow, Lower Energy): As the final outfall, it carries the highest proportion of cold water. This massive dilution significantly lowers its temperature, resulting in a very small available ΔT (a high target temperature) that negates its enormous flow rate.

Pipes 2, 13, 14, 19 (High Flow, High Energy): These major trunk sewers represent the optimal balance. They carry a very high flow but also a higher proportion of warmer (lower target temperature), undiluted base flow. This combination of a large Q and a significant ΔT makes them the ideal locations for heat recovery.

The analysis conclusively shows that the greatest potential resides not just in the pipes with the highest flow, but in high-order trunk sewers that balance massive flow aggregation with the preservation of thermal quality, typically just upstream of the final point of maximum dilution.

Conclusion

This study successfully demonstrated a methodology for optimising heat recovery from an urban sewer network, moving beyond simple assumptions to identify truly effective sites for heat exchanger installation. By using a GA on a 41-pipe network model, this research confirms that maximising recoverable energy involves an interaction between hydraulic load and thermal quality, controlled by strict environmental constraints needed to protect downstream wastewater treatment processes. Crucially, the research found that the pipes carrying the most water are not necessarily the best for heat recovery. The final outfall pipe, despite having the highest flow, was often too diluted with cold stormwater, which lowered its temperature and energy potential. The best locations were identified as major sewer lines that balanced high flow with warmer water more effectively. This provides a clear, data-driven method for selecting the most effective sites for heat recovery, ensuring investments deliver maximum benefits without harming the environment or water treatment infrastructure.

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