Assessing High-Potential Areas for the Development of District Heating Networks in France

Development and Improvement of a Network Mapping Algorithm at the Local Scale for Its Expansion at the Departmental Scale

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Abstract

To support the decarbonization of heating consumption, France has set targets to expand district heating networks (DHNs). In this context, it is important to identify the most suitable urban areas for implementing DHN and to evaluate their development potential.

This research article aims to evaluate the potential for district heating network development in France by designing and enhancing a network mapping algorithm at the local scale, with the intention of scaling it up to the departmental level.

This study introduces a novel approach to DHN potential assessment by combining geographic information systems (GIS) with advanced algorithms for network design and heat demand analysis. The methodology is conducted in two main stages: first, the mapping algorithm is developed and optimized at the local scale using data pre-processing, network mapping, and post-optimization processes applied to both the generated network and the optimal mapping constraint. In the second stage, the finalized algorithm is scaled up to the departmental level. Specifically, we selected the department of Oise and several cities within it as case studies.

For the 24 cities in Oise identified as suitable for district heating network development, our results indicate a 56.09% coverage of the heat demand for buildings exceeding a 30 kW maximum power threshold, significantly surpassing the current 19.14% covered by existing DHNs in the department. Additionally, our algorithm produces highly economically viable networks, achieving an average linear heat density of 2.36 GWh/km/year, well above ADEME's minimum threshold of 1.5 GWh/km/year.

The unique strength of our model lies in its ability to assess heat coverage potential on a broad scale while also evaluating economic viability in terms of heat supply profitability and efficiency, all while capturing nuanced specificities on the local scale.

Introduction

A District Heating and/or Cooling Network (DHCN) is a system distributing heat and cold energy to several users, with better operation and maintenance than individual heating/cooling solutions and fostering the integration of waste and renewable heat sources.

District heating networks have emerged as a crucial component in the transition towards sustainable urban energy systems in France. With the country's ambitious targets for reducing greenhouse gas emissions and increasing the share of renewable energy sources, DHNs offer significant potential for efficient heat distribution and integration of low-carbon energy sources. Today, these networks are powered 66% by renewable sources and are the most affordable heating option for collective housing, ahead of gas, electricity, and fuel oil. [1]

France currently has 761 district heating networks, with a total combined network length of 5,397 km and the largest concentration in the north and eastern parts of the country [2]. The Île-de-France region alone represents 45% of the national consumption of heat produced by district heating. DHNs serve approximately 2.4 million housing equivalents (representing 25.6 TWh of heat delivered in 2019), mostly in densely populated urban areas. Residential buildings consume 55% of the heat delivered, while the tertiary sector (including public services) accounts for 34% [3]. However, this potential cannot be fully realized due to the widespread use of individual heating systems. [7] The French government has set objectives to increase heat delivery through renewable energy-based DHNs up to between 31 and 36 TWh by 2028 [1]. To achieve this goal, it is essential to identify and prioritize areas with high potential for DHN development.

One such tool that has recently been introduced is EnRezo, a digital platform developed by Cerema with support from Ademe and the General Directorate for Energy and Climate (DGEC) [4]. EnRezo is designed to help identify potential zones for district heating and cooling networks by analyzing various factors, including building needs, existing networks, and heat recovery potential. This tool is intended for use by local authorities, engineering firms, state services, and energy observatories to facilitate the planning and expansion of DHNs. The methodology employed by EnRezo builds upon previous work carried out by Cerema in the PACA region and has been expanded to cover the entire country. The platform incorporates indicators on heating modes, temperature regimes, solar and biomass potential, and energy poverty data to provide a comprehensive assessment of DHN potential. Unlike our algorithm, which maps highly specific networks on precise roads and buildings, EnRezo identifies high potential areas based on clusters of buildings, infrastructure, and other relevant factors that are in close proximity as the crow flies. The added-value of our approach lies in accounting for road geography when constructing networks, rather than relying solely on straight-line distances. Our method more accurately reflects what is actually done in real-world conditions.

In the broader context of DHN research, several studies have explored methods for assessing and optimizing district heating potential. Martin Leurent (2018) evaluated DHN potential in France using a two-step approach by first modeling linear heat density with an "effective width" parameter based on building area and heat demand [5]. Then, he identified potential DHN areas using GIS data, classifying regions by heat density and grouping neighboring cells into agglomerations. Their findings showed that DHNs could supply 323 TWh/year under the 2015 baseline, meeting 62% of heat demand, with half of this potential in Centre-Val de Loire, Hauts-de-France, and Île-de-France. They also projected that DHN potential could be five times higher than current deliveries by 2050, highlighting structural and policy challenges. Unlike this broad national assessment, our study provides a more detailed, localized analysis of DHN potential for specific communes in the Oise case study.

Other researchers have focused on the technical aspects of DHN mapping and optimization, similarly to the first step of our study at the local scale. Fuchs and Müller (2017) used the uesgraphs Python package to assess District Heating Network (DHN) potential through a graph-based modeling approach that represents buildings and network junctions as nodes and connections as edges [6]. This method effectively captures the complex structure of urban energy systems with high spatial accuracy. The UESGenerator module automates network design using geospatial data from OpenStreetMap, facilitating rapid prototyping and scenario analysis. Verified through static and dynamic simulations, this approach closely aligns with ours by providing a flexible and efficient framework for evaluating DHN potential and optimizing urban energy systems at the local scale, serving as a basis for further modeling.

As part of the Center of Energy Efficiency of Mines Paris PSL, Rémi Patureau, Cong Toan Tran, Valentin Gavan, and Pascal Stabat already worked on *The New Generation of District Heating and Cooling Networks and their potential development in France* (2023) and assessed DHN potential to 132 TWh/y in France [7]. The methodology involved analyzing the evolution of DHCN in France and developing a district typology based on linear energy density, required temperature levels, and the residential-commercial mix. This approach identified 18 district types, nine of which showed high potential for DHN and DCN integration. While this study indicates that approximately 24.9% of IRIS zones in France could be suitable for DHN implementation, its accuracy is limited by its use of large-scale regional data that does not precisely follow road networks or commune boundaries. In contrast, our approach offers a more realistic assessment by closely aligning with road layouts and commune geometries, resulting in more accurate and real-world findings.

The present study builds upon these existing methodologies and tools, aiming to develop and improve a network mapping algorithm that can be applied at both local and departmental scales. By combining the strengths of GIS-based approaches, automated design techniques, and comprehensive data

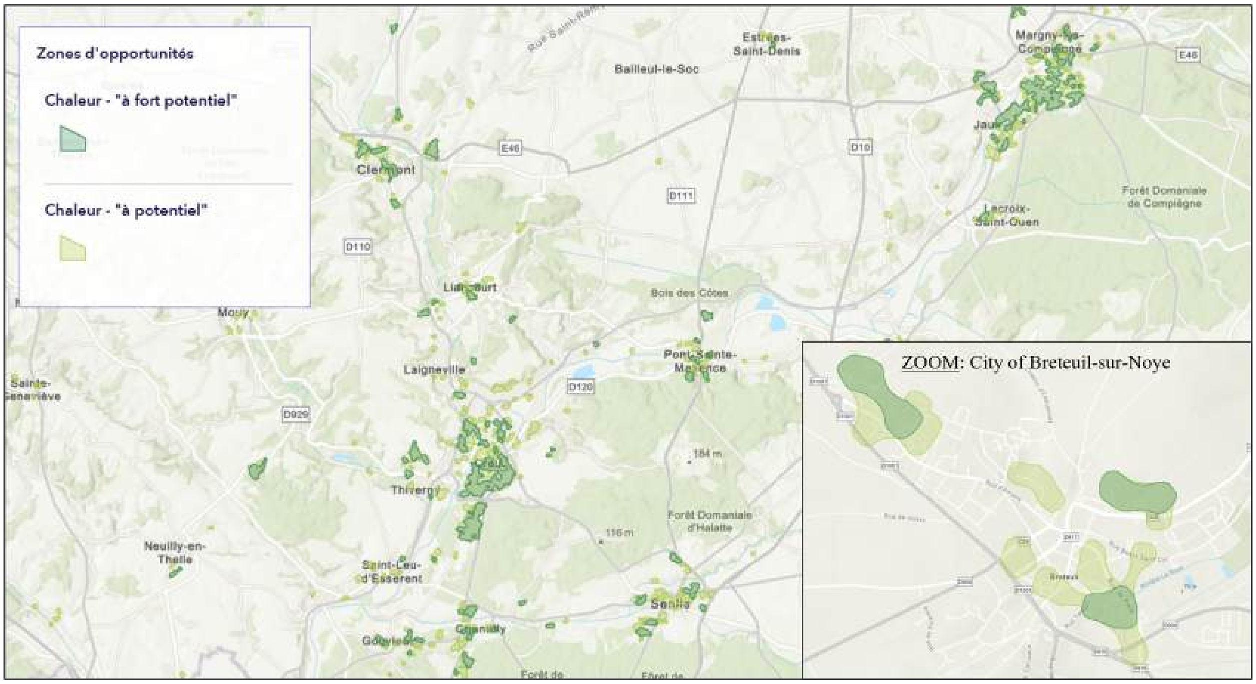


Fig. 1. EnRezo Map Platform – Oise
Dark Green: high potential areas; Light Green: potential areas

analysis, this research seeks to provide a more accurate and scalable assessment of high-potential areas for DHN development in France.

The following sections will detail the methodology employed in this study, including data sources, algorithm development, and validation processes. The results will be presented and discussed in the context of France's energy transition goals, with implications for policy-making and urban planning.

1 Methodology

The methodology is divided into two main parts, following the two-scale approach of the study:

1. Implementing the algorithm in a selected area of interest, optimizing it, and adapting it to the Dymola simulation platform.

2. Extending the algorithm's application to an entire department.

The objective of the first step is to develop a mapping algorithm and apply it to a relatively simple area of interest. Next, we implement optimization techniques based on routes pre-cutting and extremal routes removal. The route-cutting process is also adjusted to align with real-world conditions and Dymola's requirements.

The second part focuses on expanding the algorithm once it has been well set. This allows us to identify high-potential areas, defined as zones where the heat coverage ratio and linear density achieve a favorable and sufficiently high balance. Lastly, we compare the generated network to an existing network, if available, and further evaluate its potential.

1.1 Local Scale

This study is fully available in the Jupyter notebooks uploaded on the GitHub [8]. It includes three main files: the first at the local scale, which helped identify areas for improvement in the algorithm; the second at the departmental scale, used to assess the department's potential; and a third file introduced to implement specific changes to the algorithm and evaluate their impact on efficiency.

At the local scale, we selected a test city to run the algorithm for analysis. Breteuil-sur-Noye was chosen due to its small size and the presence of an existing district heating network, allowing us to compare it with the one created at the end of the analysis. Additionally, the city's small size ensures a shorter execution time, which is crucial given the potentially long runtime depending on the number of buildings and roads in a given city (*3.2.3 Execution Time*).

1.1.1 Data Preprocessing and Filtering

Data Downloading

The study is based on two main data files:

- A building dataset for a selected department, downloaded from the Géoservices BD TOPO® site (BDNB database) in Geopackage format. [9]
- A road dataset for the same department, downloaded from the Géoservices BD CARTO® site in Geopackage format. [10]

Both files were processed using QGIS software to extract and export only the relevant attributes for analysis:

- **Buildings:**`Bâtiments groupes` → `Classe DPE (DPE réels)`
- **Roads:** `BDT_3-~1 - troncon_de_route`

To download the data, we need to open the building and road files using `fiona`, a Python library for reading and writing geospatial data. It filters the data based on specific conditions and stores the valid entries in separate lists (buildings and roads):

- **For buildings:**
  - Commune code matches the INSEE commune code selected by the user.
  - Non-null geometry group.
  - Non-null construction year.
  - Building height is greater than or equal to 3 meters.
  - Non-null and valid energy consumption class.
- **For roads:**
  - Both left and right commune codes match the INSEE commune code selected by the user.

Next, the buildings and roads data are in GeoJSON format, which we need to convert into Shapely objects (a Python library for geometry manipulation) for easier handling and analysis.

It is important to note that this study is based on departmental rather than national data, though our initial goal is to assess the potential for district heating network on the French territory. This choice was made due to the format limitations of the downloadable datasets and the computational constraints involved. The department selected for this study is **Oise**.

1.2 Heat Demands Computing and Buildings Filtering

1.2.1 Buildings Heat Demands Computing

We use the `dpe_class_to_consumption` attribute to assess building consumption. The letter assigned to each building is associated with its average energy consumption in kWh/m²/year as follows:

Table 1. DPE Class and Maximum Consumption

DPE Class	Max Consumption (kWh/m²/year)
A	50
B	90
C	150
D	230
E	330
F	450
G	500

We then estimate the average annual energy consumption of each building from its DPE class, surface area, and height, using the following formula:

$$Q \approx DPE \times S \times E\left(\frac{h}{h_0}\right)$$

where $h_0 = 3$ m and E is the integer function, used to estimate the number of floors for each building.

1.2.2 Determining a Minimum Consumption Criterion to Identify Connectable Buildings

A criterion for selecting buildings to be connected to the district heating network is defined on the France Chaleur website [11]. According to this guideline, beyond a peak power demand exceeding 30kW, a building should generally be considered for network integration.

The maximum thermal power demand of residential buildings is estimated using a method detailed in the next section. Based on this criterion, buildings will be filtered accordingly.

This approach strikes a balance between maximizing connected heat demand and minimizing the length of the network to reduce costs.

1.2.3 Computing Heat Power

To simulate a district heating network using Dymola, it is essential to estimate the buildings' instantaneous

Table 2. 1974-1989 Heat Profile

Elapsed Time (s)	T_{ext} (°C)	T_{indoor} (°C)	T_{supply} (°C)	T_{return} (°C)	Water Flow (kg/s)	Total Energy Consumption (kWh)
0	1.273	17.744	291.691	289.249	0.192	0.064
3600	1.232	17.565	308.755	302.356	0.200	0.894
7200	1.374	19.084	316.640	311.968	0.200	2.493
10800	1.431	19.692	317.198	312.491	0.200	3.868
14400	1.313	19.995	317.443	312.777	0.200	5.269

heat demand throughout the year. To do so, we compare the buildings' heat demands with typical profiles.

We have three datasets corresponding to standard demand curves for buildings constructed during different periods:

- Before 1989 (excluding 1989): `RT_1974_Treated.csv` (actually based on building regulations from 1974 to 1989)
- Between 1989 (including) and 2005 (excluding): `RT_1989_Treated.csv` (reflecting standards for buildings constructed between 1989 and 2005)
- After 2005 (including 2005): `RT_2005_Treated.csv`

These datasets are available on the GitHub repository [8] and an example of the first heat profile can be seen on Table 2.

For all three files, the following physical data are recorded every second:

- T_{ext}: Outdoor air temperature (°C)
- T_{indoor}: Indoor temperature of the building (°C)
- T_{supply}: Requested temperature, which corresponds to the water temperature at the start of the secondary circuit (°C)
- T_{return}: Water temperature of the secondary circuit before entering the heat exchanger with the primary circuit (°C)
- Water flow: Mass flow rate of water in the secondary circuit (kg/s)

The laws of thermodynamics lead to the following equation:

$$\Phi_{th} = D_m \cdot c_p \cdot (T_{supply} - T_{return})$$

where:

- Φ_{th} is the heat power given by the water to the air inside the building (W);
- D_m is the water flow in the secondary circuit (kg/s);
- c_p is the specific heat capacity of water, assumed constant at 4180 J/(K·kg).

The annual energy consumption is then calculated as:

$$Q_{total} = \sum_{1\text{ year}} \Phi_{th} \Delta t = \left(\sum_{1\text{ year}} \Phi_{th} \right) \Delta t$$

where Δt is the time step, constant and equal to 3600s (i.e., 1 hour).

We adjust the water flow rate by a multiplicative factor:

$$\Phi_{th} = \alpha \Phi_{th,ref}$$

$$\alpha = \frac{Q_{total}}{\left(\sum_{1\text{ year}} \Phi_{th,ref} \right) \Delta t}$$

Finally, the water flow is adjusted using:

$$D_m = \alpha D_{m,ref}$$

The value of the alpha coefficient and the construction date will be accessible for each building connected to the district heating network through the respective properties `heat_profile_coeff` and `construction_date`.

1.2.4 Selecting Connectable Buildings

We then filter the buildings to select those with heat power exceeding the 30kW threshold.

1.2.5 Determining the location of the heat plant

Our study is based on three key principles:

- Each studied zone has only one production plant.
- The location of the heat plant is not considered, as we assume that connecting it to the network requires only about a hundred meters of piping, which is negligible compared to the total network length.
- The heat production capacity is assumed to be unlimited.

In this study, we arbitrarily choose to begin our tracing algorithm with the **largest energy consumer**. This building appears first in the buildings list due to a previous sorting in the descending order.

Note: The heat plant can also be selected manually based on the municipality's preference (*3.3.1 Heat Plant Location*).

1.3 Dijkstra Algorithm

1.3.1 Nodes Definition

In our study, we create nodes, each corresponding to either a building, a road, or a heat production plant. (Fig. 2)

The `Node_building` class models buildings by associating them with an index, spatial coordinates, and key attributes such as heat demand, construction date, and heat profile coefficient. The characteristic radius of each building is derived from its heat demand and a given heat transfer coefficient. It is important to note that the shape of each building node is not considered. Instead, they are positioned at the centroid of each building.

The `Node_road` class represents roads in the network, with its geometric center and length, which are essential for determining network connectivity. As for the buildings, the shapes of the roads are not considered; instead, their centroids are used as position points.

The `Node_plant` class is used to identify the heat production plant, which is distinguished from other buildings by its lack of heat demand and its role as the primary heat supplier. The plant node is put at the end of the buildings list, ensuring its unique position within the data structure.

These node definitions form the foundation for constructing our DHN.

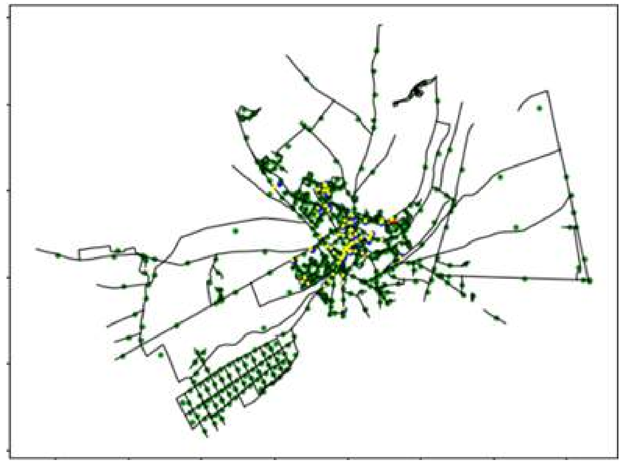


Fig. 2. Nodes for the city of Breteuil-sur-Noye. The graph shows roads nodes (green), buildings nodes (blue), the heat plant node (red), and the shortest ways between a building and its closest road (yellow lines).

1.3.2 Buildings Ranking

In the first case study at the local scale, buildings are ranked and thus prioritized in the network's creation following their heat demand, starting with the highest consumer and proceeding to the second largest, and so on (descending order). However, the algorithm can be adjusted to prioritize connections based on proximity to the heat plant instead (increasing order). This alternative logic was tested in *3.3.4 Distance Class*.

1.3.3 Edges Modelling

The presence of an edge between two nodes indicates that a pipe can directly connect them by following the route without passing through any intermediate nodes. There are thus two types of nodes:

- Between two consecutive road segments;
- Between a building and a nearby road.

We decided to only connect buildings to the roads, excluding the possibility of laying pipes directly between the buildings. As a result, there may be a slight overestimation of the district heating network cost, which should be taken into account when using the tool.

The edges will be modeled using adjacency tables represented by Python dictionaries. Although these are redundant structures, we have chosen them for their high computational efficiency. Additionally, memory usage will not be an issue given the small size of the graph (on the order of a thousand nodes).

Then, the rules for calculating the edges are as follows:

- Two roads are connected if and only if the minimum distance between them is less than 5 meters;
- A building is connected to its nearest road.

In the end, we have five lists of nodes:

- `list_nodes_buildings`, which include all buildings nodes, including the heat plant;
- `list_nodes_roads`, which include all roads nodes;
- `list_edges_roads`, which include all the roads that are connected to each road of `list_nodes_roads`;
- `list_edges_buildings`, which include all the roads that are connected to each building of `list_nodes_buildings`;
- `list_edges_roads_buildings`, which include all the buildings that are connected to each road of `list_nodes_roads`.

The length of each edge is the length of pipes that should be added to connect one node to the network from the other node.

Thanks to the creation of these nodes and edges, we can now set the algorithm.

1.3.4 Dijkstra Algorithm Definition

Priority Order for Building Connection

As said earlier, the algorithm will try to connect the buildings with the highest cumulative heat demand by going from building to building. It is therefore necessary to set a priority order for their connection. By default, this order is set so that the buildings with the highest heat demand are traversed first. Changing this priority order, for example by penalizing certain buildings with constraints (such as geographical constraints with difficult access) or by permuting buildings with similar heat demands, will subsequently result in different layouts of district heating networks, as it is the case in the *3.3 Case Study*.

Definition of Characteristic Radii

Before describing the loops of the algorithm in details, we will define the concept of characteristic radii. This involves defining for each building a radius R as:

$$R = \frac{Q}{\lambda}$$

Where Q is the annual heat demand of the building and $\lambda = 1.5$ MWh.m^{-1}.y^{-1} is a constant representing the minimum linear heat density required for a district heating network to be eligible for subsidy from the French government, defined by the ADEME (French Ecological Transition Agency) [12]. A network with such density is considered economically viable. This criterion will be used in the iterative process of the algorithm.

Physically, this radius corresponds to the maximum length of pipe that can be added to the network from each building while maintaining an economically viable network.

We will assume that the heat plant, as a place of production rather than consumption of heat, has a characteristic radius of zero.

Definition of the Radii Constraint

To connect a building A, we need to check whether it is economically viable or not. To do so, we need to use the characteristic radius and minimum heat linear density $\lambda = 1.5$ MWh.m^{-1}.y^{-1}. To characterize such constraint, we define the following variables:

- R_{network}: the radius of the network, initially equal to zero. It represents the excess of pipes that was not used to connect buildings in the previous iterations.
- R_A: the radius of the current building A, defined earlier.
- d: the shortest distance between A and the heat plant, calculated with Dijkstra's algorithm.

Thus, the hypothetical connection of A to the network is economically viable if and only if the available length of pipes is superior to the length of pipes that should be added:

$$d \leq R_A + R_{\text{network}}$$

If this criterion is True, we thus update the radius of the network with the excess of pipes:

$$R_{\text{network}} \leftarrow R_{\text{network}} + R_A - d$$

Finally, the roads belonging to the shortest path (of distance d) must be marked as part of the district heating network. In order not to count them at each iteration, their lengths will be set to zero once they are connected.

If the criterion is False, since the lengths of roads are dynamically set to zero once crossed, we can expect that the shortest distance between A and the network will decrease in a few iterations. As long as a building is connected to the network in the current loop, A will be added to the end of the queue to give it another chance to be connected to the network.

Fig. 3. Example of the iterative connection process

In this example, there are three loops:

- In the first one, (0, 2, 3, 5) are connected, 5 is the last to be connected. (1, 4) do not respect the criterion that guarantees the economic viability of the network. Thus they are added to the end of the queue and another loop is necessary.
- In the second one, 4 is connected, 4 is the last to be connected and 1 is still not connected. Then 1 is added to the end of the queue and another loop is necessary.
- In the third one, 1 still does not respect the criterion and no building is added to the network. Thus the iterations are over.

By proceeding in this way, we finally obtain a district heating network layout that is economically viable according to the criterion of 1.5 $\text{MWh.m}^{-1}.\text{y}^{-1}$. The operation of the algorithm is summarized in the flowchart on Fig. 3.

Note: The ranking based on heat demand is particularly relevant here because the higher the demand, the greater the radius. By prioritizing the connection of high-consumption buildings at the beginning of the algorithm, the network's radius R_{network} expands. As a result, the constraint becomes less restrictive, allowing more buildings with lower heat demand to be integrated into the network in the following loops. This leads to a larger network with increased building connectivity and greater heat coverage—i.e., the percentage of total heat demand covered by the network for the city's buildings at the 30 kW power threshold. The choice of ranking strategy can vary depending on the municipality's objectives, whether it aims for maximum heat coverage, highest linear density, the largest number of connected buildings, or the shortest network (see Results).

Initialization

First of all, the network, which is represented by a sub-graph of the district, is initialized with the following data:

- An initial building: the heat plant;
- Initial edges: none;
- Initial Radii: for each building, $R = \frac{Q}{\lambda}$;
- Initial network radius R_{network}: 0;
- A list of crossed buildings: all equal to 0 (none have been crossed at the beginning);
- The queue: contains all the buildings (all buildings remain to be crossed at the beginning);
- A list of buildings: all False (not connected at the beginning) except the last one (True for the heat plant);
- A list of roads: all False (not connected at the beginning).

The district heating network construction algorithm consists of a simple traversal of the buildings in the previously defined priority order. The buildings are then represented by a priority queue. At each iteration, we consider A, the first building in the queue, the one with the highest priority. We then compute the shortest path between A and the existing network using the rules explained earlier for calculating the length of edges.

Zoom into the Graph Class

In the code available on the Github [8], Dijkstra's Algorithm is implemented within a class named `Graph`, which includes several key functions:

1. `__init__` function – Initializes all necessary objects for running the algorithm, including:
   - Lists of different nodes
   - The number of buildings and roads
   - The `dhn_buildings` and `dhn_roads` vectors, which store `True` if a building or road is connected and `False` otherwise

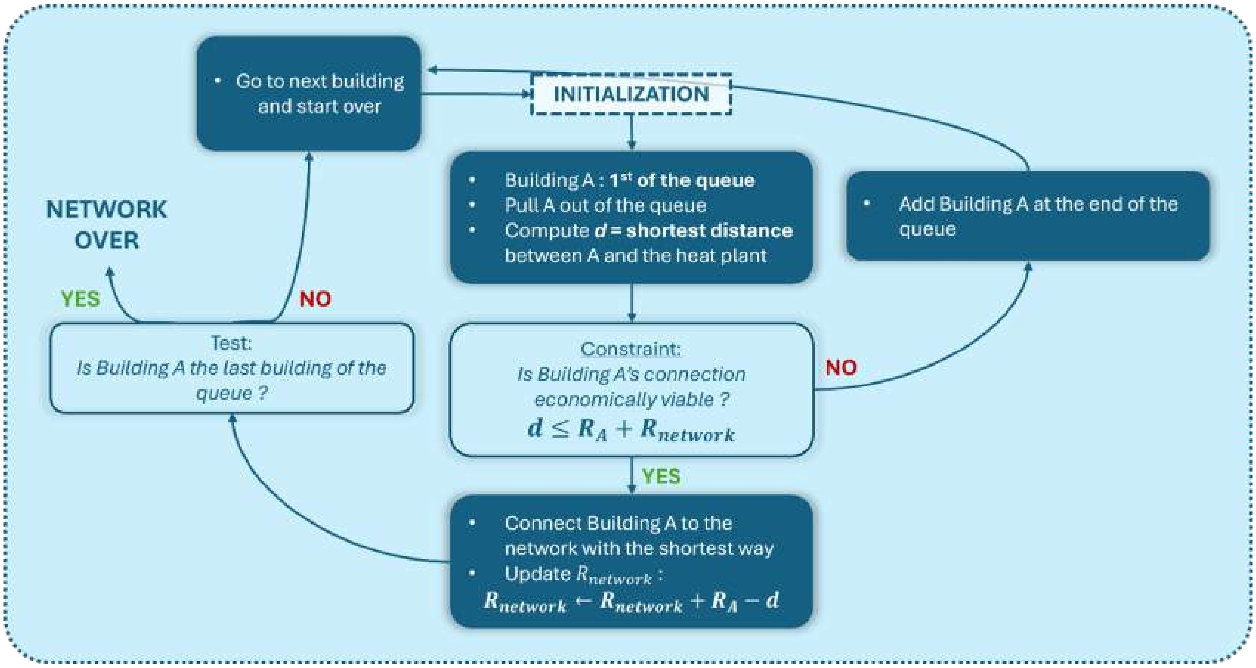


Fig. 4. Algorithm Summary.

- The predecessor of the first node (initialized as `None`)
- The radii of the buildings

2. `initialise_radii` function – Computes the radius for each building node (except the heat plant) using the formula provided earlier.

3. `connect_network` function – Connects buildings and roads to the network, updating the `dhn_buildings` and `dhn_roads` vectors by setting them to `True` when a building or road is connected.

4. `reinitialise_predecessors` function – Resets the predecessors of the building to be connected at the start of each loop by setting them to `None`.

5. `shortest_way` function – Computes the shortest distance between a building and the heat plant using Dijkstra's Algorithm.

6. `compute_dhn` function – Integrates all the functions above:

   - First, it initializes the setup according to the Initialization section described earlier.
   - Then, while not all buildings have been processed (i.e., the queue length is greater than zero), it starts over.

The whole algorithm process is summarized on Fig. 4.

1.4 Pre-Cutting

The original algorithm processes entire roads by following the length and order of their segments. Each road segment is represented as a `LineString` object from the Shapely library, composed of a sequence of points connected by straight lines. However, in the BD TOPO downloaded data, these segments are ordered and divided randomly (Fig. 5). Consequently, the algorithm may select roads that are either too long or useless for the network (Fig. 6). For example, a 1 km road with only one building located at the beginning—say, at 10 meters—would be added to the network in its entirety if that building is selected and thus add uselessly 990 meters to the network.

Furthermore, in the Dymola simulation software, each road segment is modeled as a pipe, and each pipe carries a flow that depends on the buildings upstream and downstream. As a result, the model quickly becomes complex due to the large number of segments that need to be represented. To ensure an effective simulation, each road segment should be uniquely defined between two buildings or between one building and one intersection connected to the network.

1. Merging Roads

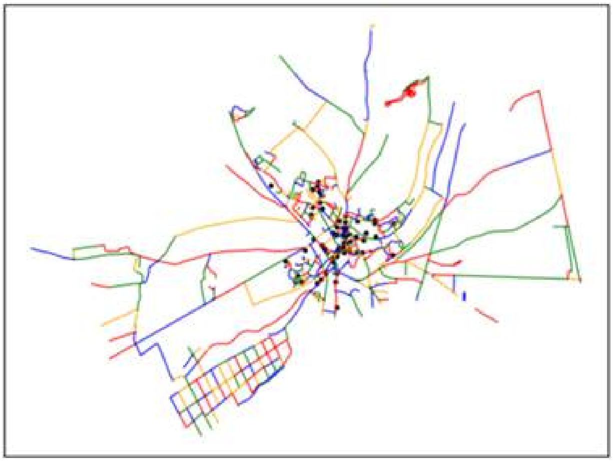


Fig. 5. Initial Division of the Roads.
Roads are printed randomly in four different colours.

The first step of the Pre-Cutting method is to merge all roads that share a common point, except when that point is connected to more than two roads. In such cases (i.e. an intersection), the roads are not merged. This process, which thus merges roads until intersections, is performed using the `linemerge` function from the Shapely library.

2. Projecting Buildings on Roads and Dividing Roads

Next, we need to divide the roads at the point closest to each building. To achieve this, we start by orthogonally projecting the buildings onto the roads. This is done by identifying, for each building, the road that is at the minimal distance from it. Once identified, we use the `interpolate` function to project the buildings onto the roads (Fig. 8).

Once the projection is complete, we need to split the roads at each projected point. To achieve this, we define a `split_route` function, which processes each road by identifying the number of projected points on it and extracting the coordinates from its `LineString`.

3. Selecting and Deleting Extremal Roads

The function then divides the coordinate list into separate sub-lists whenever a projected point is encountered. To prevent gaps in the roads, we ensure that each segment includes the corresponding projected point at both its start and end. Finally, each sub-list is converted back into a `LineString`, resulting in multiple road segments derived from the original road.

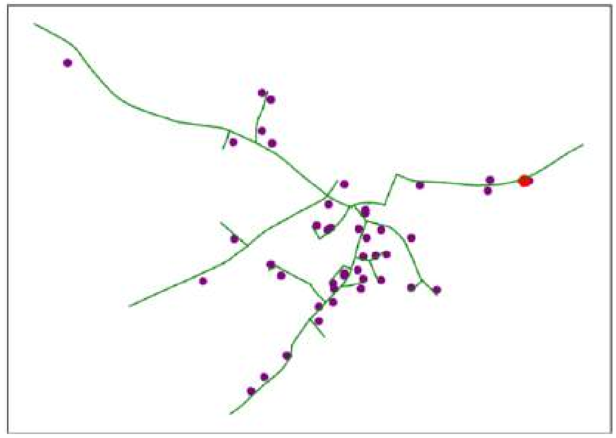


Fig. 6. DHN created without pre-cutting.
Many roads have been selected as they contain a building economically viable to connect, though they are much too long, which increases uselessly the costs.

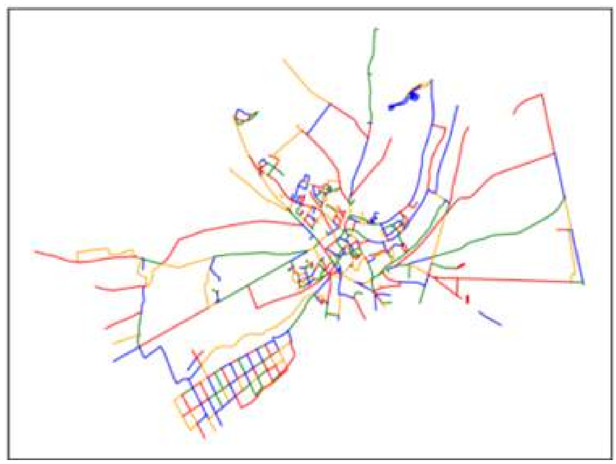


Fig. 7. Roads Division after Merging.

In the end, we obtain a roads division that is much more accurate and which selects the right portions of the roads (Fig. 9). As a result, the nodes roads, based on their centroid, are better positioned, taking into account the position of buildings. Consequently, the network is more accurate and efficient (higher linear density).

However, some discrepancies may remain after executing the mapping algorithm (some roads may still be "too long"). This is due to the fact that some projected buildings are projected on other roads than those which are actually connected to the network. In next section, we implement an optimization algorithm to address these issues.

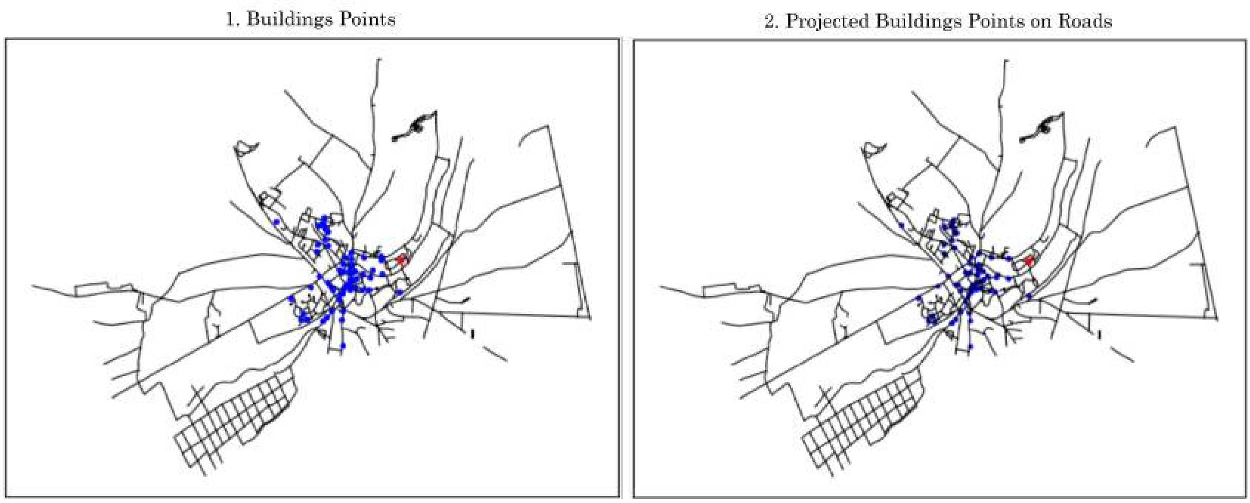


Fig. 8. Orthogonal Projection of the buildings on the roads.

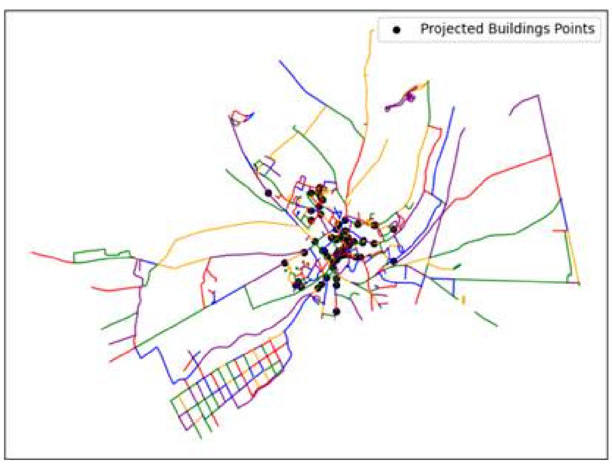


Fig. 9. Final Roads Division.

1.5 Cutting and Optimization

To resolve the issues and create an optimal network with no unnecessary length, we proceed in two steps:

- We cut the roads in the same manner as in the Pre-Cutting section;
- We then identify the extremal roads that are not connected to any buildings and remove them.

The overall process is illustrated in Fig. 10.

1.5.1 Cutting

The first step follows the same method as the Pre-Cutting section: merging roads, projecting buildings, and cutting the roads into segments at the positions of the projected buildings.

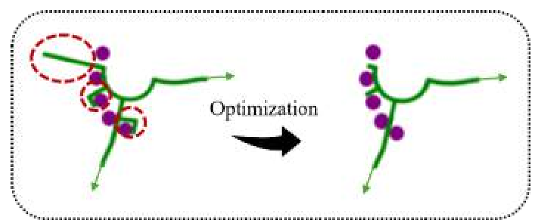


Fig. 10. Optimization Method.

1.5.2 Optimization Algorithm

The second step consists in removing parts of the roads that are unnecessary to the network. These unnecessary sections include roads positioned at the end of the network that are not connected to any building at their end. The cutting performed earlier helps us identify these extremal roads.

The process is as follows:

1. Create nodes at both ends of each road segment.
2. Select the internal nodes using the following criteria: a node is internal if it is connected to two roads. As before, a node is considered connected to a road if it is within *5 m* of the road.
3. Identify the extremal nodes, which are those that are neither internal nor projected building points. It's important to note that some nodes coincide with projected building locations, and these should not be deleted, as no additional road length should be removed at these points.
4. Select the roads connected to the extremal nodes using the `intersect` function from the Shapely library.

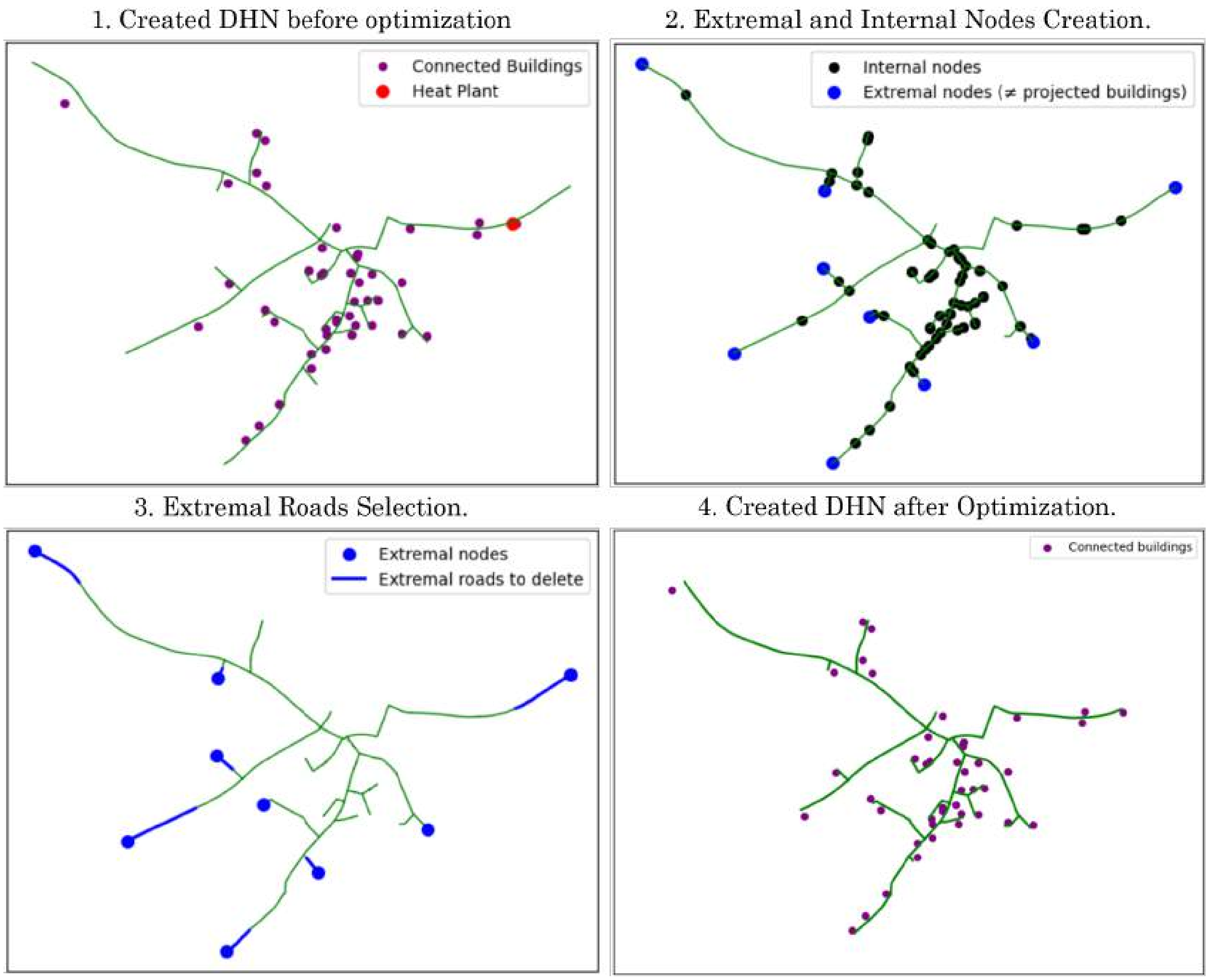


Fig. 11. Optimization Process after Algorithm Execution.

5. Delete the identified extremal roads.

This process is illustrated in Fig. 11, using the example of the city of Breteuil-sur-Noye.

This optimization algorithm significantly reduces the overall network size, thereby improving linear density and enhancing economic viability (16.70% according to section *3.1.3 Output with Pre-Cutting and Optimization*).

The final DHN network has been created and is now ready for use, particularly for simulation on Dymola.

1.5.3 Reinjecting the Reduction Percentage in the Linear Density Threshold

As described in the Algorithm Definition section, we previously set a minimum linear density constraint of $\lambda = 1.5\ \mathrm{MWh} \cdot \mathrm{m}^{-1} \cdot \mathrm{y}^{-1}$, which defines the economic viability of a connection. Consequently, the algorithm's output before optimization yields a network whose linear density satisfies:

$$\frac{Q}{l} \geq \lambda$$

where Q is the heat coverage of the network, and l its length.

Now, we apply the optimization process, achieving a reduction of $x\%$ in the total length of the DHN created. The new linear density constraint becomes:

$$\frac{Q}{l \cdot (1 - x)} \geq \lambda$$

which is equivalent to:

$$\frac{Q}{l} \geq \lambda \cdot (1 - x)$$

Therefore, if we reinject this $(1 - x)$ factor to the initial linear density constraint λ, we redefine it as

$\lambda_x = \lambda \cdot (1-x)$. This adjustment makes the constraint less restrictive, potentially allowing the algorithm to connect more buildings to the network while maintaining the economic viability. This, in turn, may or may not lead to an overall increase in linear density, following the same logic developed in the case study of section *1.5.4 Model Improvement: Finding Optimal Lambda*, Fig 12.

The results of such method can be seen on Fig. 14 of the *Results*.

Note: It is important to note that the DHN created using the following reduction reinjection method will likely, but not necessarily, result in an economically viable network. This is because, depending on the city's geography, the method could incorporate buildings that are distant from others, potentially reducing the linear density slightly below 1.5 GWh/km/year. In such rare cases, the method should be reconsidered or abandoned.

1.5.4 Model Improvement: Finding Optimal Lambda

As described in the Algorithm Definition section, we previously set a minimum linear density constraint of

$$\lambda = 1.5 \text{ MWh} \cdot \text{m}^{-1} \cdot \text{y}^{-1},$$

which defines the economic viability of a connection. Consequently, the algorithm generates a network with a linear density above this threshold. However, given the varying geographical characteristics of different communes, this constraint may sometimes be too restrictive, limiting the full potential of the area.

To illustrate this, consider a simple example featuring four roads and four buildings to be connected (Fig. 12). We apply the algorithm using two different λ values: 1.5 $\text{MWh}\cdot\text{m}^{-1}\cdot\text{y}^{-1}$ and 1.0 $\text{MWh}\cdot\text{m}^{-1}\cdot\text{y}^{-1}$. The results are presented in the table of Fig. 12.

As demonstrated in this example, a high constraint can lead to a very limited network, particularly when the heat plant is located far from the first building and its heat demand is insufficient. As a result, the mapping process may terminate prematurely, failing to reach buildings that could be valuable to connect. Additionally, the resulting linear density might be lower than its optimal potential.

Optimal Lambda Algorithm

To address this issue, we implemented a new algorithm designed to determine the optimal λ for network mapping. Specifically, we run the algorithm for λ values ranging from 0.1 to 1.5 $\text{MWh}\cdot\text{m}^{-1}\cdot\text{y}^{-1}$, in increments of 0.1. This step size was chosen to balance accuracy with computational efficiency, particularly for larger cities where execution time is a limiting factor. For each network generated at a given λ, we calculate its associated linear density and select the λ that produces the highest value.

Additionally, an optional heat coverage constraint can be introduced: λ is selected only if the resulting network connects at least a minimum number of buildings. This approach allows a municipality to prioritize either economic efficiency—by maximizing linear density regardless of the number of connected buildings—or maximizing building connectivity by setting a minimum threshold for the number of connected buildings, thereby increasing heat coverage.

After implementing this new optimal λ approach, the algorithm may produce a network with a linear density below 1.5 $\text{MWh} \cdot \text{m}^{-1} \cdot \text{y}^{-1}$, as it is the case in section *3.3.5 Changing the Constraint*, Fig. 33. In such cases, we reject the network as economically unviable since the maximum achievable linear density cannot exceed this threshold, regardless of the chosen λ value.

This method has been used in the Case Study displayed in the Results.

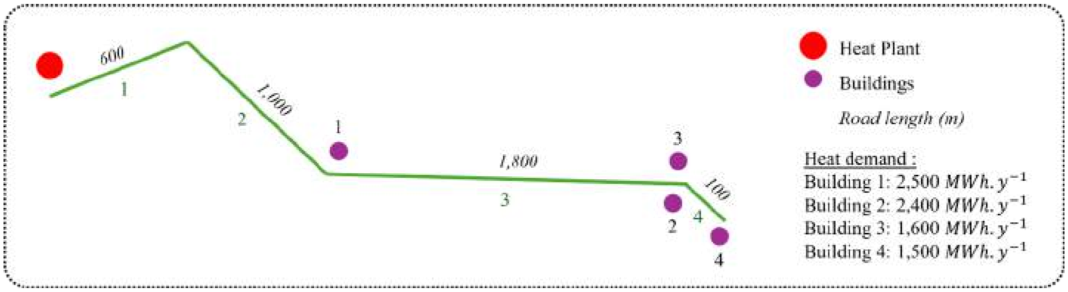
2 Departmental Scale

Once the overall process has been processed and perfected for a single commune, we expand the study to the entire department to pursue our initial goal of assessing the potential of the area. This section builds upon the previous one, though the initial inputs must be adjusted to run the algorithm for each commune, following a specific selection and ranking process.

2.1 Data Preprocessing

2.1.1 Data Downloading

Data processing is carried out in the same manner as in the previous section, with the data now split between communes. We use the INSEE commune code as a ranking criterion to organize each building list as a sublist within a larger `buildings_by_commune` list, where the size corresponds to the number of commune codes. The same approach is applied to the roads, with a `roads_by_commune` list. For easier handling, we chose to index the elements of both lists using the code of the commune they belong to. For example, to access the list



$\lambda = 1.5\ MWh.m^{-1}.y^{-1}$	$\lambda = 1.0\ MWh.m^{-1}.y^{-1}$
1st loop: Connect to Building 1 • Initialization: $R_{net} = 0\ m$ • Building's radius: $R_1 = \frac{Q_1}{\lambda} = \frac{2.5}{1.5} = 1{,}666\ m$ • Shortest distance: $d = 1{,}600\ m$ • $R_1 + R_{net} = 1{,}666$ m $d \leq R_1 + R_{net}$ ⇒ connect Building 1 • $R_{net} = 66\ m$	1st loop: Connect to Building 1 • Initialization: $R_{net} = 0\ m$ • Building's radius: $R_1 = \frac{Q_1}{\lambda} = \frac{2.5}{1.0} = 2{,}500\ m$ • Shortest distance: $d = 1{,}600\ m$ • $R_1 + R_{net} = 2{,}500$ m $d \leq R_1 + R_{net}$ ⇒ connect Building 1 • $R_{net} = 900\ m$
2nd loop: Connect to Building 2 • $R_{net} = 66\ m$ • Building's radius: $R_2 = \frac{Q_2}{\lambda} = \frac{2.4}{1.5} = 1{,}600\ m$ • Shortest distance: $d = 1{,}800\ m$ (*Roads 1 & 2 already connected*) • $R_2 + R_{net} = 1{,}666\ m$ $d > R_2 + R_{net}$ ⇒ do not connect Building 2 • $R_{net} = 66\ m$ (*unchanged*)	2nd loop: Connect to Building 2 • $R_{net} = 66\ m$ • Building's radius: $R_2 = \frac{Q_2}{\lambda} = \frac{2.4}{1.0} = 2{,}400\ m$ • Shortest distance: $d = 1{,}800\ m$ (*Roads 1 & 2 already connected*) • $R_2 + R_{net} = 3{,}100\ m$ $d \leq R_2 + R_{net}$ ⇒ connect Building 2 • $R_{net} = 300\ m$
3rd & 4th loop: Connect to Building 3 & 4 • *Same applies* • [...] ⇒ do not connect Building 3 & 4	3rd loop: Connect to Building 3 • $R_3 = \frac{Q_3}{\lambda} = \frac{1.6}{1.0} = 1{,}600\ m$ • $d = 0\ m$ (*Roads 1, 2 and 3 already connected*) ⇒ Connect Building 3 • $R_{net} = 1{,}900\ m$
	4th loop: Connect to Building 4 • $R_3 = \frac{Q_3}{\lambda} = \frac{1.5}{1.0} = 1{,}500\ m$ • $d = 100\ m$ (*Roads 1, 2 and 3 already connected*) ⇒ Connect Building 4 • $R_{net} = 1{,}800\ m$
Results: • DHN length = 1,800 m • Heat coverage = 2,500 MWh/yr ➢ **Linear density = $\mathbf{1.56}\ MWh.m^{-1}.y^{-1}$** ➢ **Number of buildings: 1**	Results: • DHN length = 3,500 m • Heat coverage = 8.0 MWh/yr ➢ **Linear density = $\mathbf{2.26}\ MWh.m^{-1}.y^{-1}$** ➢ **Number of buildings: 4**

Fig. 12. Case Study - Finding Optimal Lambda

of buildings in commune 60104, one would use: `buildings_by_commune[60104]`.

We follow the same procedure as in the previous code, running the algorithm for the buildings and roads of each commune individually.

The algorithm's complexity is therefore $O(n_c \times n_{b,c})$ or $O(n_c \times n_{r,c})$, where:

- n_c is the number of communes in the department, which is comprised between 1 (Paris) and 895 (Pas-de-Calais) [13].

- $n_{b,c}$ or $n_{r,c}$ represents the number of buildings and roads in the commune, which are respectively around 400,000 and 250,000, depending on the demography.

As a result, the downloading time can be quite long, depending on the size and density of the department (Fig. 23).

2.1.2 Limits

It is important to note that when downloading data from governmental databases, some attributes are filtered:

- The commune code must match the selected INSEE code.

- The geometry group cannot be null.

- The construction year must be provided.

- Building height must be at least 3 meters.

- The energy consumption class must be non-null and valid.

Consequently, if any of these attributes are missing, a building will not be kept, even though it might be relevant for network connection in reality. Additionally, experience shows that in some departments (such as Lozère), energy consumption data is not available in the BDNB database. As a result, our tool cannot be applied to that department.

Therefore, this study has two main limitations:

- It may overlook buildings that could be valuable for connection within a commune.

- It cannot be universally applied to all French departments due to missing data.

2.1.3 Data Preparation and Communes Filtering

For each building, we calculate its heat demand using the same method as before. Next, we compute its maximum power to apply the 30 kW threshold filter. This step significantly reduces the number of buildings, resulting in a shorter execution time.

2.2 Criterion for DHN Creation in Communes

In this approach, we assume that a city is suitable for a district heating network (DHN) if it has more than 40 buildings exceeding the 30 kW threshold. Therefore, instead of running the algorithm on the entire set of communes, we apply it only to those that meet this criterion, which we store in a `filtered_communes` list. This filtering can significantly reduce the total number of communes considered, especially in low-density departments, where numerous small villages have low population density and are therefore not viable for DHN development.

We then prepare the road division format in the same way as in the Pre-Cutting section, only on these filtered communes. The data is ready to use in the algorithm.

2.3 DHNs Creation

2.3.1 Algorithm Execution

The algorithm execution is by far the most time-consuming part of the entire process, as it is applied in the same manner as at the local scale but iterated commune by commune (see Results).

First, we generate the lists of buildings, roads, and edges, and then we execute the algorithm. In the Results section, Fig. 23 illustrates the time distribution between these two steps, with list creation being, by far, the longest step.

2.3.2 Optimization

Communes Filtering

After running the algorithm, the code outputs a set of DHNs that meet the economic linear density constraint of 1.5 $\mathrm{MWh} \cdot \mathrm{m}^{-1} \cdot \mathrm{y}^{-1}$. However, some communes may not satisfy this constraint from the very beginning.

For instance, if the largest consumer is too far from the second-largest consumer, whose heat demand is also too low, the criterion $d \leq R_A + R_{network}$ is not met for the first building. As a result, $R_{network}$ remains 0, leaving no margin for further connections. If the third building is also too far or consumes too little, the same issue arises.

Consequently, some communes end up with a DHN of total length 0, meaning they are not economically viable for DHN creation. Since optimization cannot be applied to such networks, the first step is to filter out communes where no DHN is created, if they exist.

Optimization Process

Once again, we follow the same process as at the local scale, applying it DHN by DHN: merging and splitting roads, creating extremal nodes, and selecting and removing extremal routes.

It is worth noting that the execution time of the optimization process is significantly shorter at this stage, as only a small subset of routes and buildings is selected for each commune compared to the initial dataset.

2.3.3 Comparison to Existing DHNs

France Chaleur provides a map of all existing DHNs across French territory [14]. This map can be exported in GeoPackage format, allowing it to be integrated into our code for comparison with the DHNs created. This is the objective of this section.

Data Preprocessing

Each network in this database has several attributes, including its identifier code, name, associated communes, geographical information (department, region), production data, supply information, and other energy-related details. In this study, we will focus only on two attributes: the length of the network and its heat supply in GWh.

The first filtering step involves selecting DHNs that have these attributes, as some networks may be under development or lack relevant information.

The second filtering step involves determining, for each commune from the previously filtered set, whether a real DHN exists in that commune, using the commune code. If such a network exists, it will be selected for further comparison with the created networks. We will compare the length, linear density, and heat demand coverage of the networks.

Potential Analysis

The primary objective of this work is to assess the potential for DHN creation in specific areas. Therefore, once the DHNs have been created, it is necessary to evaluate this potential. Two main attributes will be considered:

- **Linear density of the network:** It reflects the density and efficiency of the network.
- **Heat demand coverage ratio** τ: Unlike the *Heat demand coverage*, which is simply the ratio of the heat demand covered by the network to the total heat demand of the area—both calculated at the 30 kW maximum power threshold—the Heat Demand Coverage Ratio is slightly different as it accounts for existing DHNs. We define it as the percentage ratio between the heat demand covered by the network (in GWh) and the total heat demand of the selected area for buildings above the 30 kW threshold. If an existing DHN is present in the selected commune, its pre-existing heat supply is subtracted from the calculated ratio.

Therefore, if there is no existing DHN in the commune:

$$\tau = \frac{Q_{net}}{Q_{tot}}$$

And if a real DHN already exists in the commune:

$$\tau = \frac{Q_{net} - Q_{real}}{Q_{tot}}$$

Where Q_{net}, Q_{real}, and Q_{tot} are respectively the heat demands covered by the created DHN, the real DHN, and the total heat demand of the commune.

Depending on the municipality's priorities, municipal agents can focus on one of these two attributes:

- If the primary objective is economic, the linear density should be prioritized, as it reflects the efficiency and cost-effectiveness of the network.
- If the focus is on buildings connectivity for environmental or social goals, the heat demand coverage ratio should take precedence, as it indicates how well the network meets the area's heating needs.

This ratio allows us to determine what additional percentage of heat demand can be covered in the selected area. It also helps evaluate whether the created network adds value. For example, if the heat demand coverage delta is negative, it indicates that the existing DHN performs better, suggesting that our model does not provide added value and should not be considered.

However, it is important to note that the real DHNs may not have been mapped to the same buildings as those in our dataset. This is because we might be missing information on some buildings, which could lead to their exclusion from our analysis. As a result, a negative delta does not necessarily mean that our model performs poorly; it could also indicate that we are lacking data for that particular commune.

3 Results

3.1 Local Scale

At the local scale, we selected the city of Breteuil-sur-Noye (60104), a small town in the Oise department with 4,189 inhabitants and an area of 17 km². We chose it for its relatively small size, with a total of 224 buildings and 677 roads, which are reduced to 64 after filtering based on the 30 kW threshold. Additionally, we selected it because it already has an operational district heating network in the real world.

3.1.1 Pre-cutting

After explaining the Pre-Cutting process in the Methodology section, we summarized the approach on Fig. 13, along with its final result. For better visibility, the roads are randomly assigned one of five colors.

This division method reduces the number of roads from 677 to 603 after merging and then increases it to 661 after splitting. Contrary to the expectation that the new split division would significantly increase the number of roads, the total remains relatively stable. As a result, it does not impact execution time of the algorithm which follows.

3.1.2 Output without Pre-Cutting and Optimization

The main issue with the initial output, without pre-cutting and optimization, is the presence of unnecessary road segments at the ends of the network. These redundant portions reduce R_{net} in each loop, limiting the ability to connect more buildings to the network. Additionally, they decrease the overall linear density of the network, as the total length could be significantly reduced through the optimization method (Fig. 14).

Despite the flaws mentioned above, this network still demonstrates strong potential—covering more than 60% of the commune's total heat demand at a 30 kW threshold, with a linear density well above the 1.5 GWh/km/year constraint. This proves to be a very efficient and high-performing network. However, as the results of Fig. 15 show, there is still significant room for improvement, even though the current performance is already promising for the commune.

3.1.3 Output with Pre-Cutting and Optimization

After the Pre-Cutting process, we run the algorithm, generating the initial version of our district heating network (DHN) with pre-cutting and optimization. The outputs are shown and compared in Fig. 15.

These outputs highlight three key findings:

- The optimization process results in a significant 16.70% reduction in total network length, leading to a notable 20.04% increase in linear density. This demonstrates a highly efficient and well-performing network.

- The pre-cutting process allows more buildings to connect to the network, improving heat demand coverage to 65.00%.

- The linear density before optimization is slightly lower with pre-cutting (2.26) than without it (2.51) because pre-cutting prioritizes shorter road connections.

In the end, although the networks resemble each other, the Pre-Cutting and Optimization processes create networks that are more efficient than without them. We ultimately achieve a high-performing and efficient network with 65% coverage and a 2.72 GWh/km/year linear density, well above the 1.5 constraint.

As shown on Fig. 16, the roads are also well divided for better application in Dymola, with each road segment modelled separately. The water flow for each segment depends on the number of connected buildings and its proximity to the heat plant.

3.1.4 DHN Created with Reduction Reinjection in the Lambda Constraint

As seen in the previous section, the optimization process results in a $x = 16.70\%$ length reduction. We thus set a new lambda constraint at

$$\lambda_x = 1.500 \times (1 - 0.1670) = 1.2495 \text{ GWh/km/year},$$

which is therefore less restrictive than the reference one. This constraint is expected to connect more buildings to the created network, as shown in Fig. 17.

We achieve a network that connects more buildings (+3.62% compared to the previous one) while maintaining strong performance, slightly lower at 2.38

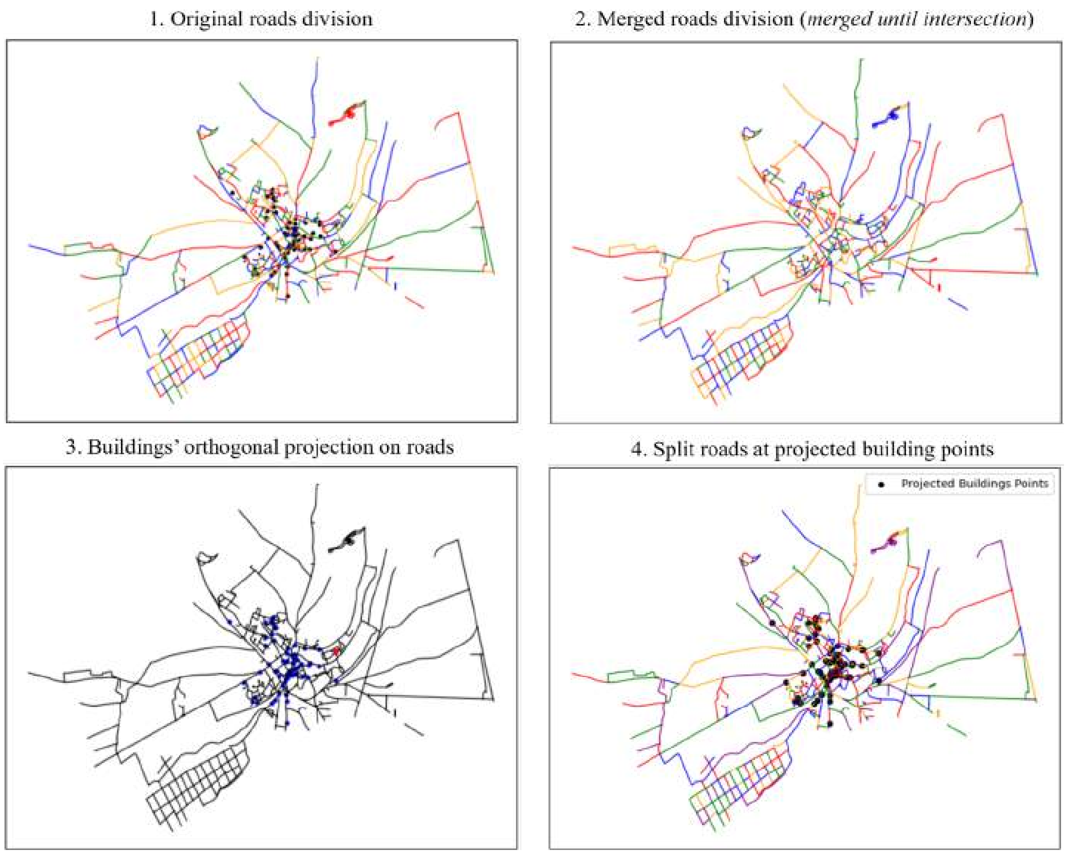
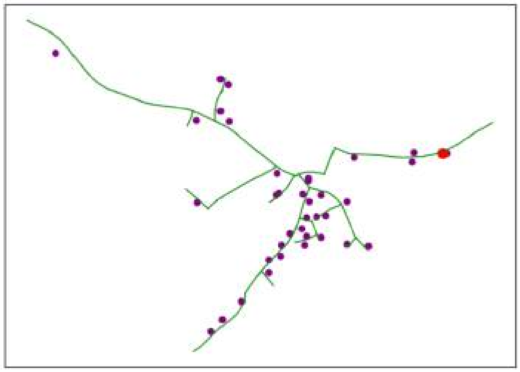
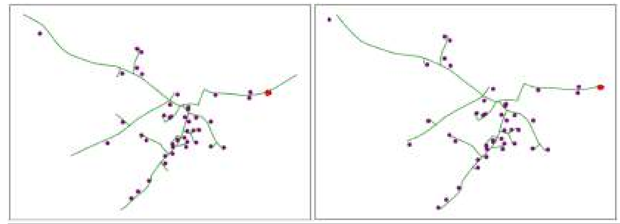


Fig. 13. Roads Pre-Cutting Steps



Network Characteristics	Value
Length (km)	4.79
Number of connected buildings	38
Heat demand covered (GWh)	12.04
Heat demand coverage rate	61.43%
Linear density (GWh/km/year)	2.51

Fig. 14. Created DHN without Pre-Cutting and Optimization
Green lines: DHN roads; Dots: connected buildings.



Network Characteristics	Before Optimization	After Optimization
Length (km)	5.63	4.69
Number of connected buildings	45	45
Heat demand covered (GWh)	12.74	12.74
Heat demand coverage rate	65.00%	65.00%
Linear density (GWh/km/year)	2.26	2.72

Fig. 15. Created DHN, with Pre-Cutting, before and after Optimization
Green lines: DHN roads; Dots: connected buildings.

GWh/km/year, well above the 1.5 reference. Therefore, this technique proves highly useful for municipalities aiming to implement a DHN with maximum heat demand coverage while preserving high economic viability.

3.1.5 DHN Created with Optimal Lambda

For this case study, the optimal lambda for Breteuil-sur-Noye is the same as the reference value (1.5 GWh/km/year).

However, this is not always the case. We ran the code for the commune of Saint-Leu-d'Esserent, whose morphology is similar to the one described in the case study developed in section *1.5.4 Model Improvement: Finding Optimal Lambda* where the heat plant is located far from a cluster of buildings at the end of the network. For this commune, the optimal lambda is 1.4 GWh/km/year. The output is displayed in Fig. 18.

The same applies to the second case study developed in the third section of the results.

3.1.6 Comparison to Real DHN

As mentioned earlier, we chose Breteuil-sur-Noye because it already has an operational DHN. For this comparison, we selected the DHN created with the reference constraint (1.5 GWh/km/year) to ensure the network is economically viable.

The results (Fig. 19) show that the generated DHN covers a significantly larger portion of the city's total heat demand (+38.16%) and offers a much more profitable network (+55.43% in linear density). We are therefore optimistic about these results, as they appear much more efficient than the real implementation. However, the department-scale analysis in Section 2 will demonstrate that this is not always the case.

3.2 Departmental Scale

3.2.1 Created DHNs

At the departmental scale, the same method has been used and run for each city including:

- Roads pre-cutting
- Algorithm execution with length reduction reinjection in linear density constraint
- Cutting and Optimization

We used the method of reduction reinjection for each commune. We have thus run the algorithm twice: a first time with the 1.5 GWh/km/year lambda reference, and the second time with each λ_x where x is the length reduction percentage for each commune.

Optimization Length Reduction Results

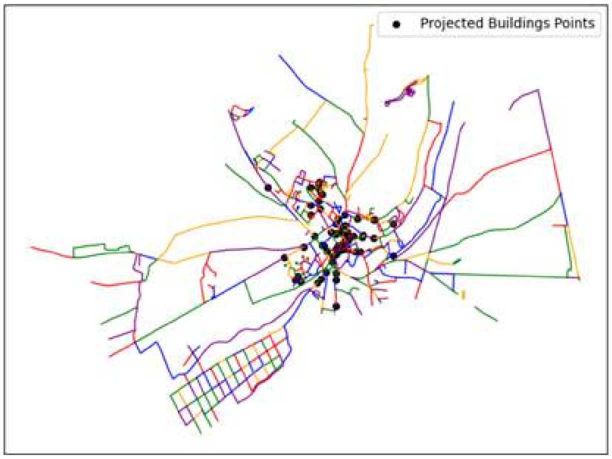
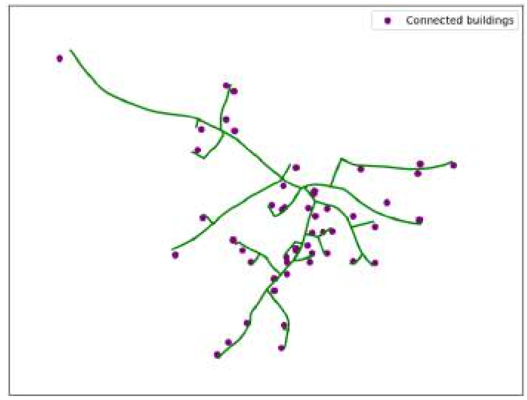


Fig. 16. Final Created DHN, Breteuil-sur-Noye. Roads are printed randomly in four different colours.



Network Characteristics	Value
Length (km)	5.66
Number of connected buildings	52
Heat demand covered (GWh)	13.45
Heat demand coverage rate	68.62%
Linear density (GWh/km/year)	2.38

Fig. 17. Created DHN with Optimization Length Reduction Reinjection in the Lambda Constraint.

The optimization process after running the algorithm at the 1.5 GWh/km/year lambda results in a 7.18% length reduction on average (Table 3), with a maximum and minimum reduction of respectively 16.96% and 0.00%.

Each of these length reductions is saved in a new vector in order to run the algorithm a second time to apply each of these reduction percentages to the constraint of the algorithm for each commune, aiming to increase the heat coverage ratio. It is important to note that, in this section, our focus is not on achieving the highest linear density but rather on finding a balance between linear density and heat demand coverage.

We could have also applied the optimal lambda technique with a minimum threshold on the number of connected buildings—for example, requiring at least 50% of the total buildings above the 30 kW threshold to be connected. However, we did not pursue this approach in this study due to the execution time constraints (section *3.2.3 Execution Time*) and the reduction reinjection, which already provides satisfying results.

Created DHNs with Reduction Reinjection in the Lambda Constraint

The created DHNs are shown in Fig. 20 based on the length reduction reinjection in the lambda constraint.

The performances of our DHNs, summarized in the table of Fig. 4, provide a promising perspective. As described in the Methodology, for cities with more than 40 buildings above the 30 kW threshold, the average heat demand ratio is 40.42%, with an average linear density of 2.36 GWh/km/year, well above the 1.5 GWh/km/year minimum.

We can thus remark that this model's main focus is on economic viability, as its linear density is very high compared to the reference (1.57 times higher). Although the heat demand coverage ratio is relatively high (40%), it could potentially be increased at the expense of economic viability, for example, by using the optimal lambda technique with a minimum threshold for connected buildings. In this study, we prioritized a model that focuses primarily on profitability and secondarily on connectivity.

However, some networks may not be reliable, as in the case of Verneuil-en-Halatte, which is only 70 m long and covers just 2.37% of the city's heat demand. Although this network shows exceptionally high economic viability on paper (with a linear density of 3.58), it is clear that such a network is not credible in practice.

3.2.2 Created vs. Real DHN

We now compare the created DHNs with the existing ones. Out of the twenty-four selected cities, five currently have an existing network listed on France Chaleur, which are visually compared on Fig. 21.

Now that we have the characteristics of the real DHNs, a few comparisons can be established with those of the created DHNs.

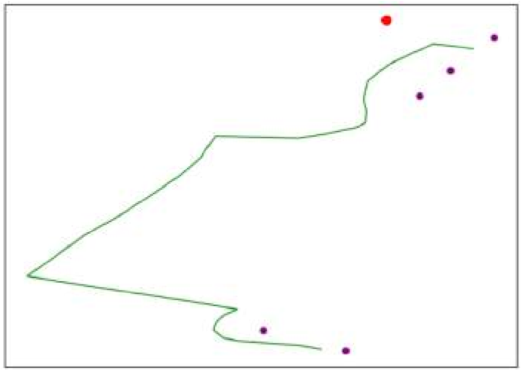
First, it is noticeable that the heat coverage of the

Table 3. Optimization Length Reduction at 1.5 GWh/km/year

INSEE Code	**Commune Name**	**Initial Length (km)**	**New Length (km)**	**Length Reduction (%)**
60057	Beauvais	65.67	61.50	-6.35%
60088	Bornel	2.54	2.12	-16.58%
60104	Breteuil	5.52	4.58	-16.96%
60139	Chambly	6.20	5.17	-16.65%
60141	Chantilly	7.75	7.61	-1.78%
60157	Clermont	3.10	2.79	-9.81%
60159	Compiègne	14.82	13.56	-8.53%
60175	Creil	20.87	18.93	-9.27%
60176	Crépy-en-Valois	3.70	3.61	-2.34%
60282	Gouvieux	1.86	1.93	0.00%
60286	Grandvilliers	1.57	1.54	-1.73%
60346	Lamorlaye	1.95	1.88	-3.51%
60360	Liancourt	1.37	1.15	-16.03%
60382	Margny-lès-Compiègne	0.63	0.63	0.00%
60395	Méru	3.42	3.19	-6.79%
60414	Montataire	5.85	5.64	-3.50%
60439	Mouy	0.66	0.52	-21.76%
60463	Nogent-sur-Oise	6.31	5.99	-5.10%
60471	Noyon	15.45	13.77	-10.90%
60509	Pont-Sainte-Maxence	3.14	3.04	-3.12%
60581	Saint-Just-en-Chaussée	1.39	1.37	-1.38%
60584	Saint-Leu-d'Esserent	0.50	0.50	0.00%
60612	Senlis	2.43	2.18	-10.32%
60670	Verneuil-en-Halatte	0.07	0.07	0.00%
Average				**-7.18%**

Table 4. Created DHNs in Oise, with Reduction Reinjection in the Lambda Constraint

INSEE Code	**Commune**	**Length (km)**	**Length Reduction (%)**	**Connected Buildings**	**Heat Demand (GWh $\cdot$y^{-1})**	**Heat Demand Coverage (%)**	**Linear Density (GWh $\cdot$km^{-1} $\cdot$ y^{-1})**
60057	Beauvais	66.06	-6.35%	401	164.80	80.94%	2.49
60088	Bornel	2.96	-16.58%	21	5.69	39.31%	1.92
60104	Breteuil	5.79	-16.96%	54	13.59	69.34%	2.35
60139	Chambly	7.23	-16.65%	62	14.61	63.26%	2.02
60141	Chantilly	7.70	-1.78%	60	20.54	68.16%	2.67
60157	Clermont	4.29	-9.81%	28	9.38	34.46%	2.19
60159	Compiègne	16.34	-8.53%	99	36.79	53.20%	2.25
60175	Creil	18.93	-9.27%	120	74.98	91.22%	3.96
60176	Crépy-en-Valois	3.78	-2.34%	31	9.06	24.99%	2.40
60282	Gouvieux	1.57	0.00%	4	2.34	11.64%	1.49
60286	Grandvilliers	1.54	-1.73%	21	4.10	41.59%	2.65
60346	Lamorlaye	1.76	-3.51%	13	4.39	16.24%	2.49
60360	Liancourt	2.23	-16.03%	21	4.95	34.51%	2.22
60382	Margny-lès-Compiègne	0.63	0.00%	5	1.33	8.55%	2.11
60395	Méru	3.99	-6.79%	26	8.12	31.35%	2.04
60414	Montataire	6.03	-3.50%	28	12.11	50.26%	2.01
60439	Mouy	1.45	-21.76%	14	3.19	26.15%	2.19
60463	Nogent-sur-Oise	6.58	-5.10%	34	14.51	44.21%	2.20
60471	Noyon	16.25	-10.90%	69	31.01	83.41%	1.91
60509	Pont-Sainte-Maxence	3.01	-3.12%	31	7.75	32.02%	2.57
60581	Saint-Just-en-Chaussée	1.37	-1.38%	9	2.79	22.43%	2.03
60584	Saint-Leu-d'Esserent	0.50	0.00%	5	1.24	12.27%	2.50
60612	Senlis	3.84	-10.32%	48	9.62	28.26%	2.50
60670	Verneuil-en-Halatte	0.07	0.00%	2	0.24	2.37%	3.58
Average					**40.42%**		**2.36**



Network Characteristics	Value
Optimal Lambda (GWh/km/year)	1.40
Length (km)	0.48
Number of connected buildings	5
Heat demand covered (GWh)	1.24
Heat demand coverage rate	12.25%
Linear density (GWh/km/year)	2.58

Fig. 18. Created DHN for Saint-Leu-d'Esserent, with Optimal Lambda.

created DHNs is significantly higher than that of the existing ones. This is understandable, as our tool aims to connect as many buildings as possible while maintaining economic viability. In contrast, real-world DHNs are often limited to smaller neighborhoods where geographic and legislative constraints can be met.

Additionally, we observe that the linear density of the real DHNs is, on average, generally better than that of the created networks. This can be explained not only by the possibility that our network is less efficient, but also, and more importantly, by the fact that we may be missing information on certain buildings that could potentially be connected to our network. If we had this information, it could increase the linear density, as these buildings might be located within the network's reach.

As outlined in the section *2.3.3 Comparison to Existing DHNs*, the objective of this study is to assess the potential of an area by considering both the created and existing DHNs to calculate the heat coverage ratio. We can thus identify high-potential areas at the local scale in terms of heat coverage. For instance, the cities of Noyon (83.41%) and Chantilly (68.16%) show particularly high potential, despite not currently having a real district network. These areas are therefore worth further investigation. Similarly, the city of Beauvais demonstrates a high heat coverage ratio (68.48%), even though it already has an existing district network in the southern part of the city (Fig. 21.(a)). This suggests that expanding this network could be a valuable opportunity.

If we now want to assess the potential of an area by also considering the linear density of the created network, we can refer to Fig. 22. The choice of the highest potential area depends largely on the specific needs of each city. Notably, cities such as Beauvais, Breteuil, Chambly, Chantilly, Nogent-sur-Oise, and Grandvilliers demonstrate an excellent balance between linear density and heat coverage ratio, with values exceeding 2.00 GWh/km/year and 40%, respectively.

Without existing DHNs, the heat demand coverage for our networks in the 24 selected communes reaches 56.09% (457.52 GWh/year out of a total heat demand of 815.70 GWh/year), significantly higher than the current 19.14% covered by existing DHNs (Table 6). This indicates a potential 36.95% increase in heat coverage that could be realized through the implementation of DHNs in Oise. Our model therefore covers nearly three times more heat demand than the current DHN system in Oise.

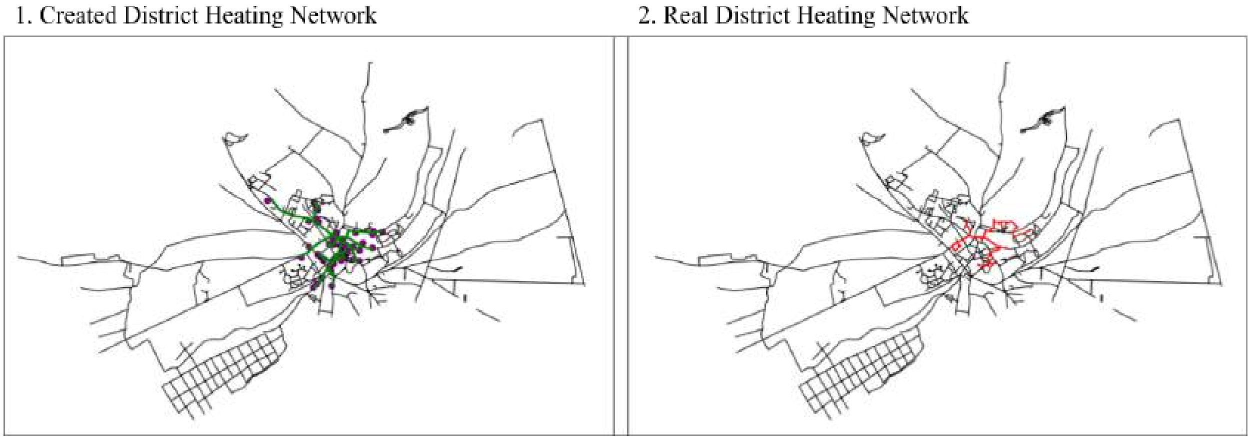
3.2.3 Execution Time

As explained in the Methodology, the execution of the algorithm at the departmental scale can be very long depending on the number of buildings and roads of the department.

For the department of Oise, the overall execution time is approximately 2 hours and 15 minutes. The entire process is divided into five main steps: data loading, heat demand estimation and building filtering, road pre-cutting, mapping algorithm execution, and optimization of the created network. Unsurprisingly, the algorithm execution is the most time-consuming step, accounting for 60% of the total execution time. However, the mapping algorithm itself is not as time-intensive as one might expect. The majority of the time is actually spent on preparing the data for the mapping algorithm, specifically the creation of the list of nodes. This step alone takes about 50% of the overall execution time (i.e., 60% of the 85% dedicated to algorithm execution) (Fig. 23).

When examining the nodes list creation process more closely (Fig. 24 and Fig. 25), we observe that the list creation scales linearly with the number of buildings but follows a quadratic trend with the number of roads.

This quadratic complexity is due to the creation of the `list_edges_roads`, where each road is checked for connections with every other road. As a result, the complexity is of quadratic order



Network Characteristics	Created DHN	Real DHN
Length (km)	4.69	3.00
Number of connected buildings	45	n.a.
Heat demand covered (GWh)	12.74	5.26
Heat demand coverage rate	65.00%	26.84%
Linear density (GWh/km/year)	2.72	1.75

Fig. 19. Comparison of Created and Real DHN for Breteuil-sur-Noye

Table 5. Heat Demand Coverage Ratio, Created vs. Real DHN.

INSEE Code	Commune Name	Created DHN (%)	Real DHN (%)	Heat Coverage Ratio (%)
60057	Beauvais	80.94	12.46	68.48
60088	Bornel	39.31	-	39.31
60104	Breteuil	69.34	26.86	42.49
60139	Chambly	63.26	-	63.26
60141	Chantilly	68.16	-	68.16
60157	Clermont	34.46	-	34.46
60159	Compiègne	53.20	75.63	-22.42
60175	Creil	91.22	71.42	19.80
60176	Crépy-en-Valois	24.99	-	24.99
60282	Gouvieux	11.64	-	11.64
60286	Grandvilliers	41.59	-	41.59
60346	Lamorlaye	16.24	-	16.24
60360	Liancourt	34.51	-	34.51
60382	Margny-lès-Compiègne	8.55	-	8.55
60395	Méru	31.35	-	31.35
60414	Montataire	50.26	60.14	-9.88
60439	Mouy	26.15	-	26.15
60463	Nogent-sur-Oise	44.21	-	44.21
60471	Noyon	83.41	-	83.41
60509	Pont-Sainte-Maxence	32.02	-	32.02
60581	Saint-Just-en-Chaussée	22.43	-	22.43
60584	Saint-Leu-d'Esserent	12.27	-	12.27
60612	Senlis	28.26	-	28.26
60670	Verneuil-en-Halatte	2.37	-	2.37

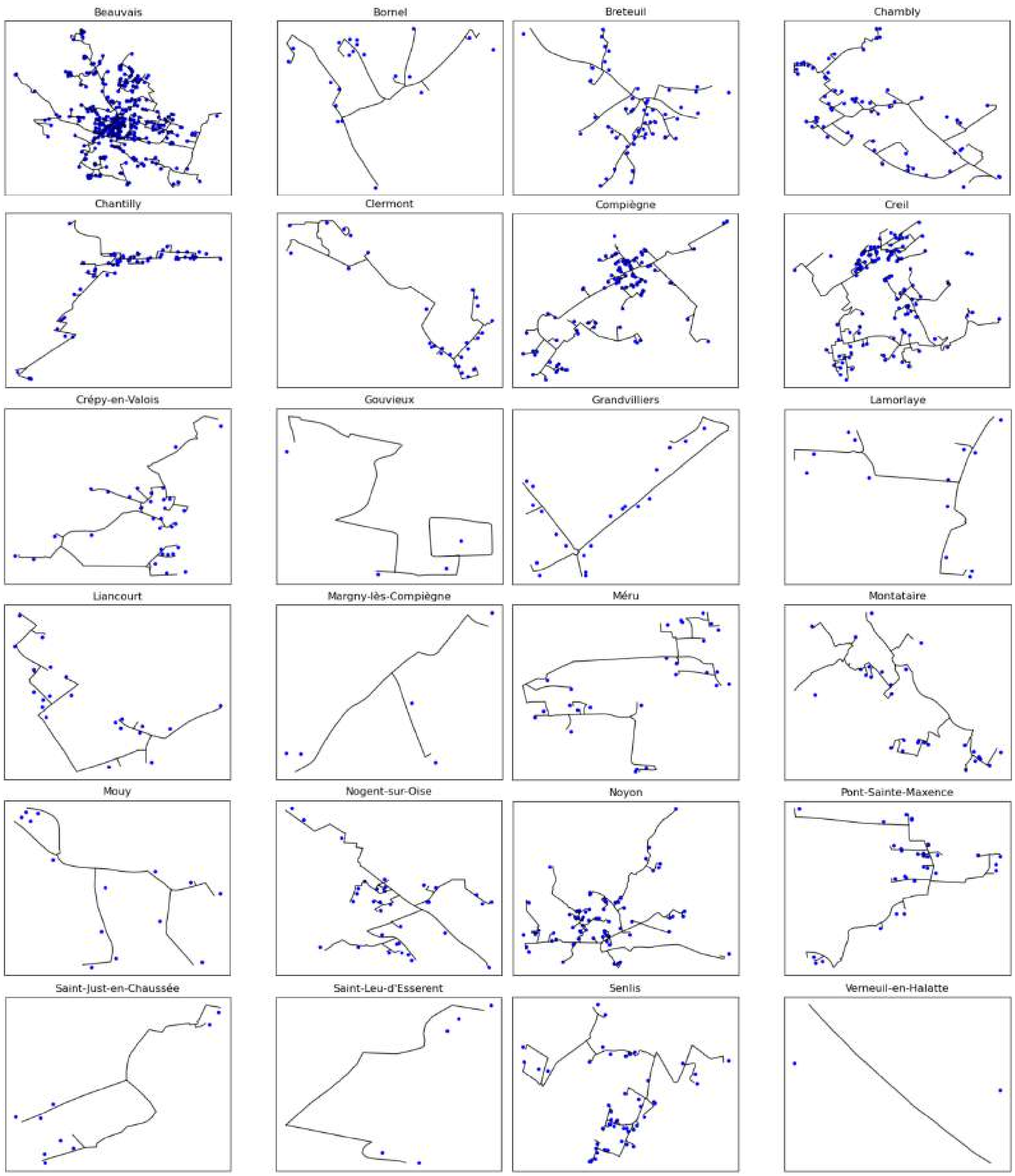
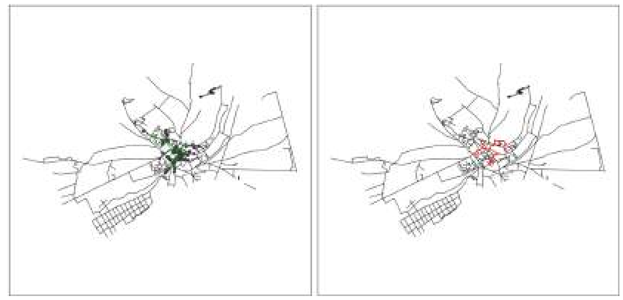
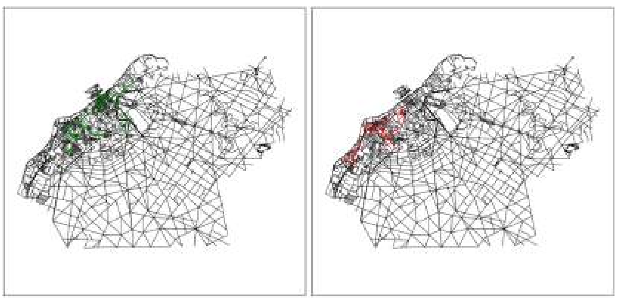


Fig. 20. Created DHNs with Reduction Reinjection in the Lambda Constraint.

(a) Beauvais

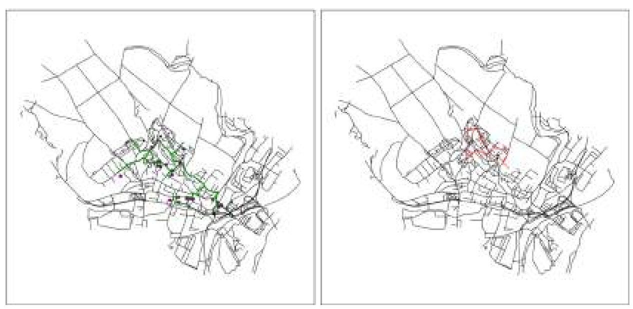


(b) Breteuil



(c) Compiègne

(d) Creil



(e) Montataire

INSEE Code	**Commune Name**	**Real DHN Length (km)**	**Created DHN Length (km)**	**Real DHN Heat Coverage (GWh $\cdot$y^{-1})**	**Created DHN Heat Coverage (GWh $\cdot$y^{-1})**	**Real DHN Linear Density (GWh $\cdot$km^{-1} $\cdot$ y^{-1})**	**Created DHN Linear Density (GWh $\cdot$km^{-1} $\cdot$ y^{-1})**
60057	Beauvais	8.00	66.06	25.37	164.80	3.17	2.49
60104	Breteuil	3.00	5.79	5.26	13.59	1.75	2.35
60159	Compiègne	13.00	16.34	52.29	36.79	4.02	2.25
60175	Creil	19.00	19.93	58.70	74.96	3.09	3.96
60414	Montataire	3.00	6.03	14.49	12.11	4.83	2.01

Fig. 21. Comparison between Created and Real DHNs for selected communes in Oise.

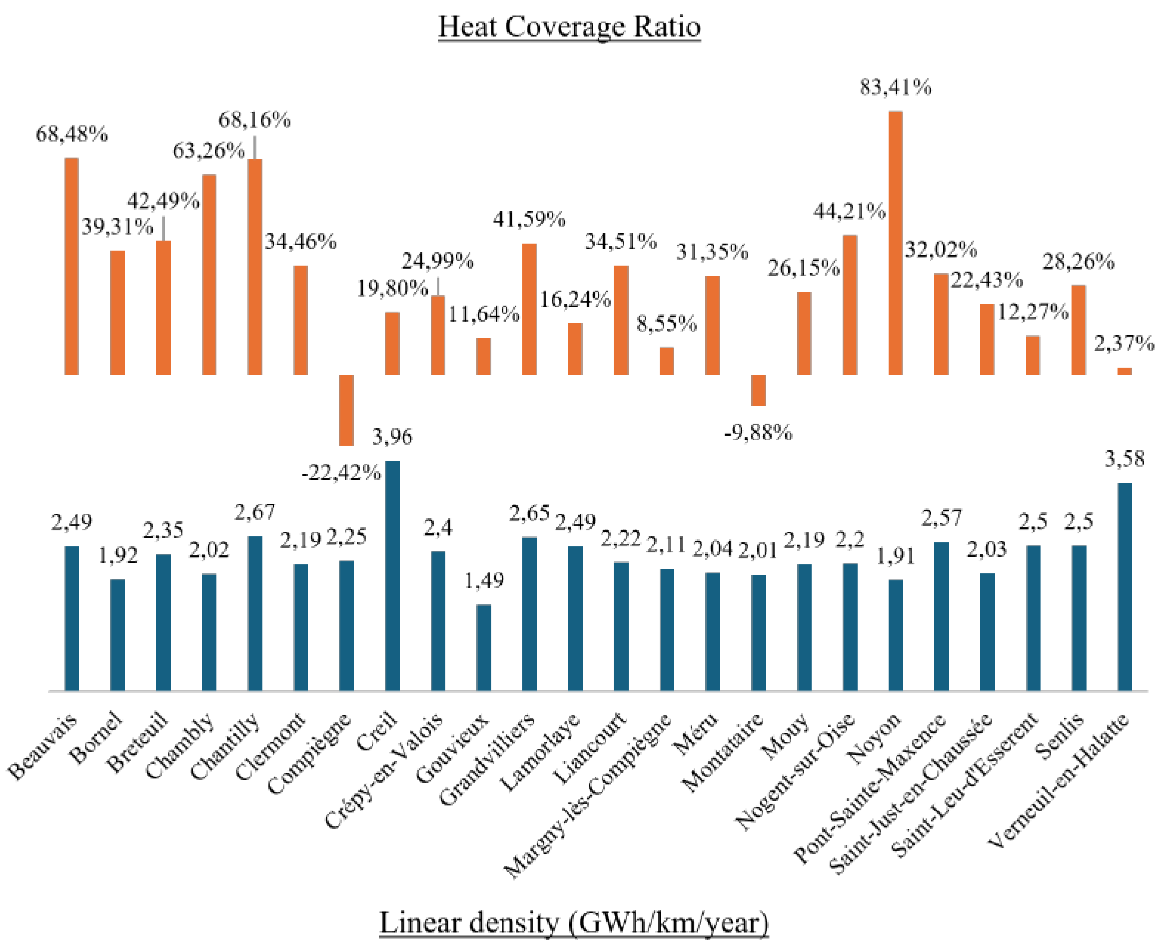


Fig. 22. Fig. Bar Plots for Potential Analysis – Linear Density and Heat Coverage Ratio

Table 6. Total Heat Demand Covered, Created vs. Real DHNs

	Heat Demand Covered (GWh)	**Heat Demand Coverage (%)**
Created DHNs	457.52	56.09
Real DHNs	156.12	19.14
Total Heat Demand	815.70	-
Delta	-	**+36.95**

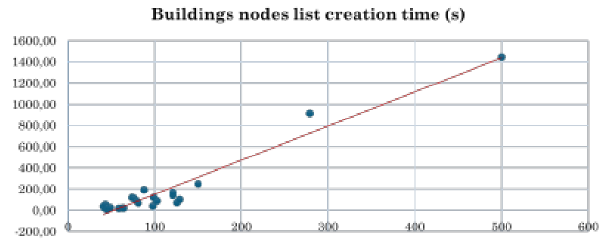


Fig. 24. Buildings nodes list creation time (s). Blue dots: datapoints for each commune; Red line: linear trendline.

($O(n^2)$). In contrast, the list creation related to buildings is linear. Nodes for buildings are created one by one, both for `list_nodes_buildings` and `list_edges_buildings`. For the latter, each building is checked once to determine its connected roads, resulting in a linear complexity ($O(n)$).

Consequently, the execution time of the algorithm increases significantly with the number of roads due to the quadratic relationship, whereas it grows incrementally and linearly with the number of buildings.

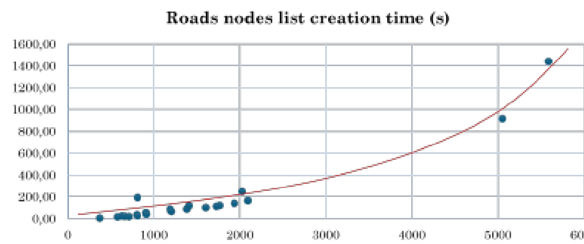


Fig. 25. Roads nodes list creation time (s). Blue dots: datapoints for each commune; Red line: quadratic trendline.

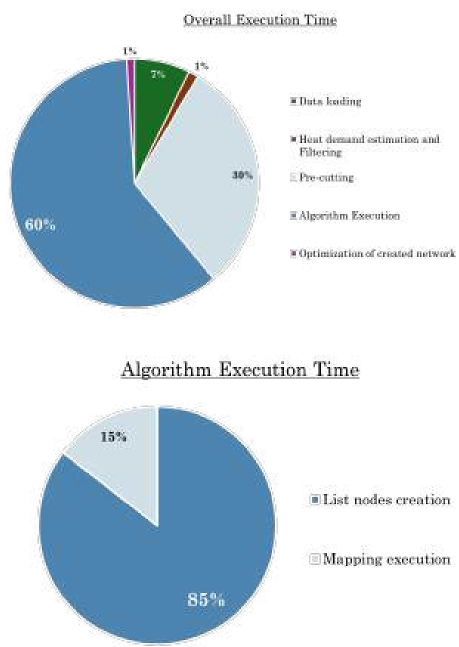


Fig. 23. Time distribution for each step of the algorithm execution.

The same logic applies to the mapping algorithm execution time concerning the number of buildings (linear) and the number of roads (quadratic) (Fig. 26 and Fig. 27). In the mapping algorithm, buildings are connected sequentially, one after another, resulting in a linear relationship with the number of buildings.

However, for roads, every road is tested for each building in each loop. This leads to a quadratic complexity ($O(n^2)$) for the roads, as the connections are checked repeatedly for all possible pairs. Consequently, the execution time increases significantly with the number of roads, while it grows linearly with the number of buildings.

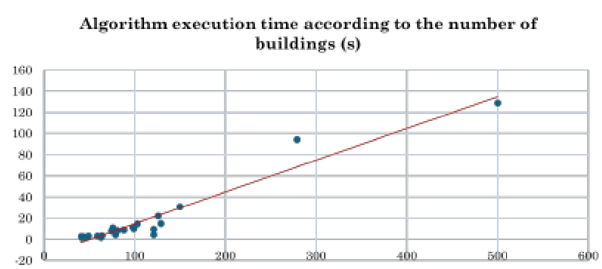


Fig. 26. Mapping algorithm execution time according to the number of buildings (s). Blue dots: datapoints for each commune; Red line: linear trendline.

3.3 Case Study

After examining the code on both local and departmental scales, we conclude with a final case study to explore the code further through very specific

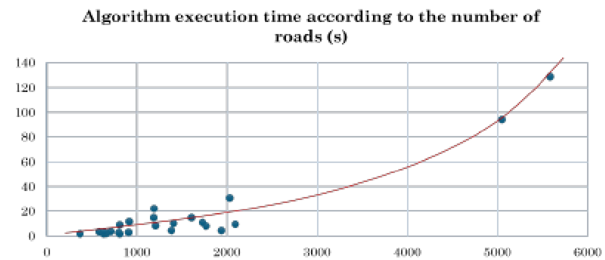


Fig. 27. Mapping algorithm execution time according to the number of roads (s). Blue dots: datapoints for each commune; Red line: quadratic trendline.

changes. We selected the town of Grandvilliers, a small municipality in Oise with 2,800 inhabitants and an area of 6.6 km**²**. The town features 153 buildings and 350 roads, which are reduced to 46 after applying the 30 kW threshold filter.

3.3.1 Heat Plant Location

From the very beginning, we arbitrarily chose the heat plant to be the largest energy consumer. However, this is not the case in reality. In practice, the heat plant is located in a specific area selected by the municipality. The goal of this case study is to determine an optimal location for the heat plant, assuming it must be situated near open fields to accommodate thermal solar panels or other sustainable heat sources (such as geothermal or biomass). This simulation, which focuses on heat plant sources, is modeled on Dymola and is not approached in this paper.

We have thus chosen to run this case study for three different plant locations near fields in order to choose the best one. These different locations are shown in Fig. 28.

Fig. 28. Aerial view of Grandvilliers and Selection of the Heat Plant Location.

Outputs for the Three Different Plant Locations

The outputs for the three different heat plant locations are shown on Fig. 29. The results vary significantly: Heat Plant 1 produces a highly profitable network but with relatively low heat coverage (37.59%). In contrast, Heat Plant 3 achieves nearly 90% heat coverage but has a lower linear density (1.72 GWh/km/year). Heat Plant 2 strikes a good balance, with both a high linear density (2.34 GWh/km/year) and a reasonable heat coverage (52.28%). Based on these results, we choose to retain this network for the city.

However, it is important to note that any of the heat plant locations could be considered viable, depending on the municipality's priorities (profitability or connectivity) as each scenario results in an economically feasible network.

Optimal Lambda

Another key observation is that the optimal lambda varies significantly depending on the heat plant's location. We can infer that when the heat plant is located farther from building clusters—such as near open fields—the optimal lambda technique proves highly effective. Conversely, when the heat plant is placed in the most energy-consuming building, which is often near other structures, the benefits of the optimal lambda technique may be less pronounced.

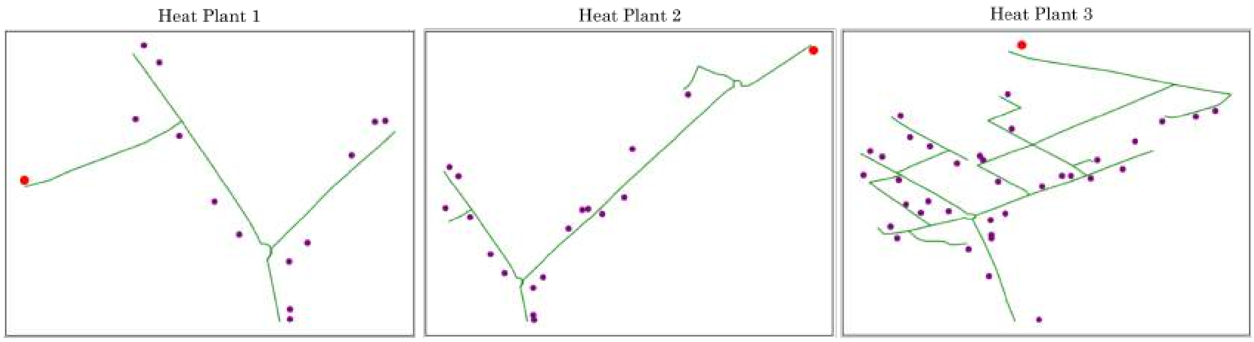
3.3.2 Random & Distance Rankings

As explained in the *Methodology*, all outputs presented throughout this study have been based on a specific ranking of buildings, which is the descending heat demand. In this section, we explore alternative ranking methods:

- **Random Class**: Buildings are ranked randomly;
- **Distance Class**: Buildings are ranked based on their distance to the heat plant, in ascending order.

3.3.3 Random Class

By assessing the network using a random ranking class, we aim to determine whether the initial ranking of the buildings significantly impacts the final network configuration. We thus ran the algorithm using two different random rankings for Heat Plant 1. The results, displayed in Fig. 30, clearly demonstrate that the initial ranking has a significant impact on the final network configuration. Random Class 2



Network Characteristics	Heat Plant 1	Heat Plant 2	Heat Plant 3
Optimal Lambda (GWh/km/year)	1.4	1.3	1.0
Length (km)	0.85	1.52	3.48
Number of connected buildings	14	15	37
Heat demand covered (GWh)	2.56	3.56	5.98
Heat demand coverage rate (%)	37.59	52.28	87.81
Linear density (GWh/km/year)	3.01	2.34	1.72

Fig. 29. Created DHNs for Three Different Locations of the Heat Plant

generates a relatively high-performing network with a linear density of 2.56 GWh/km/year and heat coverage of 29.50%. In contrast, Random Class 1 results in a poorly performing network that is not economically viable. This stark difference highlights the influence of the ranking method on network performance.

When running the code with the same random ranking across different heat plant locations, the results vary greatly compared to the heat demand descending class. In this scenario, only the Heat Plant 1 network proves to be economically viable, albeit with a relatively low heat demand coverage of 20.21%. (Fig. 31) The other two networks are not economically viable and are therefore not worth further investigation. This goes to show the impact of the initial ranking which is thus essential to build efficient networks.

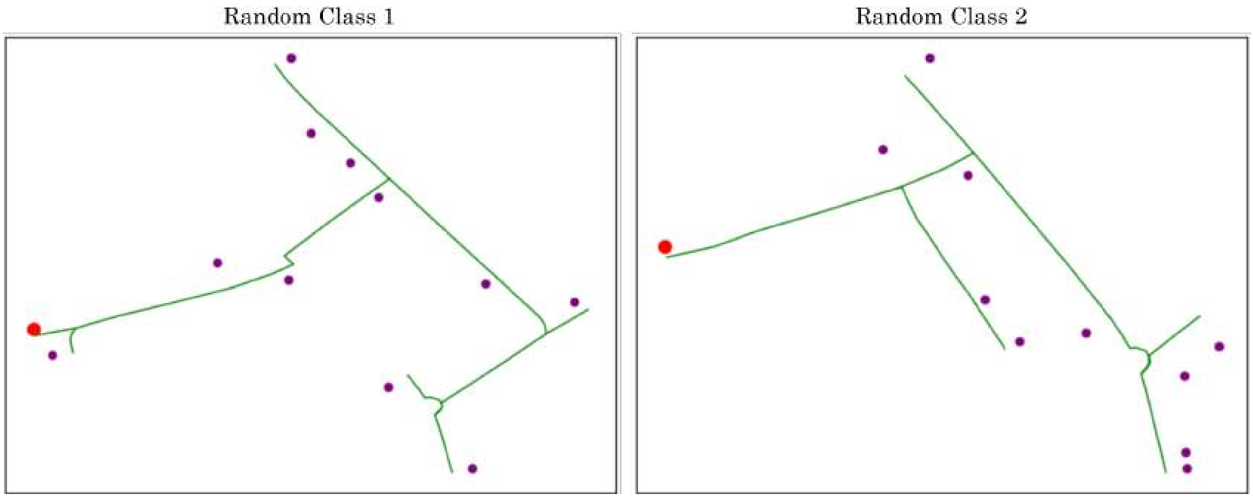
Additionally, the influence of the optimal lambda is noteworthy here, with a maximum value of only 0.7 GWh/km/year. This partly explains why the networks are not economically viable. However, without the optimal lambda process, mapping any network would have been impossible. This underscores the importance of the initial ranking, as it enables the algorithm to store a larger or smaller value in the network radius, thus influencing the continued expansion of the network.

3.3.4 Distance Class

While the random ranking does not reveal any predictable pattern, the distance-based ranking is particularly noteworthy as it prioritizes connecting the nearest buildings first, gradually expanding throughout the city.

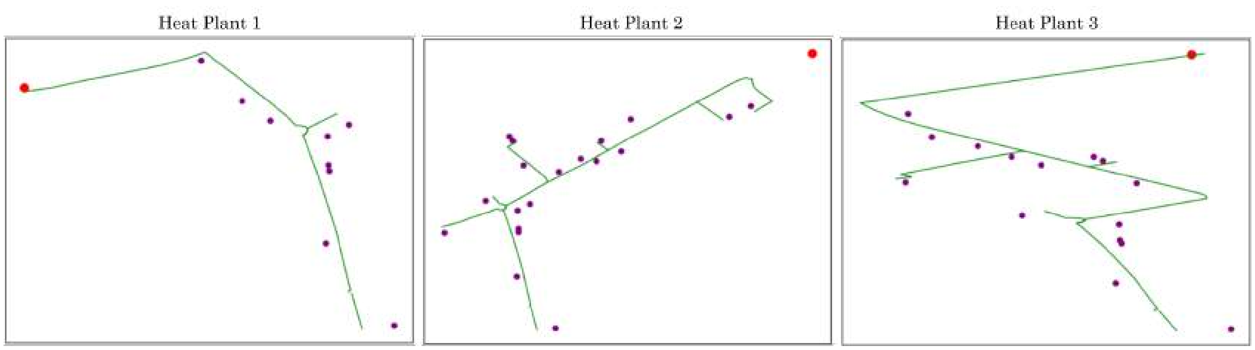
The results are significantly better than those of the random class, with two out of three networks proving to be economically viable (Fig. 32). Notably, the networks associated with Heat Plants 1 and 3 demonstrate strong performance: the Heat Plant 1 network exhibits high economic viability, with a linear density of 2.9 GWh/km/year and good heat coverage of 56.49%. Conversely, the Heat Plant 3 network achieves remarkable heat coverage (85.84%) and relatively high linear density (1.80 GWh/km/year). These outcomes are quite similar to those obtained with the heat demand descending class, although the latter performs slightly better for Heat Plant 1 and slightly worse for Heat Plant 3.

However, the distance-based method clearly excludes Heat Plant 2, which is surprising given that it was identified as the best-balanced and efficient option in the heat demand descending class analysis. This discrepancy can be attributed to one key factor: the nearest building to Heat Plant 2 is a low-consumption unit, and the second closest building is both distant and similarly low in consumption. Consequently, the network radius fails to expand rapidly enough, leading to early termination of the network



Network Characteristics	Random Class 1	Random Class 2
Optimal Lambda (GWh/km/year)	0.60	1.4
Length (km)	1.02	0.78
Number of connected buildings	12	11
Heat demand covered (GWh)	1.07	2
Heat demand coverage rate (%)	15.78	29.50
Linear density (GWh/km/year)	1.05	2.56

Fig. 30. Comparison of two Created DHNs for Different Random Rankings.



Network Characteristics	Heat Plant 1	Heat Plant 2	Heat Plant 3
Optimal Lambda (GWh/km/year)	0.7	0.5	0.7
Length (km)	0.88	1.66	1.44
Number of connected buildings	10	19	16
Heat demand covered (GWh)	1.37	1.71	1.63
Heat demand coverage rate (%)	20.21	25.22	24.04
Linear density (GWh/km/year)	1.56	1.03	1.13

Fig. 31. Created DHNs - Random Class.

loops and rendering the network economically unviable.

This observation is crucial as it highlights a limitation of the distance-based class. Specifically, it may overlook the network's potential due to the spatial distribution and heat demand of the city's buildings, even if the area has high potential in reality.

Therefore, the heat demand descending class remains the most effective ranking method, though it is still interesting to identify both options once a good heat plant location has been identified.

3.3.5 Changing the Constraint: $R_{net} \geq d$

The third and final modification we made was to the constraint, changing it from $R_{\text{net}} + R \geq d$ to $R_{\text{net}} \geq d$ for connecting a building. This new constraint is significantly more restrictive and is expected to prioritize only the largest consumers. Accordingly, we slightly adjusted the algorithm to accommodate this constraint and applied the same method with the optimal lambda.

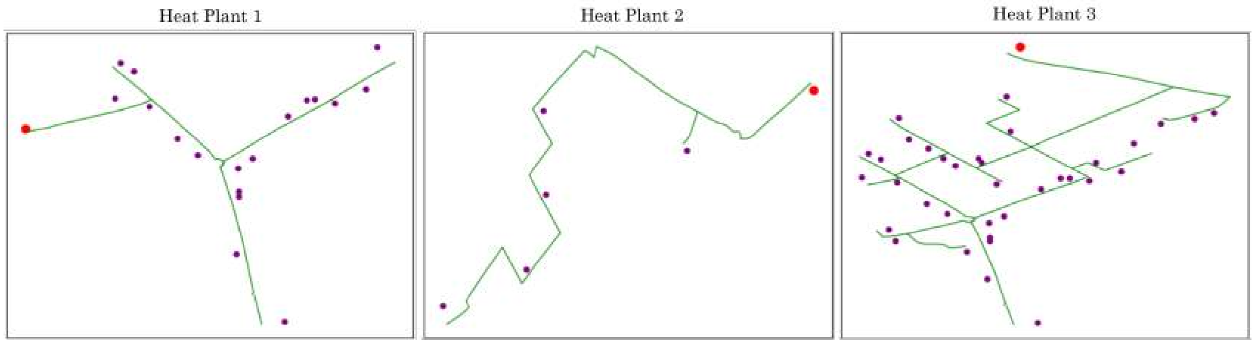
For the Grandvilliers case study, however, this constraint proved too restrictive to produce an economically viable network (Fig. 33). Instead, the most viable networks were achieved with very low lambda values (0.1 or 0.2 GWh/km/year). Setting such a low constraint caused the network radius to expand significantly at each loop

$$R_{\text{network}} \leftarrow R_{\text{network}} + R_A - d,$$

along with the building radius. This led to the connection of all buildings in the city, ultimately increasing the final linear density of the network far more than with the initial optimal lambda.

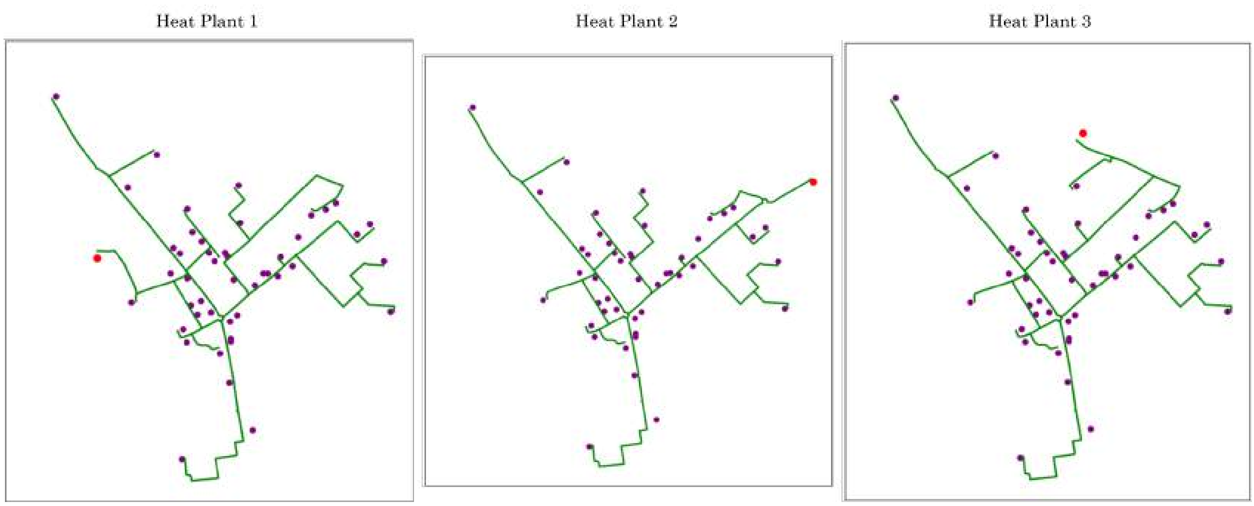
Consequently, the resulting network was nearly identical for each heat plant, encompassing every building in the city. This approach produces somewhat random outcomes: it could create a viable network if the city's layout allows it, but in most cases, it cannot.

Therefore, this method is not suitable for designing an optimal network, as it indiscriminately connects all buildings rather than selectively targeting the most advantageous ones – for instance, small consumers which form a cluster. It is also worth noting that, at the 1.5 GWh/km/year, no network could be created.



Network Characteristics	Heat Plant 1	Heat Plant 2	Heat Plant 3
Optimal Lambda (GWh/km/year)	1.4	0.7	1.0
Length (km)	1.32	1.43	3.24
Number of connected buildings	19	6	36
Heat demand covered (GWh)	3.83	1.22	5.82
Heat demand coverage rate (%)	56.49	17.99	85.84
Linear density (GWh/km/year)	2.90	0.85	1.80

Fig. 32. Created DHNs - Distance Class.



Network Characteristics	Heat Plant 1	Heat Plant 2	Heat Plant 3
Optimal Lambda (GWh/km/year)	0.2	0.1	0.1
Length (km)	5.47	5.47	5.47
Number of connected buildings	47	47	47
Heat demand covered (GWh)	6.78	6.78	6.78
Heat demand coverage rate (%)	100%	100%	100%
Linear density (GWh/km/year)	1.24	1.24	1.24

Fig. 33. Created DHNs - $R_{net} \geq d$.

Discussion

Although this study provides promising results for the Oise department, our approach may not be applicable to all French departments due to data limitations, particularly the lack of DPE classifications for certain buildings. For example, this method would not be feasible in the Lozère department where such information on buildings is not registered in the BDNB database. Even in regions where some building consumption data is available, gaps may exist in specific neighbourhoods, leading to their exclusion from the network analysis despite their potential suitability. Thus, the first limitation of this approach is the incomplete data for estimating building heat demand.

The second issue is execution time. Running the algorithm for all French departments is time-consuming, as it requires downloading and processing building and road data using QGIS for each of the 101 departments. This lengthy process is mainly due to node list creation, particularly for edges and road nodes, where the complexity is quadratic rather than linear. An alternative approach could involve creating intersection nodes in addition to building nodes and using weighted edges for roads instead of nodes to run the Dijkstra algorithm, thereby improving efficiency.

Third, the current approach does not consider the potential of expanding existing DHNs. In cities with existing networks, the newly created DHNs overlap with the existing infrastructure. Adapting the method to better integrate with existing networks could enhance the accuracy of the results.

Also, in some cities, certain roads or buildings may be unsuitable for connection to a DHN. To address this, an additional filtering step could be included in the data pre-processing phase, allowing municipalities to manually exclude any roads or buildings that cannot be connected.

Fifth, at the departmental scale, we selected cities with more than 40 buildings above the 30 kW maximum power threshold. However, lowering this constraint could further expand the overall potential of the department.

Another area for improvement in our model is the estimation of heat demand for each building. Currently, this is based solely on the building's energy performance (DPE) class, surface area, and height. However, a more sophisticated model could be developed by incorporating additional factors such as building materials, window types, and location (for example, southern regions may require less heating). Machine learning techniques, such as regression or clustering models, could also be utilized to enhance accuracy and estimate a building's specific demand even though one attribute is missing.

Lastly, this study does not capture the heat potential of France as a whole because of computational time and data format but focuses on a single department. However, Oise is quite representative, as it is a medium-sized and moderately populated area with numerous communes and a growing interest in district heating network implementation. In the Paris area, such study might have been less interesting as the study is already covered by many DHNs, leaving less room for new potential heat coverage.

Conclusion

At the local scale, we have developed a tool capable of optimally creating a district heating network for any commune within a given department.

Through the optimization process, we achieve the most efficient network length, with an average length reduction of 7.18% between before and after optimization for the Oise department. Depending on the municipality's objective—whether maximizing profitability by focusing on linear density or enhancing connectivity by increasing heat demand ratio—we can adjust the approach by modifying the lambda constraint or adding a minimum number of connected buildings.

If economic viability is the primary concern, the optimal lambda method should be prioritized, as it is much more precise (0.1 GWh/km/year here but adjustable) though more time-consuming. Conversely, if the goal is to connect as many buildings as possible while maintaining high economic viability, the length reduction reinjection can be applied, which implied to run the algorithm twice with a first implementation at the 1.5 GWh/km/year threshold. This method improves heat coverage without significantly reducing linear density or increasing computational time. The most effective solution remains the optimal lambda constraint, but, this time, combined with a minimum number of connected buildings—such as a specific share of the total building number—to meet the municipality's connectivity objective.

Lastly, during the preparation phase for implementing the DHN, the municipality can also explore different locations for the heat plant by manually selecting its connection point. This flexibility allows for strategic planning to optimize network efficiency and coverage.

This tailor-made application of the algorithm is a key strength of our tool.

Modifying specific algorithm features also helps determine the best configuration, such as building ranking. The ranking class is particularly crucial for optimal mapping. While the distance-based ranking to the heat plant can yield good results, it may overlook potential in certain cities depending on heat plant locations. The most reliable ranking remains the heat demand descending order, as it fully captures the area's potential and ensures economic viability if the heat plant is reasonably located.

At the departmental scale, for the 24 cities in Oise identified as suitable for district heating network development, our results indicate a 56.09% coverage of the heat demand for buildings exceeding a 30 kW maximum power threshold, significantly surpassing the current 19.14% covered by existing DHNs in the department. Additionally, our algorithm produces highly economically viable networks, achieving an average linear heat density of 2.36 GWh/km/year, well above ADEME's minimum threshold of 1.5 GWh/km/year. These results demonstrate the significant potential of the Oise department, both in terms of heat coverage and economic efficiency.

The departmental approach also allows for the identification of high-potential cities at the local scale, including Beauvais, Breteuil, Chambly, Chantilly, Nogent-sur-Oise, and Grandvilliers. These cities show an exceptional balance between linear density and heat coverage, consistently surpassing 2.00 GWh/km/year and 40%, respectively.

Overall, our tool effectively optimizes and expands district heating network development in Oise, unveiling France's growing potential for heat coverage. However, the unique strength of our model lies in its ability not only to estimate potential in terms of heat coverage but also to assess economic potential, pinpointing highly promising and specific areas. Consequently, this study offers a comprehensive overview of heat potential at the departmental level while also capturing the nuanced specificities at the local scale and adapting to the municipality's objectives and constraints.

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