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A New Method for the Techno-Economic Analysis and the Identification of Expansion Strategies of Neutral-Temperature District Heating and Cooling Systems

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Abstract: Neutral-temperature district heating and cooling (NT-DHC) is a recent concept in the district heating sector. The current literature does not directly address the ability to create comprehensive master plans for NT-DHC systems and reliably model their performance. This research presents a new approach for the evaluation and planning of NT-DHC systems. The methodology involves the use of a knapsack optimization algorithm to perform a comprehensive analysis of the conditions that make the NT-DHC solution competitive against individual heating and cooling technologies. The algorithm determines the optimal combination of potential extensions that maximizes overall economic value. The results of a case study, which was conducted in Italy, show that NT-DHC is more suitable in dense urban areas, while air-to-water heat pumps are better suited for low heat density zones. This methodology aims to reduce the risks associated with energy demand and provide more certainty about which areas a network can expand into to be competitive. It is targeted at energy planners, utilities experts, energy engineers, and district heating experts who require assistance and guidance in the planning and early stages of designing a NT-DHC system. This method might enable pre-feasibility studies and preliminary design to determine the opportunities and limitations of a system of this kind from an economic and technological perspective.

Keywords: neutral-temperature district heating and cooling; techno-economic model; knapsack algorithm; transition pathways; network expansion scenarios; energy planning



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1. Introduction

Climate change is a major global issue that requires action from the international community to reduce its impact. Emissions of greenhouse gases (GHGs) from human activities have been on the rise since the pre-industrial era, with particularly significant increases in the 2000s, despite the implementation of various mitigation policies [1]. Electricity and heat were the largest sources of CO₂ emissions in 2021, accounting for 42% of the global total [2]. Concerning emissions for electricity production only and their distribution among consuming sectors, industry was the most significant emitter, followed by buildings.

District heating (DH) is a service that delivers heat to customers through a network of pipes. It is based on utilizing nearby sources to fulfill heating requirements. DH has shown better performance compared to individual heating and cooling (H&C) systems in several contexts [3]. It is gaining recognition as a promising method for decreasing emissions and energy consumption for heating and cooling buildings. With proper management, DH systems can help lower GHG emissions and combat climate change.

Traditional DH systems (TDH) typically run at high temperatures (more than 80 °C), leading to significant heat losses and the need for costly piping insulation. According to Ref. [4], different DH generations can be identified. The first three generations of the DH sector are characterized by the constant trend of lowering the temperature of the distribution network, using lean materials and components, and utilizing prefabrication to

minimize human resources. Fourth-generation DH (4GDH) is a concept that aims to address the various challenges towards establishing a future H&C system that is not dependent on fossil fuels. These challenges include providing low-temperature DH for space heating (SH) and domestic hot water (DHW), reducing energy losses in the grid, incorporating renewable energy sources and waste heat recycling, and having a well-planned investment strategy for the transition to a sustainable energy system.

Neutral-temperature district heating and cooling (NT-DHC), often referred to as fifth-generation district heating and cooling (5GDHC), is a more recent concept in the DH sector that lowers temperatures to ambient levels (10–35 °C) [5] and introduces decentralized heat pumps (HPs) to set the user-side temperature at the desired level. So far, most of these systems have been established in Switzerland and Germany [6]. Their benefits include their decrease of heat losses in the distribution network, their ability to directly utilize easily available low-grade sources/sinks like aquifer wells and low-temperature waste heat (WH), and their potential to provide both heating and cooling with the use of reversible heat pumps. Currently, there is no agreement within the scientific community on whether NT-DHC/5GDHC should be considered as part of 4GDH or as an independent solution fully deserving the definition of a new generation [7–9]. In fact, on the one hand, NT-DHC presents distinguishing features (the full decentralization of heat pumps, the inclusion of cooling, stronger orientation to interoperability with the electric sector through the wider use of heat pumps); on the other, NT-DHC is not expected to replace previous DH solutions in all cases (e.g., when abundant high-temperature sources are present, as in the case of waste-to-energy plants), a fact that does not fit well with the idea of a new generation. Hence, even though the 5GDHC terminology is already somewhat established, we stick here to the NT-DHC nomenclature already used by the authors of this paper in previous publications [10].

Multiple EU-funded research projects in the DH sector have been carried out in recent years. The FLEXYNETS project [5] was the first to study the benefits and limitations of NT-DHC technology through simulations and laboratory tests. Real demonstrations of these systems are being implemented in projects such as LIFE4HeatRecovery and REWARDHeat [10–13]. The EU supports the DHC industry in general through projects such as ReUseHeat, Upgrade DH, and COOL DH, among others [14–16].

Techno-economic analysis is an active research field in the heating sector, with many ongoing studies aiming to improve efficiency and sustainability. The use of renewable energy sources like solar thermal and geothermal energy in conjunction with thermal storage systems is one area of research that has gained a lot of attention in recent years [17–19]. Researchers are working on developing new technologies and improving existing ones to make these systems more efficient and cost-effective. Research is also being conducted on using advanced controls and automation systems to improve the heating systems' efficiency [20–23]. These systems can optimize the operation of heating systems in real time based on factors such as weather forecasts and occupancy patterns and can help to reduce energy consumption and costs. Additionally, studies are also focused on developing models of DH systems that utilize multiple energy sources, as well as on their optimization [22,24–27]. Techno-economic analyses of DH systems typically focus on topics such as energy efficiency, environmental impact, and cost-effectiveness. Furthermore, a techno-economic analysis may also consider other elements, such as technical feasibility, market acceptance, engineering requirements, and financial considerations. This field is rapidly evolving, with new technologies and systems constantly being developed and tested as the need for efficient and sustainable heating systems increases.

A key distinction in the technical analysis of NT-DHC as compared to TDH systems is the added complexity in modeling decentralized HPs and the impact of variable neutral-temperature sources (NTS) on system efficiency [28,29]. Due to the simultaneous H&C of thermal networks, new hydraulic concepts are required, affecting topology, materials, and sizing [27,28,30,31]. The modeling of TDH systems involves three important blocks: sources, heat distribution, and loads. Modeling NT-DHC networks requires a holistic

approach since these three blocks cannot be addressed independently [32]. In terms of economic analysis, NT-DHC systems may be more expensive than conventional systems due to the need to invest in higher-grade technology, but they may also result in higher energy savings over time [33].

The models and tools that assist decision makers in choosing solutions for the built environment can be divided into two main categories according to their geographical application, time resolution, and purpose: detailed analyses at the building/district level and regional/national energy planning [34]. The first category of tools focuses on the load forecasting and simulation of a given system for single-building, local community, or tailor-made projects. They have a high temporal resolution and are more suitable for design purposes. Examples of these kinds of tools are TRNSYS, HOMER, and ESP-r, among others [35–37]. There are also detailed DH approaches, sometimes called physical models, suitable for network design. They provide high accuracy and may include features such as topology optimization and the routing and sizing of the network, but solving a very complex system can be computationally expensive due to the number of variables required [38–42]. These models are generally not equipped with economic data and, therefore, are not adequate for a complete techno-economic assessment (TEA) when comparing energy scenarios [7,42–44]. There are commercially available software programs, such as Fluidit Heat, that possess GIS functionality and offer an intuitive interface for analyzing complex DH systems. This facilitates the execution of business case studies, but such software's primary design is centered around TDH systems, rendering it inadequate for NT-DHC analysis. The capability of the software to make comparisons between various energy scenarios, including individual H&C systems, seems limited [45]. COMSOF Heat is another software that incorporates design and business features [45,46]. This software can analyze, and route optimize different network configurations. The current application of this GIS-based software is restricted to a single system and does not include future expansion planning. In the same way, the holistic models energyPRO and nPro do not support the analysis of future expansions into space [27,47–49]. The second category of tools pertains to simulation models that evaluate the operation and performance of multi-sector energy supply and demand systems, including heating, cooling, electricity, transport, and water. Long-term energy planning models typically have a low temporal resolution and lack the detail necessary to fully represent DH characteristics such as piping thermal losses, pumping energy consumption, and hourly HP performance. Tools that fit in this category are EnergyPLAN, LEAP, and Crystal City, though this list is not exhaustive [50–52]. In the pre-feasibility phase of NT-DHC systems, it is necessary to use comprehensive models that consider all aspects of the system, including the sources, network, and end-users, in a holistic manner. The current literature does not adequately address the ability to create comprehensive master plans for NT-DHC systems (even in TDH systems) and accurately model their performance.

The main contribution of this work is a comprehensive method for evaluating the techno-economic potential of NT-DHC systems in areas where district heating is not currently present. This approach is tailored to the case of NT-DHC as it includes the modeling of decentralized HP substations. Moreover, it allows for one to consider multiple heat sources and, as a key feature, it provides an optimization procedure for selecting the best system extension in space (where optimization relies on the “knapsack” algorithm). The methodology includes a novel approach for grouping heat demand areas using a clustering algorithm (so that these areas can be considered as the “items” for the “knapsack”, with the latter being represented by the maximum load possibly covered by available sources). An additional methodological innovation is a simplified model for quickly estimating the length of the network connecting the identified heat areas (combining the effective width approach with explicit distance calculations). Economic aspects are also properly considered, both in terms of investment and operation costs. This methodology can assist in the planning and initial design of a new type of DH system. To provide a practical example of the method, the paper also presents a specific case study wherein the

possible expansion of a small existing NT-DHC network located in a city in Northern Italy was considered.

This work is structured as follows: Section 2 presents the methodology proposed and the cross-verification carried out with a physical model and monitored data from the real NT-DHC network used as a case study. Sections 3 and 4 present the methodology's application to the case study and results. Finally, Section 5 provides conclusions and suggestions for further work.

2. Methods

The entire methodology is meant to be swift and user-friendly to support the preliminary phases of NT-DHC expansion planning. Consequently, priority is given to simplicity rather than to high accuracy. The aim is to guide the expansion of the system by determining the most profitable areas through energy assessments and subsequent financial calculations. As the spatial resolution used to analyze the NT-DHC network scenarios corresponds to the urban scale, a functional unit (FU) of 1 km² of residential areas was defined as default choice. A reference area of this size has already been investigated in previous publications [53,54]. The overall model is composed of different modules (Figure 1). Three main categories of inputs are used: heat load data (arranged in hectare-size cells), heat source data (arranged in source groups), and techno-economic parameters (including, e.g., operating temperatures and energy prices). The logic flow is as follows: (1) heat load clusters of sizes compatible with the available sources are identified; (2) an expansion iteration for the first source group is started (articulated in four steps: (i) network length estimation, (ii) yearly techno-economic analysis for each cluster, (iii) a comparison against individual H&C solutions and the exclusion of non-feasible clusters, (iv) the optimized selection of remaining clusters); and (3) the process is iterated until either the full FU is covered or no other source groups are available. The output is an expansion plan in multiple phases (given by the number of source groups), where each phase is defined by an optimal set of clusters for the corresponding source group.

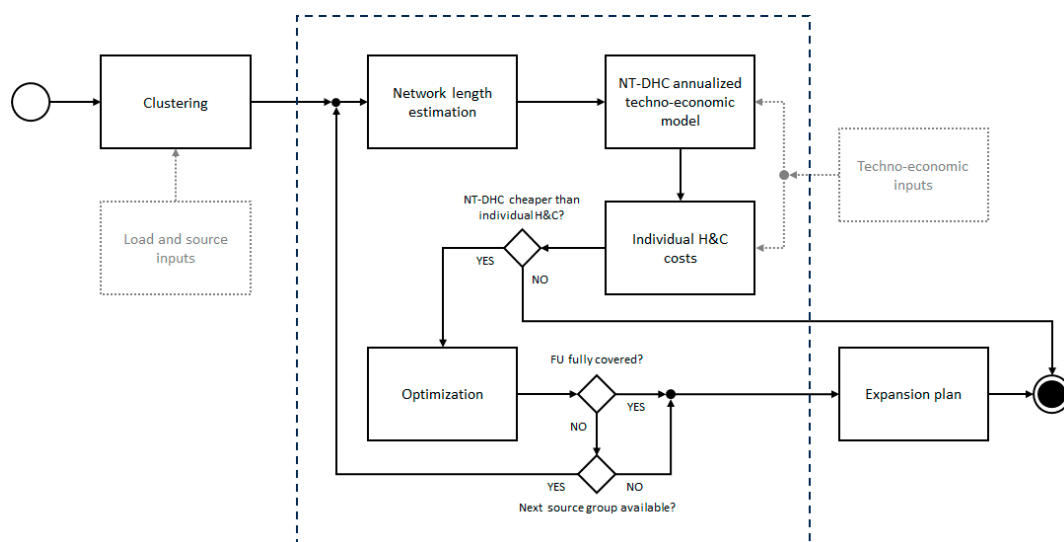


Figure 1. Model methodology. The blocks inside the dashed contour correspond to the iteration yielding different planning phases.

The core of the model relies on the four steps outlined above (see the blocks inside the dashed contour of Figure 1). The network length required to connect each cluster to the considered sources is calculated by combining an effective width approach with a star-like configuration for the network backbone. The yearly techno-economic analysis for each connected cluster is carried out separately, estimating overall annualized H&C supply costs (including investments). The resulting costs are compared with those estimated for

individual systems (air-source heat pumps in the case study considered here), and clusters non-competitive for NT-DHC (i.e., clusters where individual H&C solutions are more economically convenient) are excluded. Among the remaining clusters, an optimizer selects the most competitive ones up to a load size compatible with the given group of sources.

The various modules and sub-models used are described in the subsequent sections. Section 2.1 details the data gathering process for load demand and the clustering methodology in the preprocessing phase. The clustering process divides the study area into zones, each within the user-defined sources' capacity during peak conditions. Identifying potential NTS and their spatial locations is also an essential input for the model. Based on the spatial arrangement of the clusters, the model calculates the central point of each cluster and each source. To calculate the total network length required to connect the sources with the loads, these inputs are necessary in the network extension calculation block. The technical analysis focuses on overall results and avoids detailed network path evaluations, greatly simplifying calculations by relying on approximate indicators for parameters such as overall pipe length, pipe-ground heat exchange efficiency, pumping energy consumption, etc. The model then calculates the techno-economic viability of each potential expansion by determining the H&C network supply costs and revenues. The net present value (NPV) is calculated as a measure of value. A cost comparison with the business-as-usual case (BaU) of using individual H&C technologies is also performed. In Sections 2.2 and 2.3, the network model and techno-economic assessment are presented. Section 2.4 explains the optimization method and its application to the NT-DHC investment allocation problem. The process is iterative, considering a limited source capacity in each iteration and identifying the optimal subset of loads to join the network. This process can be repeated until all loads are considered.

2.1. Loads Analysis and Clustering

2.1.1. Clustering

The methodology was developed to use load data that are open and accessible to ensure it is broadly applicable. For this purpose, we chose to use the free online database of the Hotmaps project, developed for the planning and mapping of H&C systems for the EU28 countries [55]. It provides a spatial resolution of 100 m × 100 m, offering a satisfactory granularity level for this type of analysis and avoiding the complications and the computational burden of dealing with single buildings.

In contrast to conventional district heating, NT-DHC systems often rely on sources with limited capacity, sometimes less than 1 MW. Therefore, the assumption is that it is unlikely for a source to satisfy the H&C needs of an entire city or even of the FU defined in this approach. At the same time, the size of the smallest considered source somehow sets the granularity threshold for load aggregation. Therefore, it is useful to identify the communities to be served so that they can be provided with thermal energy during peak periods. A procedure was hence developed to group the aforementioned hectare-size cells into larger clusters, with the constraint that each cluster does not exceed the size of the smallest considered source. For computational efficiency, provided this constraint is fulfilled, minimizing the number of clusters is clearly desirable.

A phenomenological approach based on clustering techniques was hence chosen for this step. Clustering is a machine learning process that aggregates similar data points into the same cluster and separates less similar points into different clusters. The python scikit-learn library [56] provides various clustering algorithms to perform this task. No single best clustering algorithm exists for all cases. Here, the appropriate number or size of clusters depends on the capacity restrictions mentioned previously. A few clustering algorithms accepting the number of clusters as an input were compared, in particular the K-Means, the Spectral Clustering, and the Gaussian mixture methods. Each of them was tested in an iterative way, starting with the trivial case of a single cluster and progressively increasing the number of clusters until the constraint was met.

The Spectral Clustering method provided satisfactory results (see Section 2.3 for an example), yielding more even-sized clusters than the two other algorithms and showing the highest computational efficiency for the considered case.

Special buildings (SBs), including commercial buildings, public buildings, and schools, are also potential candidates for connection to the network, distinct from residential areas due to their different daily and seasonal H&C profiles.

2.1.2. Space Heating and Domestic Hot Water

The determination of the space heating profile is performed using the heating degree days (HDD) method, which is widely employed in the energy field. This method quantifies the thermal heat required for a specific building and climate in terms of both magnitude (in degrees) and duration (in hours) relative to the average daily outdoor temperature (T_{amb}). The space heating hourly profile ($E_{th,sh}$) is established by setting a base temperature (T_{b-heat}), which is set to 15 °C by default, reflecting the average European base temperature [57], but can be customized as desired. The calculation is carried out daily and then distributed on an hourly basis. Then, for day j and hour h :

$$E_{th,sh}(j,h) = E_{\%sh} \times \frac{(T_{b-heat} - T_{amb,j})}{\sum_{i=1}^{365} (T_{b-heat} - T_{amb,i})} \times f_h, \quad T_{amb,j} < T_{b-heat}, \quad (1)$$

where f_h is the share for hour h .

The energy share required for space heating ($E_{\%sh}$) is determined by building energy requirements and the European climatic zone. This term, retrieved from Hotmaps data (see previous section), depends on the size of the building area in the cluster. The customization of this value is made possible through the utilization of data on the heating, cooling, and domestic hot water (DHW) consumption of buildings in various European climates, as presented in reference [58]. The variation in energy demand for DHW is constant throughout the year and is not dependent on weather conditions. To obtain the DHW hourly profile, the daily demand is evenly spread across the year and multiplied by a random hourly profile. This profile can be tailored to the specific needs of the user using statistical means in a free software package.

2.2. Network Model

The aggregate approach developed by Persson [59] is a useful method for calculating the length of a distribution network. This approach takes into consideration its spatial and heat density limitations.

The network model simplifies the representation of the network length without incorporating detailed pipe routing information. By identifying the sources and their geographical locations, the model calculates the network length required for connection. The Virtual Source Point (VSP) is determined as the geometric center of a set of finite points, and the total network length is calculated as the sum of Euclidean distances between each source and the VSP. This investment cost (also depending on source power through pipe sizing) is considered a fixed cost (so that the sink distance can be later calculated only from the VSP) and is equal in all expansion scenarios (see Section 2.3.2 for further details on network investment costs).

The model estimates the length of the network by considering both geographical factors and the urban structure. The inter-distance (network backbone), connecting a cluster and the VSP, is estimated based on the haversine distance (based on geographic coordinates) between the VSP and the cluster's centroid. The intra-distance (service pipes) within the cluster's area is estimated through the effective width approach [59], considering urbanistic parameters such as the land and building areas, as available in the Hotmaps database. By combining both position-based and density-based calculations, the model balances the representation of both the urban environment and the distance-related factors while avoiding the complexity of a full network geometry.

The overall network length for a given configuration (i.e., a given selection of connected clusters) is hence given by the sum of the length of the inter-cluster network (the backbone) and the length of the intra-cluster networks (the distribution networks within each cluster):

$$L_{ntw} = L_{inter} + L_{intra} . \quad (2)$$

In turn, the inter-cluster network length is given by the sum of the connection lengths (calculated as haversine distance) between the VSP and the considered clusters and sources:

$$L_{inter} = \sum_j L_{VSP,j} , \quad (3)$$

where $L_{VSP,j}$ is the distance between the VSP and the j -th cluster/source, while the intra-cluster network length is given by the sum of the distribution network lengths within each cluster:

$$L_{intra} = \sum_j \frac{A_{land,j}}{w_j} , \quad (4)$$

where $A_{land,j}$ is the land area of the j -th cluster, and w_j is its effective width. In general, the effective width is defined as $w = w_0 p^{-\alpha}$, where p is the plot ratio, i.e., the ratio between the floor area A_{floor} of all buildings and the considered land area A_{land} ; the coefficient w_0 is the reference effective width for $p = 1$; and the exponent α determines the effective width decay with the increasing plot ratio (i.e., building density). Ref. [59], based on a statistical analysis of some cities with widely developed DH systems, proposes the values of $w_0 = 61.8$ and $\alpha = 0.15$. These are used as default values in the model, though it is worth pointing out that these parameters are expected to exhibit a non-negligible variability depending on the urban context.

The star-like calculation in the inter-distance estimation tends to overestimate the backbone length, as a real network would typically use existing pipes to reach nearby clusters rather than constructing a new route for distant clusters. This approximation is only considered reliable if the closest clusters are connected. The chosen clustering method aims to minimize this by producing the largest possible clusters, resulting in a small number of clusters and limiting length overestimation. Moreover, this effect is counterbalanced by the length underestimation given by the chosen as-the-crow-flies distance measurement (in reality, pipes follow street paths and hence give rise to so-called taxicab geometry lengths according to the typical rectangular street grid occurring in many cities).

2.3. Techno-Economic Model

The techno-economic model (TEM) employed in this research (see the top-right box within the dashed contour in Figure 1) is based on the methodology of an Excel tool developed in the FLEXYNETS project [5]. The aim of this tool was to conduct feasibility studies on the implementation of the NT-DHC concept under different conditions. In the next subsections, the key equations used to determine the costs and benefits of the NT-DHC solution are described.

2.3.1. NT-DHC Performance

The performance of the NT-DHC system is evaluated by considering the energy balance between the sources and loads, including both heating and cooling supply. The calculation is performed for each potential cluster or SB in the proposed new method.

The temperature delivered to the buildings for space heating (T_{SH}) is calculated using a climatic curve which considers the relationship between the required heating level and the outdoor temperature. The desired temperature range is set based on minimum ($T_{amb,min}$) and maximum ($T_{amb,max}$) outdoor temperatures, with minimum ($T_{SH,min}$) and maximum ($T_{SH,max}$) SH supply temperatures being reached accordingly. Within the range $T_{amb,min} \leq T_{amb} \leq T_{amb,max}$, the climatic curve is then given by the following equation (linear in T_{amb}):

$$T_{SH}(T_{amb}) = T_{SH,max} - \frac{T_{SH,max} - T_{SH,min}}{T_{amb,max} - T_{amb,min}} (T_{amb} - T_{amb,min}), \quad (5)$$

while $T_{SH} = T_{SH,max}$ for $T_{amb} \leq T_{amb,min}$, and $T_{SH} = T_{SH,min}$ for $T_{amb} \geq T_{amb,min}$.

The temperature for DHW (T_{DHW}) is assumed to be 55 °C. Exploiting the demand profiles described in Section 2.1.2 (HDD distribution for SH and constant distribution for DHW), a single effective temperature for users is calculated as the weighted average of the SH and DWH temperatures. In this way, a single outlet temperature profile can be assigned to the condenser side of decentralized HPs. Figure 2 shows an example of the monthly average pattern for the resulting curve. Depending on the case, it should be adjusted based on the specific climate conditions affecting the energy needed for SH, ambient temperature, and building setpoints ($T_{SH,min}$ and $T_{SH,max}$).

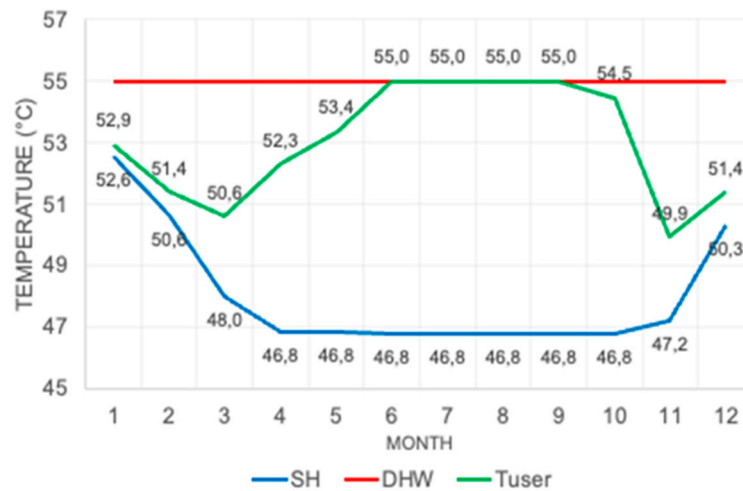


Figure 2. Example of the effective user temperature assumed by the model (green curve), valid for the case study described below. This corresponds to the outlet temperature assigned to the condenser side of decentralized heat pumps. This effective temperature is calculated as the weighted monthly average of SH and DHW temperatures (blue and red curves, respectively).

The HPs located at the users' substations operate in parallel, with a variable performance based on the network and load conditions. They are modeled in an aggregate manner, allowing for a quick estimation of a large number of users. Equation (6), reported below, was selected from reference [60] to represent a simplified understanding of the performance of the HP pool. This coefficient of performance (COP) function is dependent on the outlet temperature at the evaporators of the heat pumps ($T_{e,o}$), which varies based on the temperatures of the available sources, and on the required temperature delivered to the users at the outlet of the heat pumps' condensers ($T_{c,o}$). Additionally, a correction factor (η_{CF}) was included in the formula to account for inefficiencies in the system that are beyond the scope of the analysis. One then has the following:

$$COP = \eta_m (COP_C - 1) + 1, \quad (6)$$

where $COP_C = T_c / (T_c - T_e)$ is the (temperature-dependent) Carnot COP, expressed as a function of the condenser $T_c = T_{c,o} + \Delta T_{HX}$ and evaporator $T_e = T_{e,o} - \Delta T_{HX}$ refrigerant temperatures, which, in turn, are estimated from the external fluid outlet temperatures through the heat exchanger temperature drop ΔT_{HX} , assumed to be equal for the two cases. Moreover, η_m can be interpreted as the compressor efficiency, a parameter varying due to multiple factors such as the HP model, size, and operating conditions. For a given HP, it is possible to estimate both η_m and ΔT_{HX} by fitting the above equations to datasheet values. Typical orders of magnitude are $\eta_m \simeq 0.5$ and $\Delta T_{HX} \simeq 2.5$ K. For calculations in cooling mode, the energy efficiency ratio $EER = COP - 1$ is used.

The above formulas are mainly conceived to describe the HP operation only. In user substations, various other effects, like thermal losses in pipes and buffers or pumping consumption on the users' side, take place. Moreover, differences in actual and datasheet HP performance, losses from HPs' on/off cycles, inaccuracies in the climatic curve, and measurement uncertainty play a role when comparing with real data. To include these effects, the model includes a calibration factor η_{CF} , which is used to multiply the above performance functions. In the absence of further data, the default value $\eta_{CF} = 1$ can be used.

2.3.2. Net Present Value

Instead of using the common levelized cost of heat method utilized in other DH studies, here, the economic feasibility of a NT-DHC project is measured through the evaluation of the total net present value (NPV) of each network extension. Since NT-DHC systems can provide simultaneous H&C through the same network, this choice avoids the issue of deciding a cost allocation between the two services (possibly introducing separate levelized costs of heating and cooling), which would otherwise complicate comparisons among different extension options.

The NPV is calculated as the difference between the present value of the future cash flows from the H&C sales of the NT-DHC operation and the initial investment costs. Here, r is the required rate of return, and N is the period in years. The discount rate is company-specific, since it depends on how the funding is obtained. Generally, it is based on investors' expectations of return, or borrowing costs. The default rate of return in this assessment is assumed to be 3% in the model. In the DHC sector, the most common business models are those owned completely by public entities, which account for relatively low rates [61].

The advantages of using NPV as a financial indicator compared to others include the fact that it accounts for the time value of money, it is additive (the total NPV of multiple projects is the sum of the corresponding NPVs), and it constitutes a fast and easy metric for comparing an initial investment against the present value of the expected returns. This indicator is calculated for each potential extension scenario as follows:

$$NPV(r, N) = \sum_{n=1}^N \frac{(p_{heat}E_{th,h} + p_{cool}E_{th,c})f_{inc} + C_{fix} - C_{NT-DHC}}{(1+r)^n} - I_{NT-DHC}, \quad (7)$$

where p_{heat} and p_{cool} are the H&C prices for the services sold through the NT-DHC network, $E_{th,h}$ and $E_{th,c}$ are the amounts of yearly H&C energy delivered to the network users (herein assumed to be constant along the project horizon), f_{inc} is a possible incentive factor given by a government or utility company (the default value is assumed to be 1), C_{fix} is the fixed operation and maintenance fee, C_{NT-DHC} is the total annual cost of NT-DHC operation, and I_{NT-DHC} are the NT-DHC investments.

The operating costs of a NT-DHC solution (C_{NT-DHC}) is, in turn, subdivided into three components: operational expenses ($OPEX$), the fixed operating and maintenance costs of reversible HPs (OM), and carbon emission costs (C_{tax}):

$$C_{NT-DHC} = OPEX + OM + C_{tax}. \quad (8)$$

Here, the $OPEX$ of a NT-DHC system includes all variable costs incurred by the network manager. This includes the cost of electricity used by the heat pumps; any auxiliary systems, such as auxiliary heaters, chillers, or cooling towers; pumping consumption costs; and the cost of any waste heat (WH) sources. By default, the simulation assumes that WH recovery is free; however, the method allows the user to assign a cost to this item to explore different business models. One then has the following:

$$OPEX = E_{el,HP}p_{el,ind} + \sum_j E_{th,WH,j}p_{WH,j} + \sum_j E_{th,aux,j} \frac{p_{fuel,j}}{\eta_{tech,j}}, \quad (9)$$

where $E_{el,HP}$ is the HP electricity consumption in H&C mode, $p_{el,ind}$ is the industrial electricity price (typically different from the residential one, used in calculations for individual technologies, see below), $E_{th,WH,j}$ is the heat supplied to the network by the j -th WH source, $p_{WH,j}$ is the corresponding price (possibly zero), $E_{th,aux,j}$ is the energy produced/absorbed by the j -th auxiliary system, and $\eta_{tech,j}$ and $p_{fuel,j}$ are the efficiencies and the fuel prices of the latter, respectively.

OM includes all costs independent of the operation of the heating system, such as service agreements, spare parts, and insurance. The method relies on the cost values obtained by fitting the HPs' data from the Danish Energy Agency database [62]. Finally, C_{tax} considers the potential future taxation on carbon emissions and the expected impact on the final customer. This cost is assessed based on the estimated carbon emissions and is assumed to be either directly or indirectly paid by the customer. For HPs, it can be written as follows:

$$C_{tax} = c_{tax} f_{em,el} E_{el,HP}, \quad (10)$$

where c_{tax} is the carbon tax, and $f_{em,el}$ is the electricity emission factor. Similar terms are added for auxiliary systems if they are operating.

The investments required for the NT-DHC system (I_{NT-DHC}) include the network costs (I_{ntw}), the reversible heat pump substations (I_{HPs}), and the heat recovery equipment at the production sites (I_{srcs}). I_{ntw} is determined by factors such as its length, diameter, and the materials used. The distribution pipes consist of six different categories of pipes with varying diameters, and the proportion of each type is determined based on the maximum diameter required in the network and is set based on standard network configurations. The network pipe composition, default scaling factors, and piping prices are based on information collected in [63]. The investment in the network backbone (I_{inter}) also considers the maximum diameter needed and is designed to handle the peak conditions. See Equations (11)–(13):

$$I_{ntw} = I_{inter} + I_{intra}, \quad (11)$$

$$I_{inter} = L_{inter} p_{pipe}(D_{max}), \quad (12)$$

$$I_{intra} = L_{intra} \sum_{i=1}^6 s_{intra}(D_i) p_{pipe}(D_i), \quad (13)$$

$$D_i = D_{max} \sqrt{SF_i}, \quad (14)$$

where D_i is the diameter of the i -th pipe category (6 categories are considered according to Table 1), SF_i is a corresponding scaling factor (originally calculated from cross-section data and, therefore, put under square root for diameter calculation), D_{max} is the maximum pipe diameter (based on inter-network branch sizing), s_{intra} is the share of intra-network length with pipes with diameter D , and $p_{pipe}(D_i)$ is the specific (per unit of trench length) pipe cost, including pipe, excavation, and installation costs. The latter depends on pipe diameter, pipe type (insulation series), and district type (city center typically has higher installation costs). The model includes a default database taken from [63].

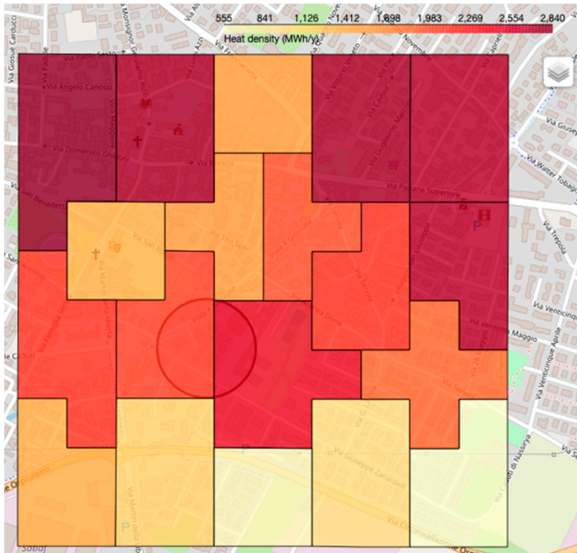
Table 1. Default distribution of pipes among 6 possible categories and corresponding scaling factors according to [63].

Pipe Category	Length Share	Scaling Factor
1	43%	0.025
2	24%	0.043
3	18%	0.109
4	8%	0.244
5	4%	0.665
6	3%	1.000 (i.e., $D_6 = D_{max}$)

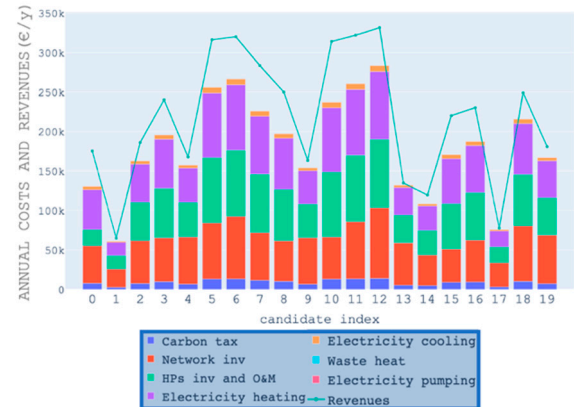
The feasibility of the NT-DHC solution is evaluated in comparison to the BaU cases, which include the use of reversible air-to-water heat pumps (A/W HPs) and individual

gas boilers with split cooling units (individual H&C scenario). The emissions from the individual gas boilers are accounted for using the corresponding emission factor ($f_{em, gas}$). The carbon emission costs are calculated based on the energy consumption using equations similar to Equation (10).

A case study (see below) was evaluated using the methodology outlined above. The breakdown of revenues and expenses for each potential network extension scenario is illustrated as an example in Figure 3b.



(a)



(b)

Figure 3. (a) The clustering method applied to the case study. The inputs are the latitude, longitude, and heat density of each city hectare. (b) Annual costs and revenues per candidate. The difference between the green line and the bars represents the net economic margin per year (EUR/y).

2.4. Optimization

This section describes how the model uses the knapsack approach for making investment decisions in potential network extensions where there is a limited number of WH sources and loads, each with a defined maximum thermal power (in MW) and economic value (in EUR, as calculated using the estimated NPV described in Section 2.3.2).

The standard knapsack problem (KP) is the so-called 0–1 knapsack problem, which consists of identifying a subset among n items, each with a weight (w) and a value (v), so that the overall value of the subset is maximized and a maximum weight W (which can be interpreted as the weight capacity of a knapsack) is not exceeded. Each of the n possible items is either included (1) or not (0), which can be represented by the indicator function x of the subset. Mathematically, given a set of n items (labeled from 1 to n), each with a weight w_i and a value v_i , along with a maximum weight capacity W , this can be written as:

$$\text{maximize } \sum_{i=1}^n v_i x_i, n \text{ items}, \quad (15)$$

subject to $\sum_{i=1}^n w_i x_i \leq W$ and $x_i \in \{0,1\}$. In the model, the evaluation is limited to items that add value to the overall knapsack (only those extensions whose NPV has a positive outcome):

$$v_i > 0 (i = 1, \dots, n). \quad (16)$$

Finally, based on the clustering process described in Section 2.1.1, the items must be smaller than the knapsack to avoid trivial solutions:

$$w_i < W (i = 1, \dots, n). \quad (17)$$

The KP is considered to be NP and a hard optimization problem [64]. A trivial attempt to solve it would be to make an exhaustive search of all 2^n possible subsets of n items. For instance, if there are 60 items, it would take more than 30 years to complete the search at a rate of 1 billion vectors per second. This is because the number of combinations doubles with each additional item. The model hence exploits the dynamic programming approach introduced by Bellman [65], which offers a more efficient solution with a time complexity of $O(nW)$ compared to $O(2^n)$ for a brute force approach. Its implementation requires W to be an integer, which can be easily enforced by properly discretizing/rounding the “weight” value.

The computational effort required to solve the network extension problem depends on the number of periods selected and the number of items to optimize. The evaluation of the NPV of each item is linear (it takes approximately 0.2 s using the current non-optimized TEM version). Once the value of each item is determined, the average time required to solve the KP is 0.05 s.

2.5. TEM Dynamic Performance

The TEM outputs were cross-checked with a more detailed physical model that takes into account the thermal and hydraulic characteristics of the network [11]. The original Excel tool of [5,63] was modified to enhance its flexibility by converting it into a Python implementation. The lumped approach was maintained, but it was enhanced with the ability to conduct hourly analysis over the course of a full year (in [63], a time-slice approach based on a single representative day for each month was used). This upgrade also facilitated the integration of a basic storage modeling component. Figure 4 illustrates some representative results, considering the presence of cooling. The figure shows the dynamic system performance over the course of a week in both winter and summer, highlighting the importance of the variable network temperature and the source–load temperature difference in determining the overall efficiency of the system.

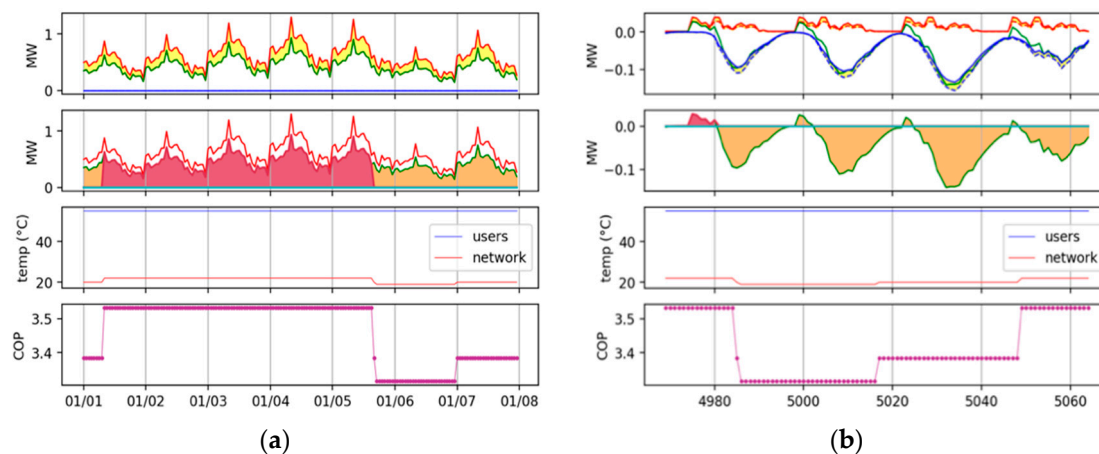


Figure 4. Example of energy balances calculated by the techno-economic model for the case study considered below. (a) Behavior of a representative winter week. First panel from top: load power (red/blue: heating and cooling loads; solid/dashed: gross/net values, i.e., user/network side; green: overall net load). Second panel from top: source power (red areas: waste heat; orange areas: aquifer wells; when visible, individual curves are the same as in the top panel). One can recognize the five working days when WH is available and the weekend when aquifer wells are exploited. Lowest panels: operating temperatures and COP values according to axis and legend. A drop in COP is visible in the weekend due to the lower source temperature provided by the aquifer wells with respect to WH. (b) Behavior of a representative summer week.

The validity of the lumped model was then evaluated through a comparison with real data collected from a NT-DHC network in Ospitaletto, Italy. Hourly data from 2020, which included temperature and flow rate measurements, and weekly/biweekly data from

2019 were made available by the network operator. The results showed that the model provides the proper order of magnitude for various values, such as seasonal COP (SCOP), seasonal performance factor (SPF), and thermal losses [12]. However, to achieve a good agreement between the model and real data (a few percent difference in the most important indicators), two phenomenological coefficients were calibrated (the substation calibration factor defined above and a calibration factor related to thermal losses to the ground). It was concluded that an aggregate approach is appropriate for a small network like the one in Ospitaletto, as most deviations between the non-calibrated model and real data can be explained by physical details unrelated to user granularity.

3. Case Study

In this section, the method from the previous section is applied to the Ospitaletto case study. The different types of NTS within the municipality were identified through manual analysis to provide inputs for the model, along with their temperature level, estimated thermal capacity, and location. Three groups of sources were selected based on temperature availability and proximity, and they are presented in Table 1 and Figure 5. According to the waste heat estimates presented in the FLEXYNETS project [5], hourly availability profiles were estimated for industries and supermarkets. The heat demand for the study area, retrieved from Hotmaps, is 35.7 GWh/year, with a peak demand of 17.3 MW. The cooling demand was assumed to be 10.7% of the heat demand based on findings from [66]. The Spectral Clustering method was used to determine the configuration shown in Figure 5, starting with one large cluster and increasing granularity while considering the smallest industrial WH plant of 1.58 MW. Table 2 summarizes the inputs used in this reference scenario.

Table 2. Source characteristics and grouping selection for the given case study.

Source	Category	Capacity [MW]	Temperature [°C]	Group
Powell Park	Park	1.1	15	G1
Steel plant	Industry	1.6	22	G1
SABAF	Industry	6.0	25	G2
Piazza Mercato	Park	12.3	15	G2
Carrefour	Supermarket	0.1	18	G3
Ori Martin	Industry	15.0	25	G3

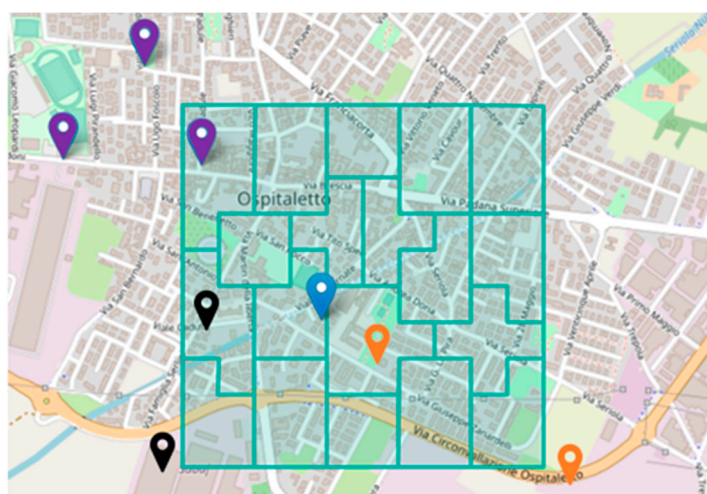


Figure 5. The location of clusters and source groups is represented by different colors. G1 is in orange, G2 is in black, and G3 is in purple. The blue marker represents the centroid of SBs.

The energy prices vary significantly based on the customer type (residential or industrial) and taxes. The assumptions were made using 2020 data from Eurostat [67], yielding

the typical values reported in Table 3 (note that these are consequently pre-crisis values; the same holds for the assumptions about investment costs). It is assumed that a NT-DHC system would not be subject to electricity taxes. Conversely, the performance of alternative individual solutions is evaluated with the assumption that customers pay residential electricity and gas prices, inclusive of all taxes and fees. The highest heat price sold through the network is assumed to be equal to the cost of the competing solution.

Table 3. Energy prices selected for the reference scenario, related to 2020 data.

Variable	Price (EUR /kWh)	Description
p_{gas}	0.100	Residential gas price in Italy including taxes.
$p_{el,ind}$	0.150	Industrial electricity price in Italy excluding taxes.
$p_{el,res}$	0.200	Residential electricity price in Italy including taxes.
p_{heat}	0.100	Assumed to be equal to gas price.
p_{cool}	0.100	H&C network services are assumed to be equal.

In Table 4, a set of technical inputs based on the current operating conditions of the Ospitaletto network is provided [12]. Additionally, a carbon tax is considered. Emission factors in the Italian electrical grid, as reported by the Italian Institute of Research and Environmental Protection (ISPRA), are utilized to determine an up-to-date value for the electricity emission factor [68]. In this study, 0.281 tCO₂/MWh represents the emissions from electricity consumption (calculated using a standard method) for the reference year of 2018. Emission factor for gas is taken from Ref. [69].

Table 4. Technical inputs used in a default simulation.

Parameter	Value	Description
T_{DHW}	55	DHW temperature [°C]
$T_{SH,max}$	55.7	Max indoor SH temperature for buildings [°C]
$T_{SH,min}$	46.8	Min indoor SH temperature for buildings [°C]
η_m	53	HPs' compressor efficiency [%].
c_{tax}	75	Carbon tax [EUR /tCO ₂]
$f_{em,el}$	0.281	Electricity emission factor [tCO ₂ /MWh]
$f_{em,gas}$	0.202	Gas emission factor [tCO ₂ /MWh]

4. Results

The methodology considers a phased implementation of sources and loads based on the thermal capacity and number of time periods. The sources are assumed to be available in the order specified in Table 2. WH capacity should be determined considering industrial sources' capacity, as their stable schedules and constant heat supply are key for network operation. Complementary sources such as supermarkets, small shops, bakeries, etc., should be considered to meet the total load but not for sizing. Parks or ground source sites are considered auxiliary systems to help meet demand during weekends or when WH plants are unavailable.

In Figure 6, the NPV of each potential extension project is calculated and represented by a heatmap. The clusters with a high NPV appear in red, while those with a lower NPV appear in yellow. The model then determines the optimal combination of clusters with the highest total NPV while staying within the thermal capacity limit (as shown in Figure 6b).

The first iteration prioritizes cluster 10 for its highest NPV. Cluster 1 is included even though it has marginal economic advantage, as its addition still meets the 1.58 MW thermal power limit (see Figure 10a). The second iteration recalculates the NPV of the remaining clusters, with 6 MW of WH capacity available. Figure 7a shows the markers representing the locations of sources in group G2. The model selects the zones shown in Figure 10b based on the best compromise between economic value and peak capacity.

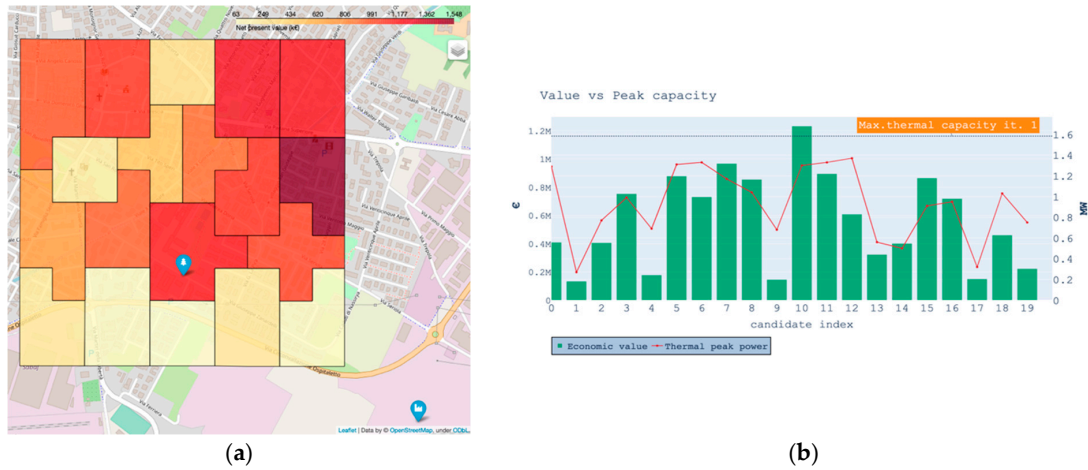


Figure 6. The first optimal extension uses 1.58 MW of thermal power. (a) NPV calculations for each cluster. (b) Cost–benefit analysis of extension scenarios. The dotted line indicates the maximum capacity that can be exploited from the WH plant.

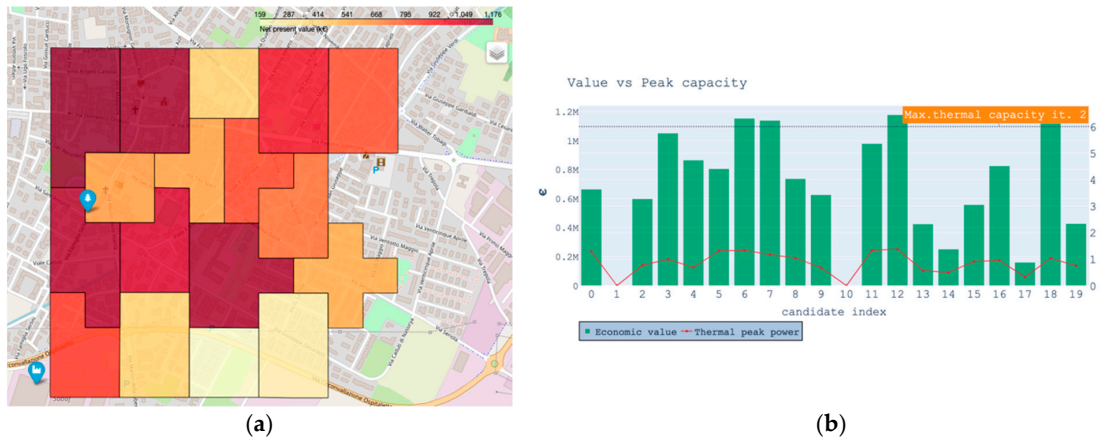


Figure 7. (a) Heatmap representing the NPV of each cluster in the second network extension. (b) Cost–benefit analysis.

The model calculates the NPV of the remaining loads, including SBs, in the third iteration. All feasible loads are served by the NT-DHC system with 15 MW thermal capacity. Zones in the southern part of the FU are not connected to the network (Figure 8) and can use reversible A/W HPs at a lower cost than the NT-DHC solution (Figure 9). The process concludes if a better scenario cannot be reached compared to the BaU case or if the NT-DHC fully serves the FU. The expansion pathways for the NT-DHC system are shown in Figure 10.

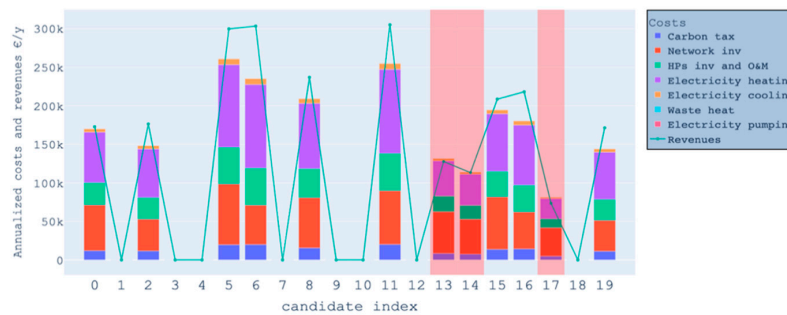


Figure 8. Clusters 13, 14, and 17 produce unfeasible scenarios, as they generate insufficient revenue to offset the high network connection costs with G3.

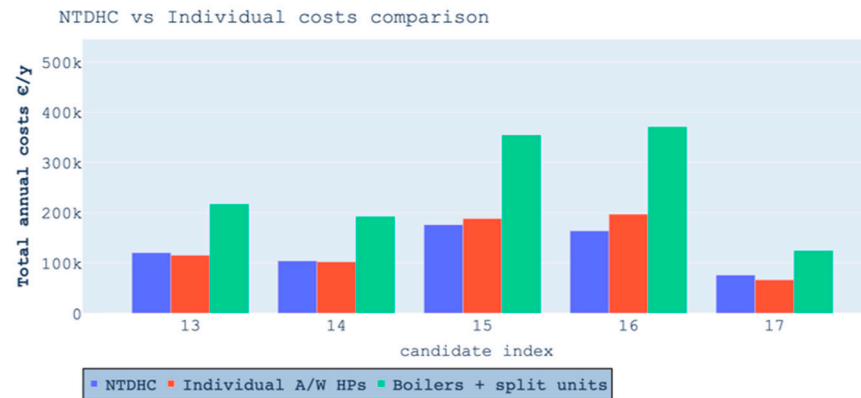


Figure 9. Cost comparison of H&C options. A/W HPs are preferred in Clusters 13, 14, and 17 over NT-DHC due to their lower cost.

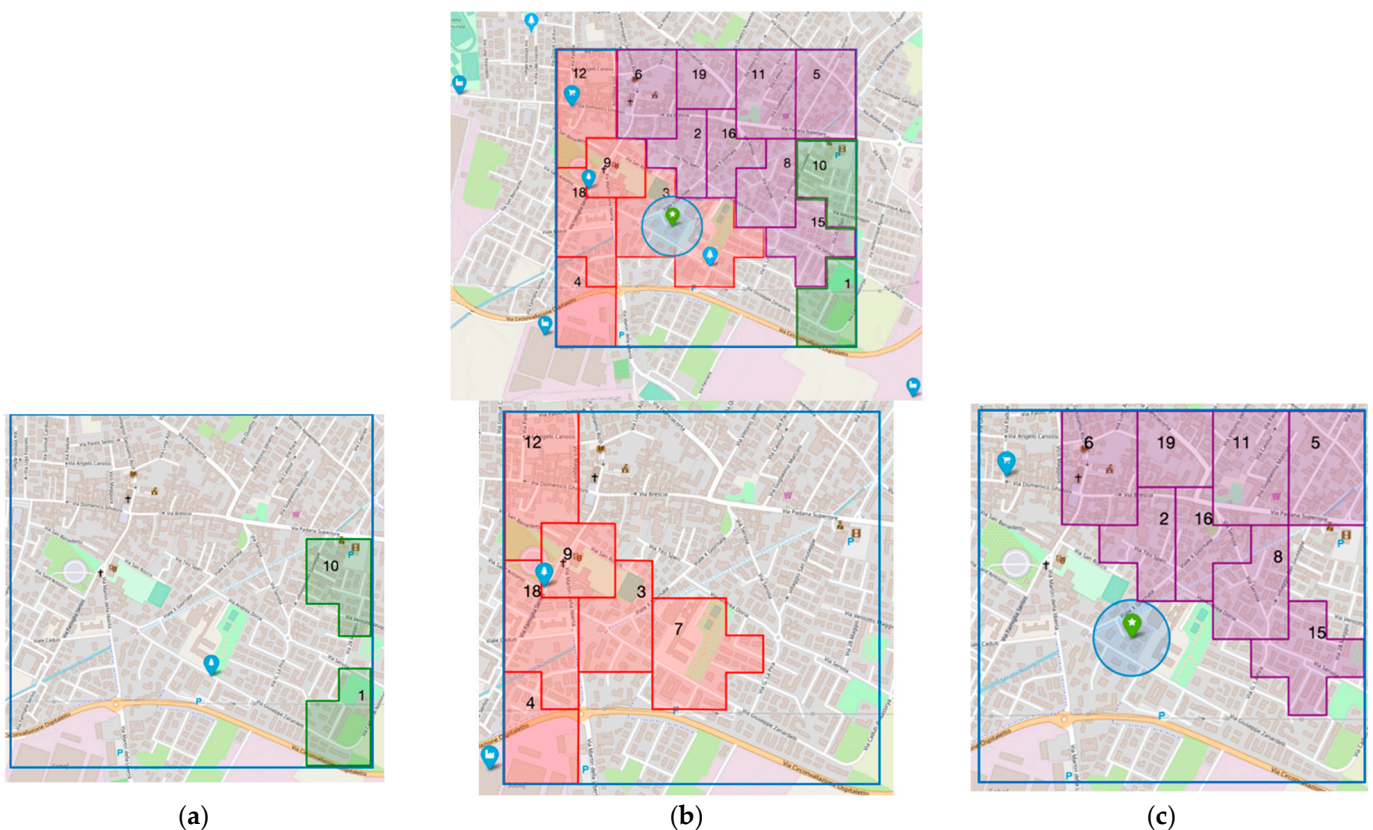


Figure 10. Methodology outputs. (a) First optimal extension: 1.6 MW thermal power. (b) Second iteration: 6 MW WH available. (c) Third stage: optimal extension with 15 MW thermal heat.

5. Conclusions

This work presents a comprehensive methodology for modeling NT-DHC systems which includes technical and economic factors. A knapsack optimization approach was used to identify the best spatial expansion scenarios. The core techno-economic model was validated using data from a demo case but has general applicability. It combines a spatial clustering method for H&C loads and a simplified method for estimating network length, coupling the effective width approach with a star-like backbone geometry. The techno-economic model can yield accurate estimates of the main energy metrics, even with simplified default inputs. With the adopted simplifications and for the considered case (100 initial hectare-size cells), the entire model can be run in a few tens of seconds on a standard laptop.

The results show that NT-DHC systems are better suited for densely populated urban areas, while individual air-source HP systems may be a more cost-effective solution for areas with low heat density. Despite having low building heat density compared to larger cities, feasible scenarios were still identified for the case study of Ospitaletto; in particular, out of the 19 resulting spatial clusters composing the considered 1 km² urban functional unit, only 3 clusters were excluded as non-feasible for NT-DHC. The expanded network could then cover more than 90% of the 35.7 GWh/y of load of the entire unit. It is also worth noting that, while the non-feasible clusters have a low heat density, they are not the lowest density ones. It is indeed a combination of heat density and distance from sources which determines the competitiveness of NT-DHC with respect to individual solutions.

The proposed model offers a detailed analysis of the conditions that make NT-DHC an attractive solution compared to individual H&C technologies. It helps to evaluate different business models and to determine the tipping points of viability. The methodology aims to minimize energy demand risk and provide more certainty in network expansion plans. It can be used for the early-stage planning and design of NT-DHC networks, contributing to a deeper understanding of its opportunities and constraints.

Further research could expand the approach to locations with higher heat density or varied climatic conditions (with more significant cooling requirements). Research could also compare NT-DHC to 4GDH, where heat pumps are located at sources rather than at user substations and the network temperature stays higher. Finally, studying the effects of introducing different types of storages at different locations would allow for analyses of system resilience with respect to source fluctuations and maximize low-grade heat recovery.

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