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Assessing district heating potential at large scale: Presentation and application of a spatially-detailed model to optimally match heat sources and demands.

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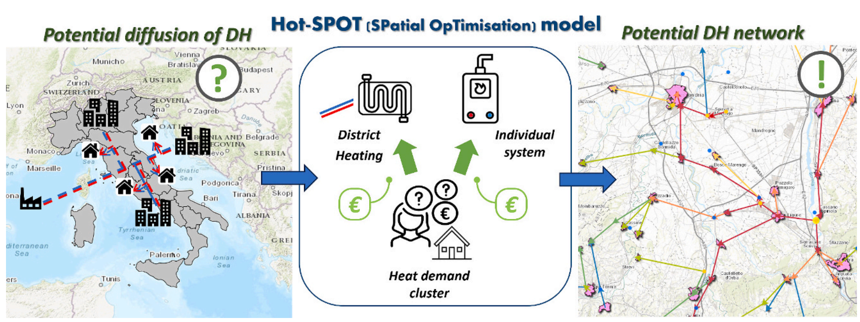
HIGHLIGHTS

- Novel methodology to assess techno-economic potential of district heating at large scale level.
- Spatially detailed model based on open-source data and tools - replicable and adaptable model.
- Optimization algorithm on delivered heat cost minimisation with no thresholds set a priori.
- 38 TWh of district heating potential in Italy, equivalent to a four-fold expansion to 12% of the civil sector heat demand.

GRAPHICAL ABSTRACT



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ABSTRACT

This paper presents a newly developed methodology aimed at assessing at national level the techno-economic potential of district heating (DH) based on renewables and excess heat sources. The novelty of the model lies in the use of an optimization approach to match heat demand and heat sources at large scale level, while keeping a high degree of spatial detail. Areas suitable for DH adoption are identified by minimizing heat delivery costs, and therefore by choosing the most economical technology between district heating and the alternative individual solution. The optimization approach, usually applicable at limited analytical scope because of the computational burden, is here adapted to large scale analysis through the introduction of novel methodological elements with which the network topology is simulated nationwide.

The methodology applies to preliminarily identified maps of available heat sources and eligible heat demand, with the quantification of the latter including retrofitting and low connection rate scenarios. It then consists in two steps: connecting elements in a graph through triangulation and routing algorithms and optimizing connections to minimize the overall heat delivery costs, either by adopting district heating or individual heating systems. The whole methodology is based on open-source data and tools for broad applicability. The paper presents the elaborated methodology together with the application of the entire model to Italy. The outcome is a map of the potential district heating systems identified with significant spatial detail nationwide. A four-fold

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expansion is envisaged, covering 12% of the national heat demand with renewables- and excess heat- based district heating.

1. Introduction

District heating (DH) enables to exploit heat generated by renewable energy sources (RES) [1] and to recover waste heat (WH) generated as a byproduct of several activities [2], such as industrial processes and wastewater treatment plants. The exploitation of already existing and otherwise wasted heat flows translates in a reduced use of primary energy sources, with an increased overall efficiency of the energy system at urban scale and a reduction of fossil fuel consumption and greenhouse gases emissions. Therefore DH can play a crucial role in the complete decarbonization process of a national energy system [3,4].

For this reason, EU has asked all member states, through the Energy Efficiency Directives [5,6], to assess the potential of Efficient DH based on RES and WH [7,8]. Similar analysis have been carried out at national level in UK [9] and in Switzerland [10] as well.

Despite an increasing effort from the EU to focus on the heating sector, national heating strategies are still weak and require concrete figures and measure to reach the decarbonization ambitious targets. DH is in fact still a niche technology in several EU countries mainly because of the high investment costs required for the construction of the network. In Italy, e.g., it only covers 3% of the heat demand [11].

It is in this framework that the authors of this paper have developed a methodology to assess the techno-economic potential of DH based on RES and WH at large-scale level. This modelling framework has been built and then applied on the Italian territory to estimate DH at national level [12]. The generation of a new model able to properly assess DH potential at large-scale level with an adequate spatial detail is not a trivial task. The developed model has to cope with several local constraints and alternatives: multiple sources and different end-use buildings need to be considered and their connection in space and time must be modelled according to their availability, location and costs. Spatial and systemic constraints have been therefore included in an optimization model specifically developed to identify the DH system configurations that leads to the least overall heat supply cost to the end user. The outcome of the study is twofold: the model itself, able to estimate the DH potential at large scale level with a high spatial detail and with limited computational effort required, and the results of its application to Italy, that can provide a reliable starting point for energy planners, local authorities, DH operators and policy makers.

1.1. Motivation of the work

This work joins the list of contributions and existing works related to the assessment of DH in cities or wider contexts described in detail in the following paragraph. While addressing this topic, a still open research question is found to which this paper wishes to answer with a newly developed methodology. The question consists in how to optimally match suitable demand and sources through DH so to find potential network development areas at large scale level. Due to the local nature of this technology, the mapping of suitable heat demand and of the available RES and WH sources is the preliminary step in most of the works that can be found in literature. Then, in the majority of the studies conducted at large scale level, national or regional e.g., DH potential areas are defined based on a comparison with threshold values of certain indicators, such as distribution costs [13] and fractions of waste or renewable heat on total demand [14,15]. These approaches, however, exclude a priori certain areas and do not reflect the real feasibility of DH, which is given by comparing individual heating solutions' cost to the heat delivery cost (see Fig. 1.1 in [16]). The latter includes the local distribution network costs, related to demand density, together with the heat production and transport network costs, based on the heat sources' characteristics and location.

Another category of works focuses on small areas, such as single networks or cities, and uses optimization approaches and detailed grid modelling to estimate the potential expansion of district heating in specific cases [17–19]. This is possible because of the reduced analytical scope that translates in a limited computational burden. The work presented in this paper wants to fill this gap: including simulation of network topology at large national scale level and applying an optimization algorithm to minimize the overall heat delivery cost.

Therefore, the two main added values of the model are that i) the model is not constrained a priori, thus providing realistic and location-dependent results, and that ii) heat demand areas and sources are connected in a virtual energy graph that simulate real networks topology so to calculate realistic investments cost. This graph is then solved through an optimization algorithm minimizing the overall energy system cost. Based on that, the optimizer can choose to supply heat to the users through a DH system or via individual technologies.

An additional strength of the model is that it is entirely based on open-source data and free software and can be adapted and applied in different contexts. One of the aims is to make energy planners and decision makers aware of what the possibilities related to this technology are and to provide them a starting point in the formulation of adequate strategies and policies for DH uptake in areas where the results suggest that DH is feasible from a technical and economic point of view, including the reduction of emissions.

1.2. State of the art

A wide range of alternative in assessing DH potential configurations reflects in a wide range of studies that can be found in literature addressing the potential analysis. Methodologies aimed at assessing DH potential may differentiate for the scale of the analysis, the approach used and the type of potential defined, but they always require a preliminary quantification and mapping of the heat sinks and the heat sources in the territory under study. These last represent the main components of a DH potential assessment problem, which therefore must present a spatial resolution as higher as possible.

Two referenced studies that paved the way in this field of research are: Heat Roadmap Europe 4 (HRE4) [20] and Hotmaps [21]. With a top-down approach and with a deep spatial planning, they addressed all the key steps in the DH potential assessment: analysis of the building stock and the heat demand, analysis of heat resources and their potential, mapping and definition of suitable DH regions. The main outcome

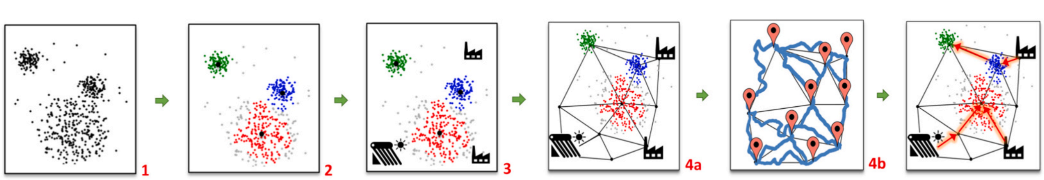

Fig. 1. Illustration of the five steps composing the methodology.

of both the projects have been an online available heat map for EU 28 Member States: *PETA 4.3* (Pan-European Thermal Atlas) [22] and *Hotmaps Toolbox* [23], respectively. They have been, and still are, sources of georeferenced data for the assessment of DH potential in each European Country. However, being the first studies of this kind and of this scale, the available resulting data have an informative value of generic character. They can give an overview of the potential of this heating technology, but further analysis would be needed a-posteriori in order to choose the most economic sources to be connected to the heat demand sinks through DH networks.

The matching of the heat demand and of the available heat sources represents the main gap in the existing research. The methodological approach to perform it, that can be spatial and/or temporal matching, is at the core of this paper.

1.2.1. Approaches for matching heat demand and heat sources

The concept of areas in which DH is assumed to be feasible has been introduced in the pre-study Heat Roadmap Europe 1 [10] where heat synergy regions have been defined. Based on spatial analysis and ocular observations by means of Geographic Information Systems (GIS), the identification of these areas was made by establishing a simple *"excess heat ratio"* describing the fraction between the existing excess heat and the low temperature heat demands in a given region. However, no distinction was made regarding the actual magnitude of them: hence, compresence of energy source and demand (which means excess heat ratio ≥ 1) could exist even if both numerator and denominator of the excess heat ratio are very low, as in sparsely populated areas. During the years this preliminary approach has been developed and in 2016, in HRE4, the main update was the introduction of the *"priority grouping"* [24]. The first priority group includes all the regions with high levels of both heat supplied and heat demanded, determining the most suitable regions for excess heat recovery projects such as district heating; the lowest priority group includes all the regions in which there is the possibility to exploit excess heat, however where both heat demand and excess heat availability are low. No priority regions are the ones without heat sources and/or heat demands.

Since then, many other studies have been performed and various approaches for the demand and supply allocation and matching have been used. In general, a trend toward higher spatial resolution can be seen. Always in the framework of Heat Roadmap Europe project, in 2019 Möller et al. [15] assessed the techno-economic potential of DH at local level, in all Europe, by putting the focus on heat supply sources' characteristics. Excess heat from industries and waste-to-energy plants is allocated to neighboring agglomerated DH areas based on capacity and distance constrains. A gravity allocation model was applied with the aim to give priority to high heat volumes at short distances, thus promoting the allocation of larger plant in the vicinity before considering smaller plants and/or larger distances. The latter case will also imply higher costs for heat transportation and therefore this method favors dense areas and lower total costs. Similarly, in Ref. [25] Bühler et al. assessed DH potential as a function of resource magnitude and distance, but considering also the temperature level and the extraction rates that in Ref. [15] are not considered. The application is however restricted to Denmark. For each identified and mapped industrial excess heat source, the available heat is delivered to the nearest DH area. If the industry is located outside a DH area, a cut-off distance is identified based on the costs and the capacity that will be required for the transmission pipes. In Ref. [26,27] only the distance between sources and heat sinks has been considered, instead.

Being this type of analysis dependent on the mapping of heat sources and sinks, it is strictly related to the availability and quality of data. Studies at large scale level generally present some limitations such as the lack of detailed data or the use of empirical equations, with a general meaning, to assess the costs or the amount of recoverable heat from a source. For example, a parameter called effective width has been introduced in this type of analysis since 2010 [28] for the estimation of distribution costs in areas where networks are not yet existing. The cost of potential networks is defined based on urbanistic and demographic parameters assessing the population density in an area. Since then the effective width has been at the base of such studies, as in [8,29], and has been recently adapted to other contexts and reformulated, as in [30] where Dénarié et al. made it dependent on the concentration of building over a certain area. Further investigations have been then carried out by Sánchez-García et al. in [31]. Otherwise, in small-scale analysis specific data may be available, enabling a better quantification of the local features. In these cases, specific mathematical relations between sources and heat demands can be used or even qualitative assessment can be done by directly looking at the map. This is the case of the study in Ref. [32], where six interesting areas are defined based only on the location, the density and the load magnitude of the available heat sources and heat demands.

The gap in this field of research is the capability to address large-scale areas by maintaining a spatial resolution and a detail in the analysis that is very high and able to represent any smaller case. Moreover, an increase in resolution generally causes a higher computational effort, that may entail longer resolution time of the problem or again the inability to consider broader areas. Researchers therefore are more and more including in their studies algorithms to reduce the spatial complexity of the problem. For example in Ref. [33] Chambers et al. applied a clustering algorithm in order to identify polygons in which there is a relevant heat demand density. Within a radius of 5 km around each polygon, the available industrial sources are identified and those that have an acceptable value of linear connection demand density are retained. The source-demand pairs are then converted in a graph and the available heat is allocated according to a breadth-first approach. However, even though a mapping-based method is used, the resulting DH potential can be overestimated since economic considerations are not taken into account. The authors of this present work managed to evaluate the economical aspect when applying a similar mapping-base methodology over the whole Italian territory. Spirito et al. already presented in 2021 two papers ([34,35]) illustrating the developed method and the obtained promising results. There the method was firstly described in all its main steps, with a particular focus on the heat demand estimation at census level,[1] on the applied density-based clustering algorithm, on the estimation of the distribution costs and on the mapping and the quantification of recoverable excess heat from the available sources. DH potential was finally estimated by performing a cost comparison with the individual heating technologies currently installed, but in [34] a preliminary, simplified approach was used for the estimation of the transportation cost related to DH, thus the cost for each pair of heat demand-source. This aspect was improved in the last years and now stands at the core of this current paper together with the optimization phase. Similarly to what is done in [33], a virtual energy graph has been created by connecting through a triangulation algorithm all the mapped heat sources and the heat demand clusters. A routing algorithm was then applied so that real distances, traced along the streets, could have been considered and more realistic transmission costs estimated.

With the aim to sum up and compare the main aspects of the afore mentioned studies, Table 1 is presented. The methodology described in this paper, whose characteristics are listed in the last row of the table, is the only one among the large-scale analysis in which local conditions are considered, based on GIS framework, together with both technical and economic aspects. There are no assumed threshold values, as generally occurs in small-scale analysis, and an optimization is performed. In a way it includes aspects common to large-scale and small-scale analysis.

[1] Census areas are geographic regions defined for the purpose of taking population and housing censuses and they generally represent the smallest territorial entity for which these types of data are available in most countries.

Table 1
Review of the aforementioned methodologies for heat recovery and DH potential estimation (continued).

METHODOLOGIES	[7] Fallahnejad et al. (2022)	[13] Fallahnejad et al. (2024)	[14] Persson et al. (2014)	[15] Möller et al. (2019)	[17] Girardin et al. (2010)	[18] Finney et al. (2012)	[19] Résimont et al. (2021)	[25] Bühler et al. (2017)	[26] Hammond et al. (2014)	[27] Manz et al. (2021)	[33] Chambers et al. (2020)	Methodology of this paper
SCALE OF THE ANALYSIS	Large (National: Austria)	Large (EU-27)	Large (EU-27)	Large (14 EU Member States)	Local (City scale: Geneva)	Local (City scale: Sheffield)	Local (City scale: Herstal)	Large (National: Denmark)	Large (National: UK)	Large (EU-27 + UK)	Large (National: Switzerland)	Large (National: Italy)
SPATIAL RESOLUTION	Hectare level for heat demand; LAU2 level for heat sources and grid infrastructure.	Hectare level for heat demand and DH areas.	NUTS3 regions for heat demand; Site data for fuel combustion activities.	Hectare level for heat demand; Site data for heat sources.	Heterogenous zones (comparable to census areas) for heat demand; Site data for heat sources.	Heterogenous zones for heat demand; Site data for heat sources.	Building data for heat demand; Site data for heat sources.	5x5km Danish Square Grid	Site data for heat sources.	Hectare grid cell for heat demand; Site data for heat sources.	Hectare resolution.	Census areas for heat demand; Site data for heat sources.
TEMPORAL RESOLUTION	Hourly resolution	Yearly resolution	Yearly resolution	Yearly resolution	Yearly resolution	Yearly resolution	Hourly resolution over a year + selection of 3 representative days per month.	Yearly resolution	Yearly resolution	Yearly resolution	Monthly time scale	Yearly resolution
MODELLING APPROACH	Linear dispatch model. The objective function minimizes the total costs for heat generation minus the revenues made from electricity generation.	DH potential is defined in terms of heat demand density and required infrastructures.	Quantitative assessment and qualitative evaluation.	Gravity allocation model. Optimization problem minimizing the total costs of all heat volumes transported.	Pinch analysis and MILP aggregation procedure applied in GIS framework to find the optimal DH pathway through the areas that minimize the network specific cost [CHF/kWh].	Qualitative evaluation.	Multi-period MILP optimization model.	Spatial analyses in GIS to link excess heat sources with district heating networks.	Georeferenced, qualitative evaluation.	Process-specific approach to estimate bottom-up excess heat from energy-intensive industries with a spatial matching to DH areas.	Technical potential for supplying industrial recovered heat to DH is assessed as energy balance over the months, based on spatial constraints.	LP optimization problem minimizing the total heat delivery cost at system level.
ASSUMED THRESHOLD VALUES	Lower bound for the heat demand in district heating areas; Upper bound for the average heat distribution costs.	Minimum annual DH demand value; Heat distribution cost ceiling as criteria for identifying DH areas.	Lower bound on the share of waste and RES heat on total heat demand.	Lower bound for heat demand density; Upper bound on distance for the allocation of baseload demand to excess heat); Maximum annualized transmission costs.	–	–	–	Resource magnitude and distance + temperature level and extraction rates.	Upper bound on heat transportation distance.	Lower bound on the current heating demand density; Fixed value of the search radius.	Clustering based on threshold for the linear demand density of the heat source/demand connection; Fixed value of the search radius.	–
HEAT SOURCES AND HEAT DEMAND MATCHING: APPROACH	Overlay DH potential map with heat sources and	–	Regional heat balances (volume of recovered	Excess heat allocated by capacity and distance constraints.	MILP aggregation method to define the best neighboring	Interesting areas defined based on location, density and load magnitude of	Optimization based on a graph following the streets of	Excess heat sources are located in a DH area or a cut-off distance is	Heat demand filled through surplus heat is estimated based on a feasible	Spatial matching based on Euclidean distance	Local connections between sources and demands are determined by a	**Optimization based on a graph connecting heat demand**

(*continued on next page*)

Table 1 (*continued*)

METHODOLOGIES	[7] Fallahnejad et al. (2022)	[13] Fallahnejad et al. (2024)	[14] Persson et al. (2014)	[15] Möller et al. (2019)	[17] Girardin et al. (2010)	[18] Finney et al. (2012)	[19] Résimont et al. (2021)	[25] Bühler et al. (2017)	[26] Hammond et al. (2014)	[27] Manz et al. (2021)	[33] Chambers et al. (2020)	Methodology of this paper
	infrastructure maps.		excess heat over heat demand).		zones to be covered by a DH system that has access to a given heat source.	the available heat sources and heat demands.	the analyzed area.	defined based on the costs and the capacity of the transmission pipes.	transportation distance and efficiency.	between industrial site and respective DH area. Performed through ArcGIS proximity tool.	graph-theory based clustering.	**clusters' centroids and heat sources. Graph built on a GIS framework.**
NEGLECTED ASPECTS	No point data (building, heating systems, heat sources distribution is missing).	No optimization. Heat generation sources and costs not considered.	No economic and environmental considerations.	Local conditions neglected, primarily temperature levels and extraction rates.	No economic and environmental considerations.	No economic and environmental considerations.	No environmental considerations.	No economic and environmental considerations.	No georeferenced heat demand. Heat recovering potential is intended to be indicative.	Economic potential is not evaluated. Excess heat availability is considered constant all over the year: no temporal matching between excess heat availability and demand.	No simulation or optimization. No economic and environmental considerations.	No environmental considerations.

1.2.2. Modelling and optimization framework

Regarding the optimization phase, the open energy modelling framework *oemof* [36], originally conceived for energy system modelling, has been chosen, adapted and applied. Oemof is a flexible and open source optimization framework that allows a good degree of resolution in time (hourly), in space (any spatial scale), in sector coupling, in techno-economic detail, in transparency and with the ability to take into consideration multiple assessment criteria [37,38]. Moreover, since it is designed as a modular python library consisting of a set of sub-libraries constantly developed, it allows a very flexible modelling approach. Even though oemof can deal with the high temporal resolution, the present study was performed on annual basis. This was done in order to limit the computational effort since at present is very difficult to deal with thousands of time-varying elements with a standard computing machine. In general, when working at small scale level the lower complexity of the problem allows the use of site-specific data and a higher resolution and contemporary integration of the spatial and temporal aspect. When dealing with large-scale analysis, a higher spatial resolution can hinder the temporal resolution or viceversa. Some aggregation algorithms may be useful to simplify the problem complexity.

Together with its flexibility, oemof was chosen by the authors of this paper also because of its open-source nature. Indeed, as derived from the review conducted in Ref. [37], over 17 tools only 4 are open-source and deal with district heating studies. They are Balmorel [39], CEA [40,41], HUES [42] and oemof [36]. Balmorel can be used for energy system cost-constrained optimization at large-scale level with an hourly time resolution and for a time horizon of N years; CEA can still perform simulation analysis with an hourly time resolution, on a city/district, but with a time horizon of one year. HUES and oemof are two optimization tools with a N year time horizon and hourly resolution, but while the first one has a building/district scale the latter is applicable to any spatial scale. Even though requiring programming skills on python, oemof appears to be the most flexible open-source tool in terms of considered energy services, spatial scale and temporal resolution.

Oemof also enables to incorporate financial criteria and that is another reason why it was chosen for this study. According to the review conducted in [43] of 154 tools generally utilized for the modelling and optimization of multi-energy systems in districts, only 4 are suitable to incorporate also financial criteria: EnergyPLAN [44], eTransport [45], oemof, urbs [46]. Only the last two are available with an open-source license. Urbs may be interesting since it is more user-friendly. Its implementation is indeed based on spread-sheet files and does not require the use of a programming language. However, even though oemof may require a longer learning phase, it is considered more accurate and versatile thanks to its flexible modelling approach.

1.3. Structure of the paper

An overview of the entire methodology is presented in Chapter 2 with a major focus on the construction of the virtual energy graph, treated in paragraph 2.2 which is solved by the optimization model described in paragraph 2.3. In Chapter 3 the application of the methodology to Italy is presented and results are illustrated in Chapter 4 in terms of identified optimal energy flows and assessed DH potential. A critical analysis of results is discussed in Chapter 5, while conclusions are drawn in Chapter 6.

2. Methodology

This chapter presents the five-step methodological approach developed to estimate the potential diffusion of renewable-based DH at large scale. The goal is the identification of all the areas in which the heat delivered by DH is more economical sustainable than the one delivered by individual heating system (e.g. domestic boilers or heat pumps). The mathematical description of this research question is the optimisation problem that minimizes the total cost of the heat delivery. A linear programming model has been created based on the open-source modelling framework oemof [36].

After a general overview, particular attention is paid to two of the five main steps that compose the method, namely:

- the construction of a virtual energy graph through the application of triangulation and routing algorithms connecting demand points to available heat sources;
- the creation and application of the linear optimization model to solve the virtual energy graph by the identification of the heat flows minimizing the overall heat delivery costs.

The spatial representation of the potential DH network, made up by nodes and connecting edges, is a necessary step of the methodology since the modelling framework oemof does not include a network simulation model.

2.1. The overall procedure in brief

Five main steps make up the overall procedure. They are illustrated in Fig. 1 and then described.

1) **Heat demand mapping** - The methodology starts with the estimation of the heat demand from residential and service sector buildings, in a current and refurbished scenario in *step 1*. This is done at the maximum level of spatial detail available, i.e. on a census level, where census areas are geographic regions defined to take population and housing censuses. They generally represent the smallest territorial entity for statistics in most countries, corresponding to neighbourhoods. The application of this step to the case study can be found in 3.1.1.
2) **Heat demand clustering** - The demand in each census cell is then grouped in *step 2* by applying a density-based clustering algorithm. In this phase the areas with a high value of heat demand and/or that are close to each other are grouped and identified as the most suitable for DH connection. This step allows identifying most dense areas (not in absolute terms but relative to local characteristics) and to reduce the computational effort of the optimisation by reducing the number of demand nodes in larger aggregates. The application of this step to the case study can be found in 3.1.2.
3) **Heat sources mapping** - In *step 3*, the existing renewable and excess heat sources are mapped and the amount of recoverable heat coming from them is estimated. The application of this step to the case study is treated in 3.2.
4) **Virtual energy graph -** *Step 4* and *step 5* are the core of this paper. In *step 4a* a triangulation algorithm is used to generate a virtual energy graph whose nodes are the centroids of the identified heat demand clusters and the heat sources. The potential connections may link sources with clusters of demand, but also clusters with other clusters and sources with other sources. This is done so that the heat from a source that exceeds the demand of a cluster can potentially be conveyed to adjacent clusters and so that multiple sources can be potentially used together to meet the heat demand of one single cluster. *Step 4b* consists in the application of a routing algorithm to turn the linear connections, as just defined, into more realistic paths along the streets. *Step 4* is described in par. 2.2.
5) **DH potential assessment through optimization -** At the end, in *step 5* the optimization algorithm indicates what are the optimal heat demand clusters and heat sources to be connected and how. By considering the costs associated to each source and to each pipe, the best configuration is identified with the aim of minimizing the overall heat delivery costs, thus the sum of heat generation, heat transportation and distribution, with the latter two strictly dependent on the network length. By comparing a portfolio of different alternatives in terms of DH with different potentials heat sources and individual solutions, for each demand cluster the algorithm defines if

the same amount of supplied heat can be met by any alternative individual heating solution currently present in the buildings (e.g. natural gas boilers, air or water heat pumps) in a more cost-effective way than district heating. This step is described in par. 2.3.

The result of the methodology is the definition of a techno-economic potential of district heating with a high spatial resolution at large-scale level. Indeed, for the Italian case study a map with the optimally designed network is generated. The logical sequence of the methodological approach is more detailed in the scheme of Fig. 2, where the combinations between all the elements are made clearer.

From a logical point of view, the five methodological steps can be grouped in three main phases: i) the mapping of the current heating technologies, of the heat demands and of the heat sources; ii) the creation of the virtual energy graph; iii) the optimization phase. It can be seen that the mapping stage and the creation of the graph are preliminary phases, prior to the optimization process, needed to assess the costs of the network's elements to be compared with the individual heating solutions. The nodes of the graph that the optimization step aims to solve are constituted by the heat demand clusters and heat sources with spatial coordinates with which the length, the heat losses and the costs of the connections between the nodes of the graph can be determined.

The architecture of the model is made even more clear in Fig. 3, where it is possible to distinguish between the inputs, the steps required to process them before the optimization phase, and the post-processing phase eventually.

2.2. Construction of the virtual energy graph

The input for the optimisation algorithm is given by the virtual graph connecting all the identified sources and the heat demand points. These elements represent the nodes, while the edges connecting them are defined with a triangulation algorithm. Among the existing methods, the Delaunay [47] triangulation was chosen. It creates homogeneous triangles mesh, meaning that triangles with very long/thin shapes are avoided. The output of this technique is given by multiple pairs of nodes (demand-demand, demand-source, source-source) that will be used as input for the optimization problem. In particular, the distance between each pair of nodes is used to assess the cost required for transporting the heat along these paths after the following routing step. In fact, since the triangulation defines linear edges, an intermediate step is required so that the linear distances are translated in more realistic lengths by following the streets. Indeed, by considering the linear lengths, the associated costs would be underestimated and the natural and artificial barriers (such as rivers and railway) would not be considered. A routing algorithm based on the package OSMnx (Open Street Map Networkx) [48] was applied in Python. The drivable street networks in each Italian region have been downloaded from the OSM database and then the *nearest_nodes* function of the OSMnx's distance module identifies for each node of the triangulation its closest point on these streets. The length of the route connecting each pair of points is then calculated through the *get_route_edge_attributes* function of the *utils_graph* module. Basically the list of pairs of coordinates is converted into a geopandas.GeoDataFrame, that is a common pandas.DataFrame at which a column with geometry is added. A coordinate reference system can be selected and in this way the length of the identified paths, i.e. the distance between two points, is an attribute already included into the python object. A link between the coding framework and the georeferenced system on QGIS is therefore created.

Based on this graph of the drivable streets with the distances, the *shortest paths* function of the OSMnx package has been then applied. It uses Dijkstra's algorithm [49] and returns the list of the nodes constituting the shortest path between them. The length of the resulting path is also assessed. On average the ratio between the route and the linear distances is 1.7.

As an example, in Fig. 4 a focus on the city of Milan is illustrated. It is possible to see how the linear edges of Fig. 4(a) are converted in corresponding paths along the drivable streets in Fig. 4(b).

2.3. Construction of the optimization model

The chapter here deals with the last step of the overall procedure: the definition of the heat flows that minimize the overall cost of the system. Such step is performed by means of a linear programming model expressly built for this purpose through the existing open-source modelling framework called *oemof* [36]. The model has been called *hot-SPOT*, where *SPOT* stands for SPatial OpTimisation and *hot* identifies the thermal sector, i.e. district heating. Both the oemof framework and the *hot-SPOT* model are described in the following to explain the logical structure that combines all the outcomes of the previous georeferenced steps and translates them into the results.

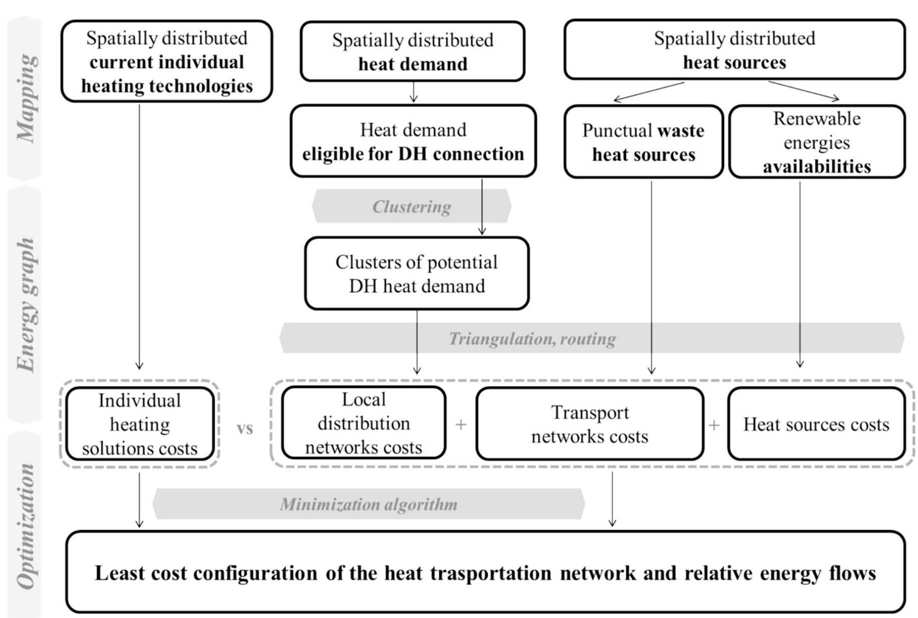

Fig. 2. Generation of the energy graph.

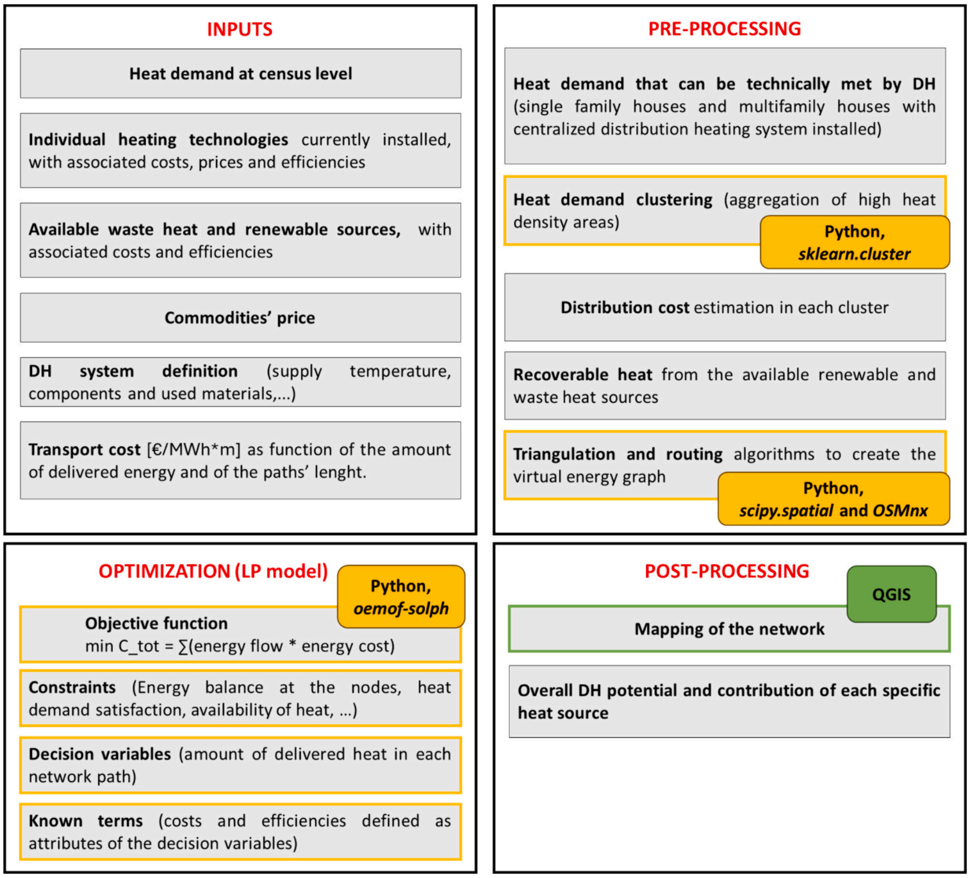

Fig. 3. Architecture of the model.

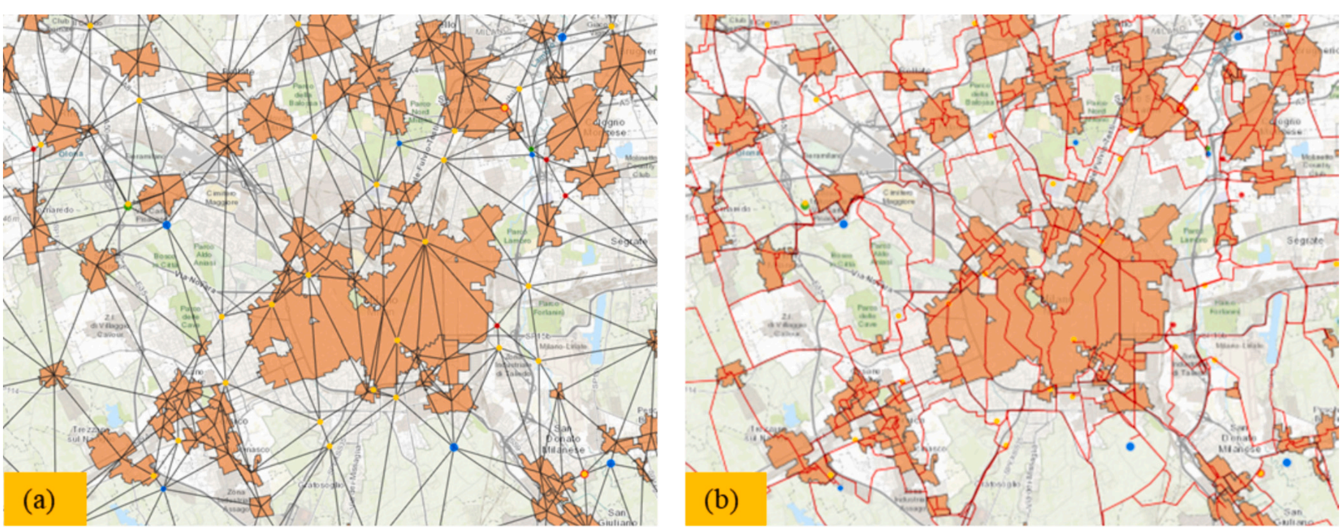

Fig. 4. Linear edges generated by the triangulation algorithm (a) and corresponding paths along the streets generated by the routing algorithm (b). Focus on the Municipality of Milan.

2.3.1. The oemof modelling framework

Oemof (open energy modelling framework) is an open-source modelling framework that includes several libraries focused on specific tasks for energy system modelling. The most recognized library, oemof-solph [50,51], is used to model energy systems with linear programming (LP) or mixed-integer linear programming (MILP) techniques. In this specific case, the authors used the model generator oemof-solph with a LP approach and with the open-source solver CBC (Coin-or branch and cut).

A simplified description of the oemof-solph components is provided here, while in-depth information can be found in the paper by Hilpert et al. [52] and in the website [36]. In order to model an energy system, oemof-solph makes use of five main elements,[2] as reported in Fig. 5:

[2] The list reports the nomenclature used by the authors of oemof.

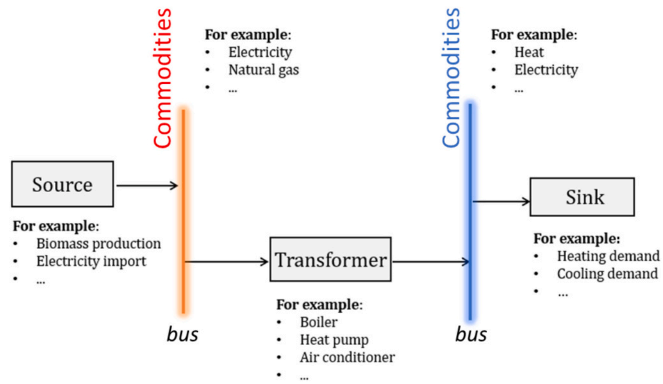

Fig. 5. Schematic representation of the five main elements of the oemof framework and their relation within a modelled energy system.

- *Transformers*, i.e. nodes that represent technologies or processes, with specific efficiencies and costs, transforming a commodity into another commodity with different properties (e.g. biomass boilers convert biomass into heat).
- *Sources*, i.e. particular transformers with no modelled input, from which a commodity can be obtained (e.g. solar irradiation).
- *Sinks*, i.e. particular transformers with no output commodities, usually representing demands (e.g. heating demand) or the disposal of excess commodities (e.g. wasting heat).
- *Buses*, i.e. nodes that represent the collection of a specific commodity (e.g. heat) that can be input and/or output of different transformers.
- *Flows*, i.e. flows of commodities that connect buses with transformers, sources, and sinks, representing the actual (as it results from the model) output or input of a technology. All the flows of a certain commodity pass through a bus.

All these elements can be described with the chosen spatial and temporal resolution and can be combined throughout different configurations to represent any specific energy system. In the specific case here presented the temporal resolution is of one year. Each element making up the virtual energy graph is identified by a pair of coordinates and is modelled as one of the oemof-solph components. Therefore, the heat demand points are modelled as *sinks*, the heat sources are modelled as *sources*, and some technologies such as heat pumps are modelled as *transformers*. All of them, identified by a pair of coordinates each, are connected one another through the *buses*. As an example, Fig. 6 specifies how each source and sink point is represented by a pair of coordinates (Long and Lat) and how these coordinates become an attribute of the name of every other component connected to them. Therefore in the image, overlayed over a portion of the resulting map, it is possible to look at a point A representing a low-temperature industrial source, which is for example named as "11.788_44.444_source_LT". This is connected to a sink point B named as "11.829_44.446_demand" through the transport network and the distribution network that are modelled as two transformers. The first one is named "11.788_44.444__11.829_44.446" while the latter is identified as "11.829_44.446_dist". Moreover, in the area of the cluster there can be the possibility to use a local source such as solar, identified as "11.829_44.446_solar", and an individual solution identified as "11.829_44.446_s".

The optimization occurs on the entire national system and the model's structure is such that it is eventually possible to recall which points are connected one to the other and how, i.e. through which connecting path among all.

Regarding the mathematical formulation of the linear programming model, in Fig. 7 is possible to distinguish between the listed elements:

- *The objective function*, representing the mathematical relation that is to be minimized or maximized. In this specific case the aim is to minimize the total cost of the system that is a composition of capital and operational costs, CAPEX and OPEX. They are evaluated over the timeframe of one year and they are related to the amount of thermal energy flowing in/out every node of the system.
- *The decision variables*, representing the output of the problem resolution. They are the energy flows in input and output of each node making up the system. Potentially, also the investments in additional technologies and processes can be part of the decision variables.
- *The known terms*, that are decision variables' attributes defined in input. They represent the levelized cost of energy (LCOE) in [€/MWh] according to which the energy system is then optimized. They are indeed defined for all the components of the system, so that

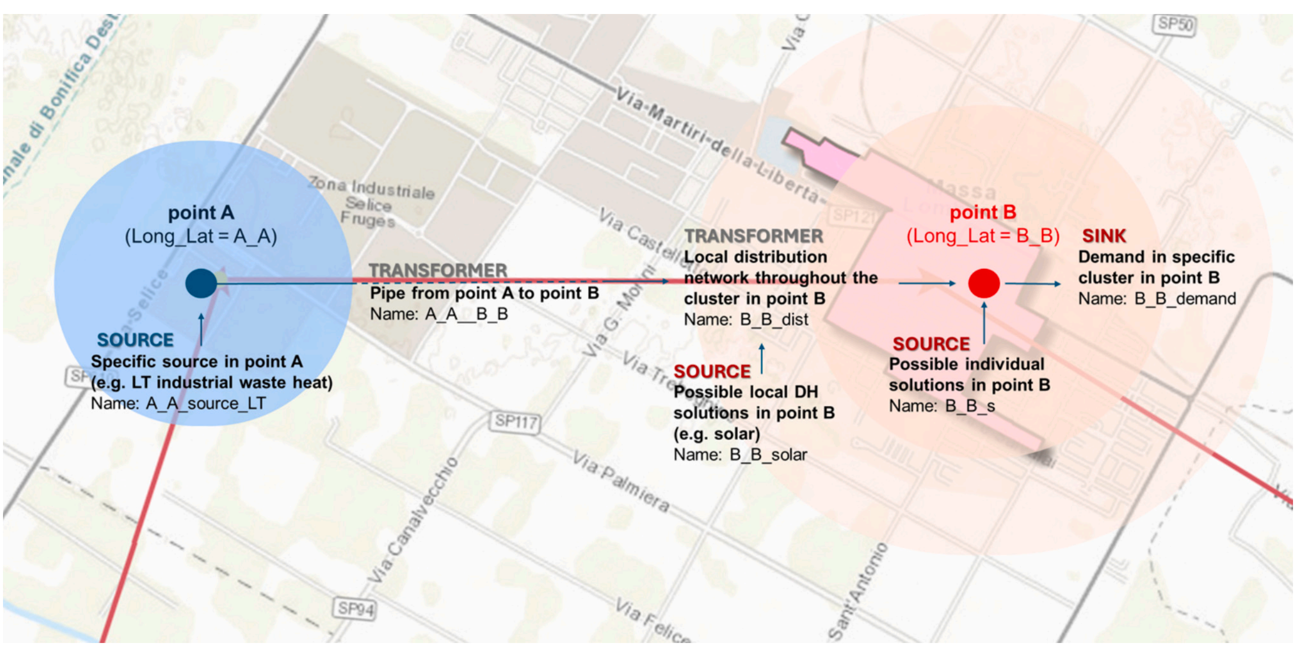

Fig. 6. Image clarifying how the components of the system (heat sources, heat demand clusters etc.) are interconnected both spatially, on the map, and mathematically, in the model.

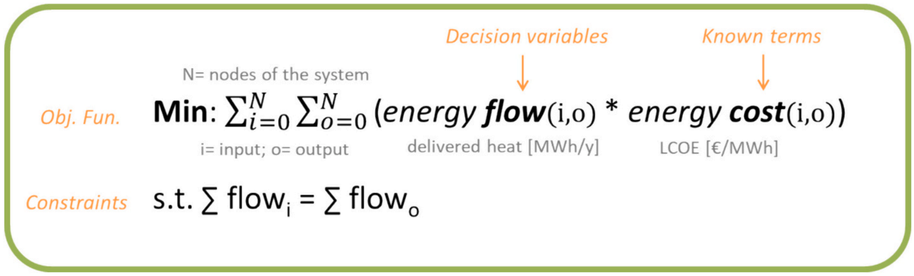

Fig. 7. Mathematical formulation of the linear programming model.

the total cost of the system can be minimized by selecting the energy flows the most convenient. Efficiencies are attributes of the decision variables too.

- *Several constraints* which guarantee that the demands are satisfied, i. e. at any node of the network the energy balance must occur, and that the availability of sources are respected. Other non-physical constraints can be introduced in the model to represent limits on the emissions or on the energy consumption, policy targets, etc.

Once the model's structure is set, the optimisation algorithm defines the set of heat suppliers to match the aggregated heat demand at minimum overall cost for the system, on annual basis. The decisions that are taken by the solver therefore comprise i) whether a supply unit is connected to the district heating network; ii) how much energy a unit is supplying; iii) how much energy is flowing on each branch of the distribution network. It chooses the technological solutions that minimize the cost of heat delivery at system level, choosing from a range of alternatives of various individual technologies, including retrofitting, and district heating fuelled by the available heat sources.

The final optimal system is not the result of thousands single optimizations but is the outcome of a single run of optimization that minimizes the sum of the costs related to each node of the system, as in the objective function.

2.3.2. *The hot-SPOT model*

The logic on which the oemof modelling framework is based, presented in the previous section 2.3.1, is used in this work to build the specific problem of DH potential estimation at large-scale level. In particular, to represent the national energy system to be optimized, the five main elements of oemof-solph are used in the configuration shown in Fig. 8.

The general scheme in the figure is made up of four blocks: (i) the blue block scheme is replicated for each cluster of demand; (ii) the green block scheme is replicated for each source of waste heat; (iii) the yellow block scheme is replicated for each local area in which the availability of biomass is known and (iv) the orange block scheme is replicated for each connection defined by the triangulation process. In total, the model comprises about 73,000 transformers, 87,000 sources, 6500 sinks and 18,000 buses. It implies 266,000 decision variables and it requires 60–90 min to be solved on a computer with average performance.

Looking at Fig. 8 more in detail – and going from the right to the left – we can see that:

- A *heating demand* is defined for each cluster of demand. Such demand represents the overall demand of the cluster, no matter how it is met.

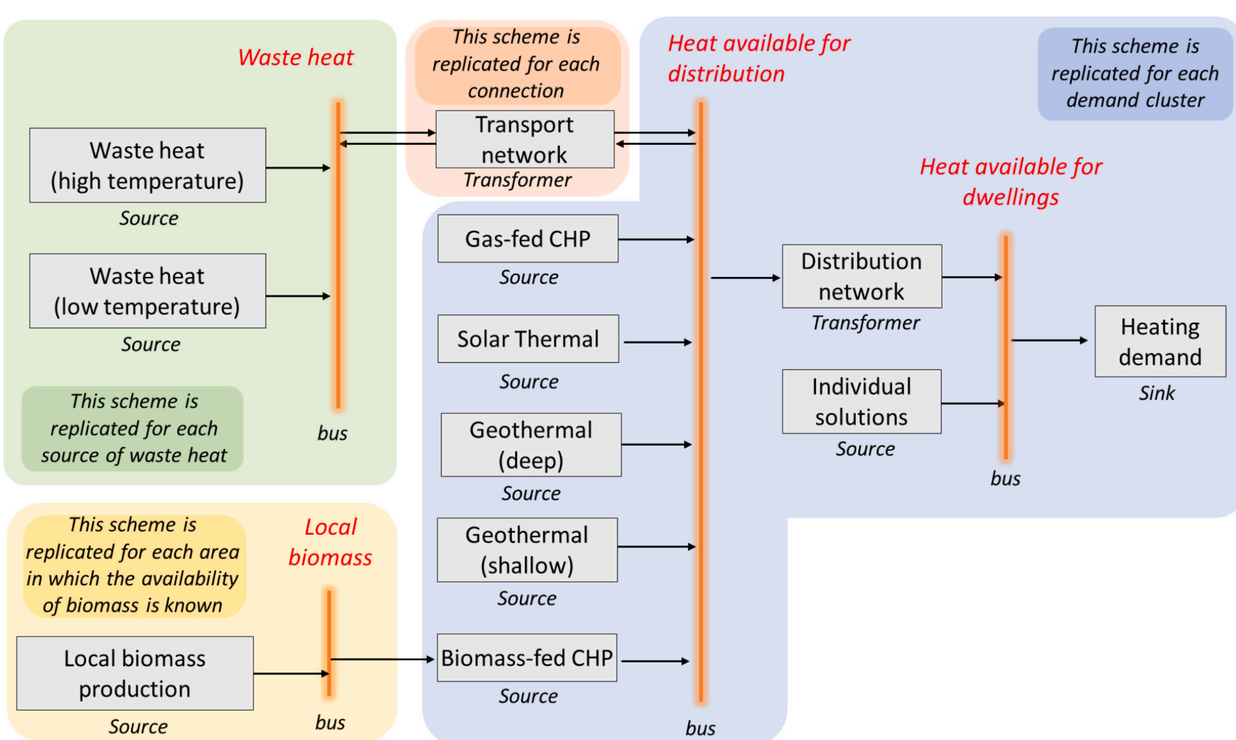

Fig. 8. General scheme (also known as Reference Energy System) of the hot-SPOT model.

- The *heat available for the dwellings* can be provided in two different ways: (i) by means of a DH *distribution network*, or (ii) by means of *individual solutions*, including efficiencies and losses for both.
- If the DH solution is chosen by the solver, then a list of multiple sources and transformers can be used to provide the *heat available for distribution*: (i) a *transport network*, with its losses, (ii) *gas-fed CHP* plants, (iii) *solar-thermal* plants, (iv) deep and shallow *geothermal* energy and (v) biomass-fed CHP plants. They are not mutually exclusive and can rather be used in synergy if convenient.
- If some *heat available for the distribution* comes from a *transport network*, it means that a new transport network is built and that some waste heat is recovered from an available *waste heat source*, at high or low temperature, accordingly to its availability.
- In case some *heat available for the distribution* comes from the *biomass-fed CHP*, then some local biomass is used and thus must be produced. The overall biomass produced and used in that local area cannot exceed the local availability.

3. Application to the Italian case study

The elaborated methodology is applied to the case of the Italian territory to estimate the potential of RES- and WH-based district heating at national level. The steps described in the previous paragraphs are here contextualized to the specific analyzed case.

3.1. Heat demand estimation and clustering

3.1.1. Heat demand

In this step the national heat demand from the civil sector is estimated with the maximum spatial detail allowed by the national input database: the census areas. In more than400,000 census areas making up the Italian territory, the analysis returns an overall heating demand of 329 TWh for 2030 starting from existing heat demand in 2018 and estimating refurbishment scenarios.

The Italian heating needs from residential and service sector are estimated with a statistical method based on a bottom-up approach developed by Pozzi et al. in the framework of the project in Ref. [12]. Data for the residential sector are derived from the national census database provided by ISTAT [53] and from the Energy Performance Certification (EPC) database available on CENED website [54]. For the service sector they are derived from the Hotmaps Toolbox [23] and the GSE report [55], where the incidence of each sub-sector on the total tertiary demand can be found.

The fraction of residential heat demand suitable for the connection of DH in each census area has been assessed considering all single-family buildings and the fraction of multi-family already equipped with a centralized heating system. In the latter case it is assumed that they can be connected to DH networks without modification of the installed heat distribution plant inside the buildings and internal retrofit. Regarding the tertiary sector, the allocation of heat demands derived from the Hotmaps Toolbox is proportioned to their intended use and to the number of employees derived from ISTAT database [53]. Further details can be found in [12,56]. At the end of this steps the result is the potential heat demand connectable to DH. It is equivalent to 114 TWh, with a variable share across the Country as can be seen in Fig. 9.

3.1.2. Clustering

In order to reduce the problem complexity and the required computational effort due to the high number of energy demand points, i.e. the number of census areas, a spatial aggregation is performed through the application of a clustering algorithm. The algorithm DBSCAN (Density-based spatial clustering of applications with noise) is chosen and its application has been already described by the authors in the previous paper of Ref [34]. Among the parameters required by the DBSCAN algorithm, one of the most impacting is the radius of the clustering. A parametric analysis has been performed [34] to identify a radius for each municipality.

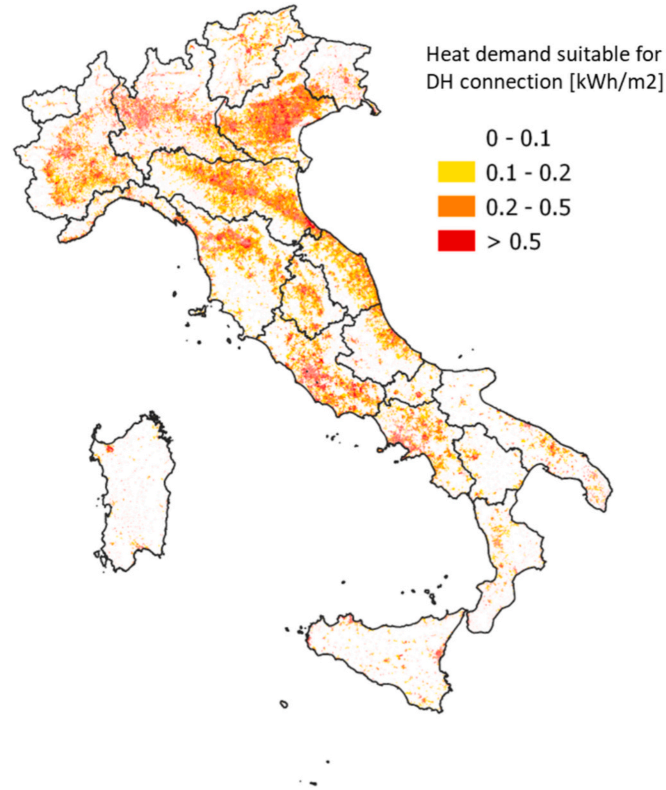

Fig. 9. Spatial distribution of the heat demand technically connectable to DH (114TWh in total).

The objective of the clustering step is twofold: to reduce the number of variables and to only keep the highest heat density areas. The demand that is clustered and that is thus considered in the assessment of potential diffusion of DH amounts to 48 TWh. 6432 clusters are obtained and, as explained in Chapter 2.3, they constitute the demand nodes of the energy graph, modelled as *sinks*. In Fig. 10 an extract of the Italian map is reported. The layer of Fig. 10(a) illustrates the DH-suitable heat demand at census level. It is overlapped by the obtained clusters represented in green in Fig. 10(b). As expected, where the heat demand is higher and more concentrated, larger and/or more numerous clusters are obtained.

3.2. Waste heat sources and renewables

The considered waste heat sources are industrial processes and thermoelectric plants for a total of 982 facilities, 39 waste-to-energy (WTE) plants and 3891 wastewater treatment plants (WWTP). They are point sources, whose location and mutual distance is known. Their mapped values constitute the nodes of the energy graph together with the heat demand clusters. The methodology for the identification of the available excess heat sources in Italy and for the quantification of the recoverable excess heat has been already treated in [35] by the authors. In short, the released excess heat from each source is computed as a fraction of its primary energy consumption. This latter value was derived from the Emission Trading Scheme (ETS) registry by ISPRA [57] for what concerns the industries and the thermoelectric plants, from the Italian waste cadaster [58] for the WTE plants and from the Hotmaps Toolbox [23] for what concerns the WWTPs. The amount of recoverable heat, on annual basis, is then estimated distinguishing between high temperature and low temperature processes. If the temperature is sufficiently high (>50 °C) a direct exchange can occur through a heat exchanger, while if the temperature is lower a heat pump is required to

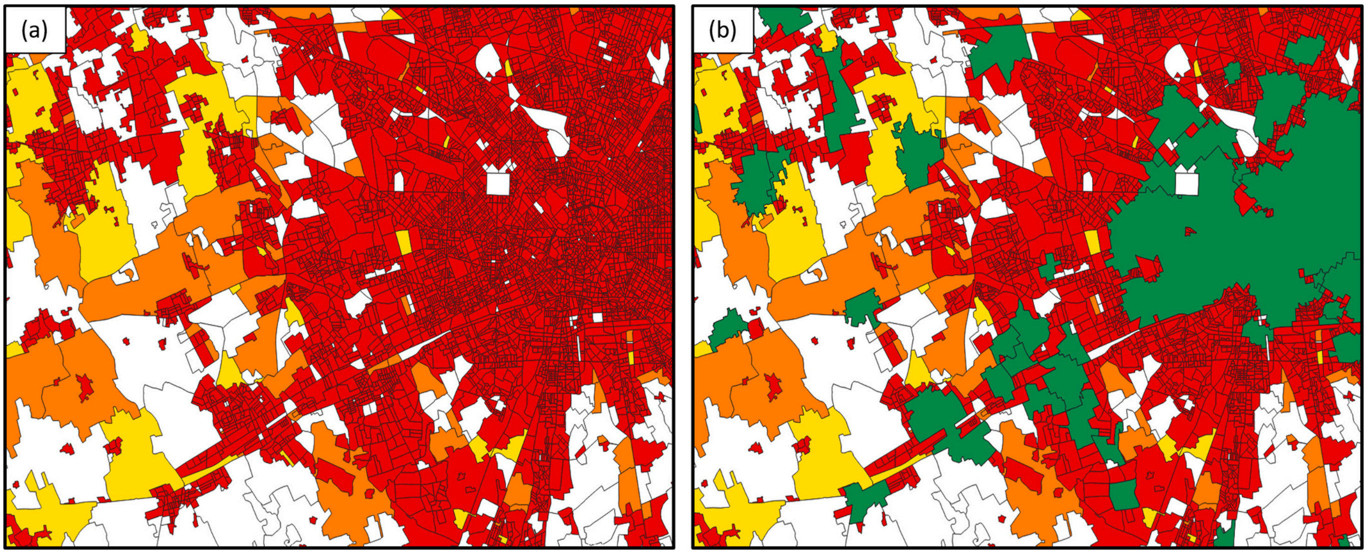

Fig. 10. Image (a)- Census areas colored according to the amount of heat demand technically connectable to DH, as in Fig. 9. Image (b)- Heat demand clusters marked in green. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

increase the temperature of the heat flow so that it can be used in a DH network. This means that different heat transfer efficiencies and costs are considered in the two cases. Contemporaneity factors between waste heat availability and heat demand has been as well considered using equivalent hours. Indeed, while waste heat can be assumed to have a homogeneous profile during the year, the heat demand is strongly

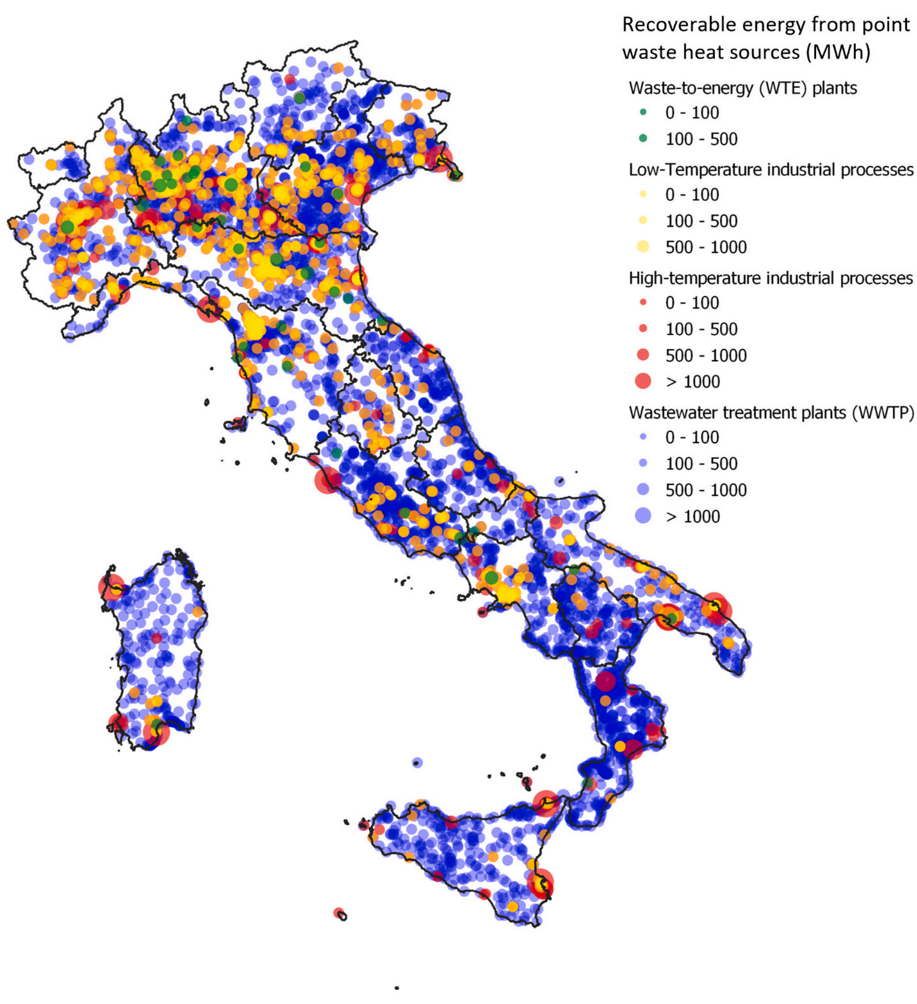

Fig. 11. Spatial distribution of the point waste heat sources in Italy.

affected by the seasonal variations, by the outdoor weather and by the users' behavior. That is why, for example, we assumed 7000 equivalent hours per year (hh_{heat}) for industrial processes, and an average value of 3500 h per year for DH systems (hh_{DH}). In this case the amount of excess heat effectively recoverable in DH networks is therefore furtherly reduced by 50%, given as ($\frac{hh_{DH}}{hh_{heat}}$). More details can be found at Ref. [35]. This is an important simplification introduced in the temporal modelling of the problem and it is therefore the intention of the authors to deepen the research on this aspect with future works.

At the end of this phase the available waste heat is estimated to be 122 TWh: 79 TWh come from high temperature industrial processes and thermoelectric plants, 8 TWh from cooling industrial processes, 31 TWh from WWTP and 4 TWh from WTE plants. Their distribution in Italy can be seen in the map in Fig. 11, where the size of the point is dependent on the amount of heat annually recoverable, and the color defines the typology.

Regarding the renewable energy sources, the authors considered biomass, solar thermal and geothermal energy. In this case point data are not available and it is the maximum availability of heat from these sources that is used as input of the developed hot-SPOT model. The availability maps have been derived from the Stratego project [59] for what concerns the biomass, from the Ministry of Economic Development that provides cartographic data about geothermal energy [60] and from empirical estimates based on already installed plants for what regards the solar thermal energy. For further details please refer to Ref. [12,35].

These sources are integrated in the optimization algorithm as maximum threshold limiting the technological choice by the solver.

3.3. Economic assessment

Once the amount of heat technically exploitable in DH systems is estimated, the economic assessment is done so that each element making up the system can have an economic attribute based on which the optimization may occur. As thoroughly described by the authors in Ref. [34], in every census cell the cost associated to the investment and the operation of the local distribution network is assessed considering also the costs related to the waste heat recovery and the costs of the alternative individual solutions.

3.3.1. Heat distribution costs

The cost of the distribution network is estimated by applying the distribution capital cost model developed in Sweden by Persson et al. within the Heat Roadmap Europe project [29]. This costs component is extremely important since it generally accounts for more than half of DH total cost.

The annualized investment cost of the distribution network $C_{I,d}$ is calculated as:

$$C_{I,d} = \frac{a\cdot(C_1 + C_2\cdot d_a)}{\frac{Q_{DH}}{L}} + C_{I,ST}\ [€/MWh] \quad (1)$$

where a is the annuity factor, d_a is the average distribution pipe diameter, C_1 indicates the size-independent construction cost constant [€/m], C_2 is the construction cost coefficient [€/m^2] directly proportional to the pipe diameter d_a, and $\frac{Q_{DH}}{L}$ [MWh/m] is the linear heat density and $C_{I,ST}$ [€/MWh] is the investment required for the users' substations installation. The average diameter is computed following again Ref. [29].

$C_1$and C_2have been defined from a data collection campaign on network costs within Italian DH association members. A correlation with city size (population - p) was identified as in Eqs. (2) and (3).

$$C_1 = -1834 + 191ln(p)\ with\ 110 < C_1 < 1000\ [€/m] \quad (2)$$

$$C_2 = +1770 + 25ln(p)\ with\ 1800 < C_2 < 2400\ [€/m2] \quad (3)$$

The linear heat density $\frac{Q_{DH}}{L}$ is a crucial parameter when calculating distribution costs, strictly connected to the effective width parameter w that represents the ratio between the total land area A_l [m^2] of the grid section and the length L [m] of the potential distribution network in that section. In this work the authors used the formulation (5) of w developed in [61], where it was extended to sparse areas and adapted to Italian urban context. Its correlation with linear heat density is formulated as in Eq. (4):

$$\frac{Q_{DH}}{L} = q_{DH} \bullet w(n_b)[MWh/m] \quad (4)$$

Where $q_{DH} = Q_{DH}/A_l$ [MWh/m^2] is the heat demand over the total land area and $w(n_b)$ is the effective width expressed as a function of the number of building ratio n_b, namely the ratio of number of total buildings, residential and tertiary, over the total land area A_l.

$$w(n_b) = 50.25 \bullet n_b^{-0.127}\ [\text{m}] \quad (5)$$

In addition to the investment costs, two operational costs need to be added due to hydraulic and thermal losses. The first one is expressed in terms of pumping costs, related to the electrical consumption usually quantified as a percentage of the delivered heat: according to empirical data provided by the members of the Italian DH association, AIRU, we considered a value equal to 5% of the heat supplied into the network. The second one is taken into account by increasing the heat demand to be covered by the potential DH adding the distribution losses calculated according to [29]. Together with the distribution costs, also the costs related to the DH substations must be considered. Again, the investment cost has been estimated based on the data provided by the DH association's members. With these data it was possible to evaluate the investment cost specific to the amount of installed power Q_u as in Eq. (6).

$$C_{Q_u} = 2389 \bullet Q_u^{-0.715}\ with\ 25 < Q_u < 145\ [€/kW] \quad (6)$$

3.3.2. Heat transport costs

The cost of the transport network is assessed in a different way since it does not depend on the heat demand density, but on the distance between the source and the demand and on the amount of heat that is supplied and effectively delivered. Indeed, this last factor has an influence on the size of the required pipe. However, the link between two elements making up the DH system is an output of the optimization problem, as well as the amount of heat transmitted. It means that the optimization algorithm requires in input the investment and the operating cost related to each possible branch of the grid so that at the end it could define what is the best network topology for which the overall cost is minimized. To solve this sort of recursive issue, the transport network has been sized based on an empirical correlation as in Eqs. (7), already presented by the authors in [62], for which the size of each pipe coming from a source is linearly dependent on the maximum amount of heat that can be provided by the source itself, E_{source}. The maximum length for a transport network pipe has been set to 60 km.

$$Distance = \begin{cases} E_{source}/10\ \ E_{source} \le 300\ GWh \\ 60\ \ E_{source} > 300\ GWh \end{cases} [km] \quad (7)$$

Regarding the estimation of the transmission losses along the network, some specific case studies have been evaluated and a curve correlating the transport losses to the amount of supplied energy has been derived. It is represented in orange in Fig. 12. However, since a linear programming model is used, a linear correlation needs to be determined and is represented in blue. Based on that, a value of 3% as been chosen.

On the basis of the correlation found before, related to the sizing of the analyzed case studies, and based on the assumed distribution costs explained in the previous paragraph, the cost of the heat transport network has been parametrized according to the amount of supplied energy. A dimensionless cost is therefore determined as presented in Fig. 13. The obtained curve has been once again linearized and a value of

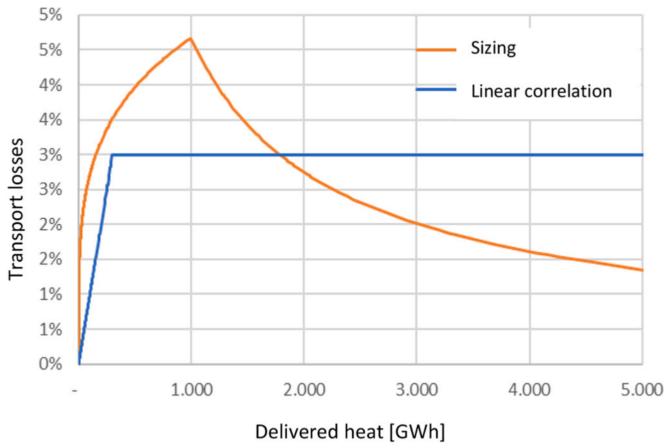

Fig. 12. DH transport network losses expressed as percentage of the amount of delivered heat.

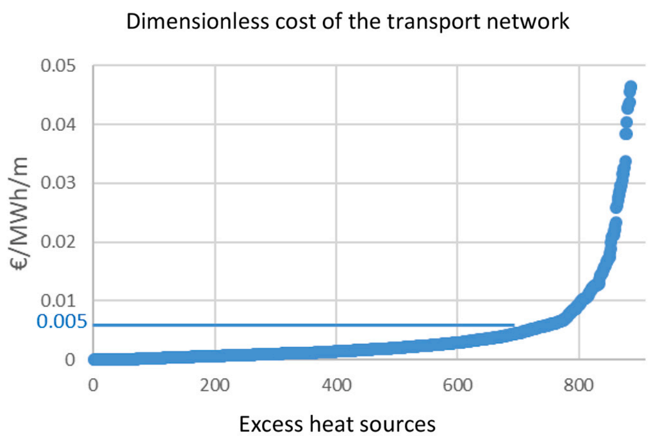

Fig. 13. Dimensionless cost of DH heat transport network.

0.005 €/MWh/m has been selected as constant cost value. It is a simplification that however is representative for most of the analyzed point heat sources.

3.3.3. Individual solutions' costs

With the same spatial grid as for the mapping of heat demand, the current technologies to provide heat with individual solutions (e.g. boilers) are identified according to their performances and used fuel types. Their costs, C_{Ind}, are estimated in terms of levelized costs of energy according to Eq. (8) as the sum of the investment costs $C_{I,ind}$, annualized according to the annuitya, and the operational costs $C_{O\&M,ind}$ which includes fuel consumption and maintenance. Q_{DH} is the heat provided to the users.

$$C_{Ind} = \frac{C_{I,ind} \bullet a + C_{O\&M,ind}}{Q_{DH}} \; [\text{€}/MWh] \tag{8}$$

Commodities costs are presented in Table 2.

3.3.4. Waste heat sources' costs

The same is done to estimate the total costs of the heat sources exploitation. It is calculated as in Eq. (9) as the sum of the annualized investment costs, $C_{I,WH} \bullet a$, and the operation and maintenance costs, $C_{O\&M,WH}$. $Q_{WH,rec}$ is the heat recovered by the waste heat source and supplied into the DH network.

$$C_{WH} = \frac{C_{I,WH} \bullet a + C_{O\&M,WH}}{Q_{WH,rec}} \; [\text{€}/MWh] \tag{9}$$

Table 2
Assumed commodities and fuel prices.

Commodities and fuel price		€/MWh
Natural Gas (NO VAT)	Single House	123
Natural Gas (NO VAT)	MultiFamily Building	83
Electricity (NO VAT)	Single House	281
Electricity (NO VAT)	MultiFamily Building	236
Electricity (NO VAT)	Utility (PUN+Taxes)	107
National Single Price (PUN)		65.8
Diesel fuel		132.8
GPL		204.8
Wood chip		35.7
Wood chip (forestry)		42.7
Pellet		68.8
Firewood		50.5
Natural Gas (NO VAT)		32

The annualized costs are presented in Table 3. They are specific to each considered source of heat, for which a distinction between high-temperature heat recovery through a heat exchanger and low-temperature heat recovery through a heat pump is also made.

3.4. Network topology

The application of the Delaunay triangulation to Italy led to the definition of 33,000 links, from which the ones of length above 60 km have been excluded since they generally represent unfeasible connections, such as between the big islands. In like manner the inter-regional links have been excluded, mainly to reduce the computational burden in the following step of routing algorithm application. Moreover, the development of a network covering two adjacent regions may be not feasible because of bureaucracy and some other social aspects such as different policies ad tariffs applied. A simplification of this sort can be therefore considered plausible and it has a limited impact on the results. After the routing process the ratio between the linear distances and the more realistic ones obtained has been computed and checked. The obtained length along the drivable routes appeared to be consistent and on average they are equal to the linear ones incremented by a factor of 1.7. Ratios lower than 1, that represent just 2% of the total (669 cases), have been considered irregular and treated differently according to the actual length. In case they measure >5 km they generally represent links between islands and they have been excluded. If they measure <5 km they have been maintained since they mainly refer to cases in which the distance from the drivable route is so high to impact on the ratio or

Table 3
Annualized investment and operating cost values [€/MWh] assumed for each considered heat source.

Heat source	Annualized investment cost: $C_{I,WH}$ [€/MWh]	Annualized operating cost: $C_{O\&M,WH}$ [€/MWh]
HT industrial excess heat (direct recovery)	4	21
LT industrial excess heat (indirect recovery)	23	25
Recovery from Wastewater Treatment Plants	23	36
Recovery from Waste-to-Energy plants	4	1
Recovery from Biomass-CHP plants	19	98
Solar thermal plants	69	0.5
Deep geothermal (HT: direct recovery)	34	21
Shallow geothermal (LT: indirect recovery)	15	45
Recovery from NG CHP plants	26	50

because they refer to small secondary streets improperly defined in the OSM database.

As an example, in Fig. 14 a focus on the Lombardy region in the north of Italy is presented. It is possible to see how the linear edges, in red, are converted in corresponding paths along the streets, in black.

4. Results

As a result of the application of the methodology, the optimisation algorithm defines the technological solution that minimizes the cost of heat delivery at system level, choosing from a range of alternative individual technologies, including retrofitting, and district heating fuelled by the heat sources available in the geographical surroundings.

For every cluster whose outcome is the connection to DH, it is possible to know the share of each source to cover the heat demand, e.g. waste heat, solar thermal or fossil fuel cogeneration, and the topology of the connecting transport network. By aggregating the cluster level results, the regional and national potential can be calculated.

This chapter shows the results obtained by the application of the developed methodology to the case study of Italy. The results, together with the created maps and the python code, are available at the following link: https://zenodo.org/record/4284531.

The identified optimal paths making up the single DH networks cluster by cluster are presented in Par. 4.1 while DH potential in the Country is presented in quantitative terms in Par. 4.2.

4.1. Results at cluster level

Based on the estimates and on the distribution in the Country of the heat demand and of available recoverable and renewable heat sources, the optimizer defined the least cost configuration of the heat transportation network and the relative energy flows. This result is obtained for the whole Italian territory ad an extract can be seen in the map in Fig. 15 as an example. It is possible to look at some relevant decision variables of the model, i.e. at the estimated heat demand and the clusters (*sinks*), at the excess heat sources (*sources*) and also at the grid (*transformers*). In Fig. 15(a) is also possible to clearly identify the triangulation step, at the basis of the definition of the optimal energy flows among all the possibilities. The optimal choice is done considering the lengths along the drivable roads, as previously explained, but for ease of creation and use of the map the linear paths are then reported.

The flows are colored according to the amount of heat distributed and they connect heat sources to heat demand clusters, but also clusters to other clusters (as in the upper right side of the picture). The heat demand clusters, given by the aggregation of neighboring census areas, are reported in grey in Fig. 15(a). Their size and shape are different from one to another since they depend on the local conditions in terms of heat demand density. In Fig. 15(b) only the clusters that are not connected to the DH system remain in grey, while all the others are colored in pink. Therefore, in the grey clusters heat demand is met by individual solutions as boilers and heat pumps, while in pink ones the heat demand is supplied by the DH network, which distributes the heat coming from the available heat sources. Heat sources are represented with dots, whose color identifies the typology and whose size specifies the amount of estimated recoverable heat that the optimizer suggests using. In this specific portion of the Italian map reported in Fig. 15, the available point heat sources are wastewater treatment plants and industries.

Biomass, solar thermal and geothermal energy are not represented as dots, but their availability is still considered as input of the optimization algorithm. Indeed, in Fig. 16 it is possible to also see their contribution in covering the heat demand of the biggest cluster of the image, taken as example. Of a total of 222 GWh/year of heat demand that can be potentially met by DH according to our esteem, 22 GWh/year are met by solar thermal energy and 67 GWh/year by geothermal energy. The remaining thermal energy required to satisfy the cluster's heating needs corresponds to 140 GWh/year that are distributed by the DH network. Most of it (13.59 + 73.8 GWh/year) is derived from the neighboring industrial sources (yellow dots), while the remainder (52.55 GWh/year) comes from another further-located cluster of heat demand from which exceeding energy is available.

4.2. DH potential at national level

The least cost renewables- and excess heat-based DH configuration suggested by the optimization potentially meet a demand of 38 TWh/year in Italy. As it is shown in Fig. 17, it corresponds to 12% of the overall estimated heat demand, equal to 329 TWh. Only 9 TWh, corresponding to 3% of the overall heat demand, is currently covered by DH.

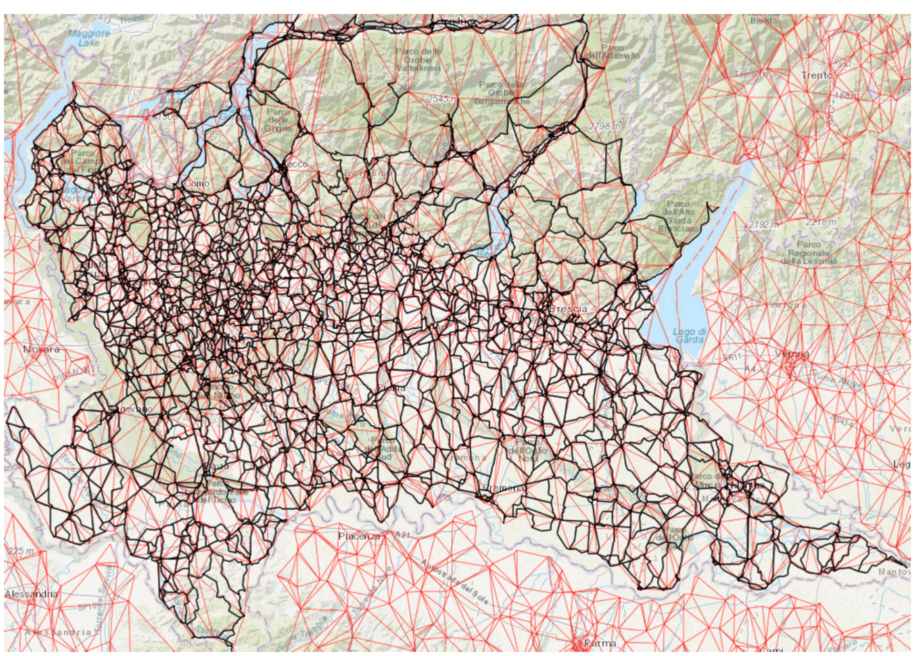

Fig. 14. Detail of the Italian map in which it is possible to distinguish between the red paths, defined with the Delaunay triangulation algorithm, and the black paths, defined in the routing phase. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

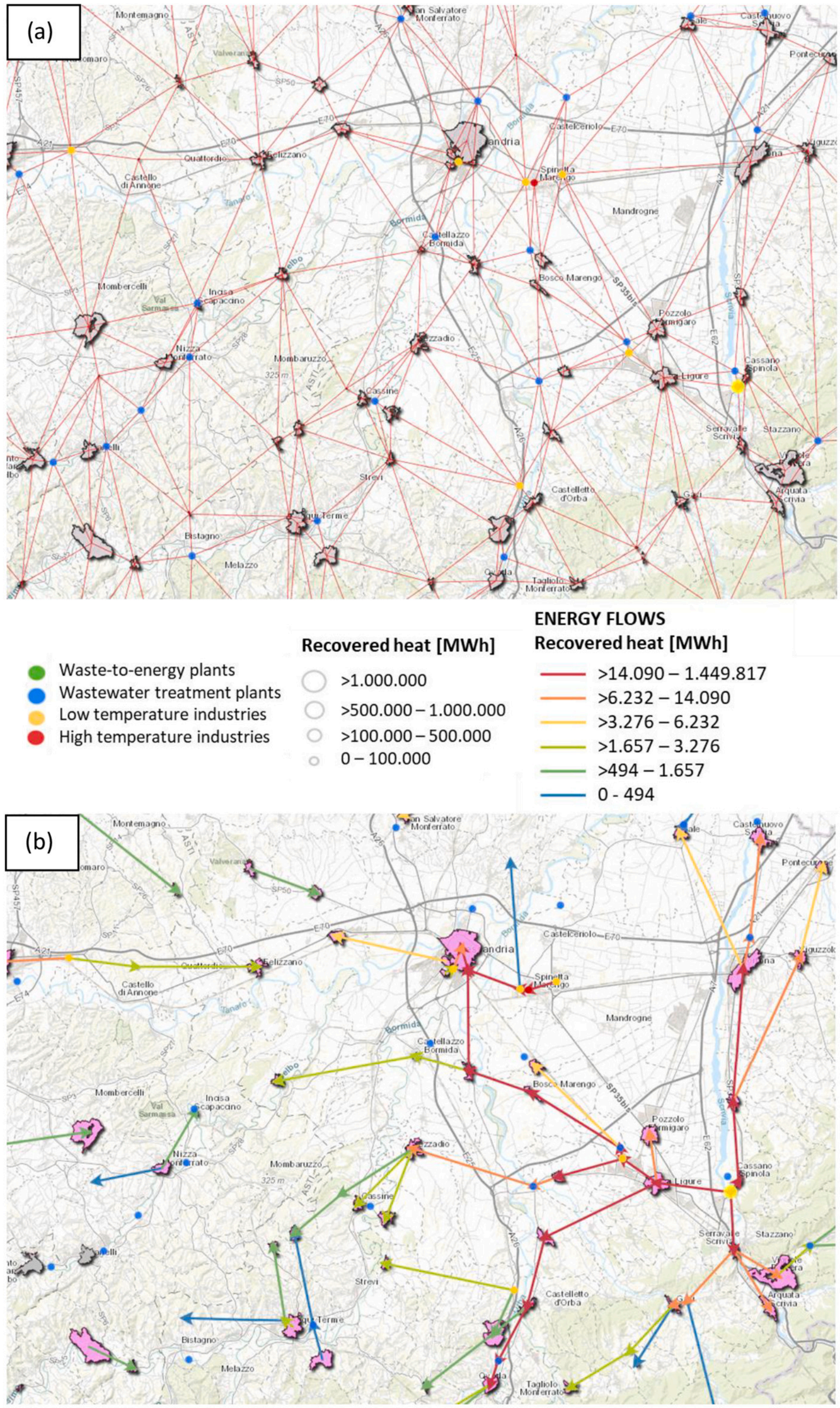

Fig. 15. Image (a)- Heat demand clusters (polygons), heat sources (dots) and Delaunay triangulation. Image (b)- Thermal energy flows defined in the optimization. Portion of the Italian map.

Therefore, a four-fold expansion is envisaged by 2030.

Fig. 17 also identifies industrial excess heat as the major contributor in the overall DH potential, with 23 TWh over the total 38 TWh. The second contribution is given by geothermal energy, with 10 TWh, which include both the deep geothermal energy that is directly recovered and the shallow geothermal energy that requires a temperature upgrade performed by heat pumps. 2 TWh are then potentially met by solar thermal, while 3 TWh by CHP plants and natural gas boilers, used in case an integration is needed especially to cover peaks of demand. These NG-fueled technologies do not include already installed plants, but they only represent an additional quota with respect to what currently exist. Further analysis may require introducing in the model even policy regulations, especially in terms of natural-gas based sources, in order to properly manage them according to the decarbonization strategies. For example, only existing NG CHP plants could be considered until their end of life and no more additional capacity could be added. These are

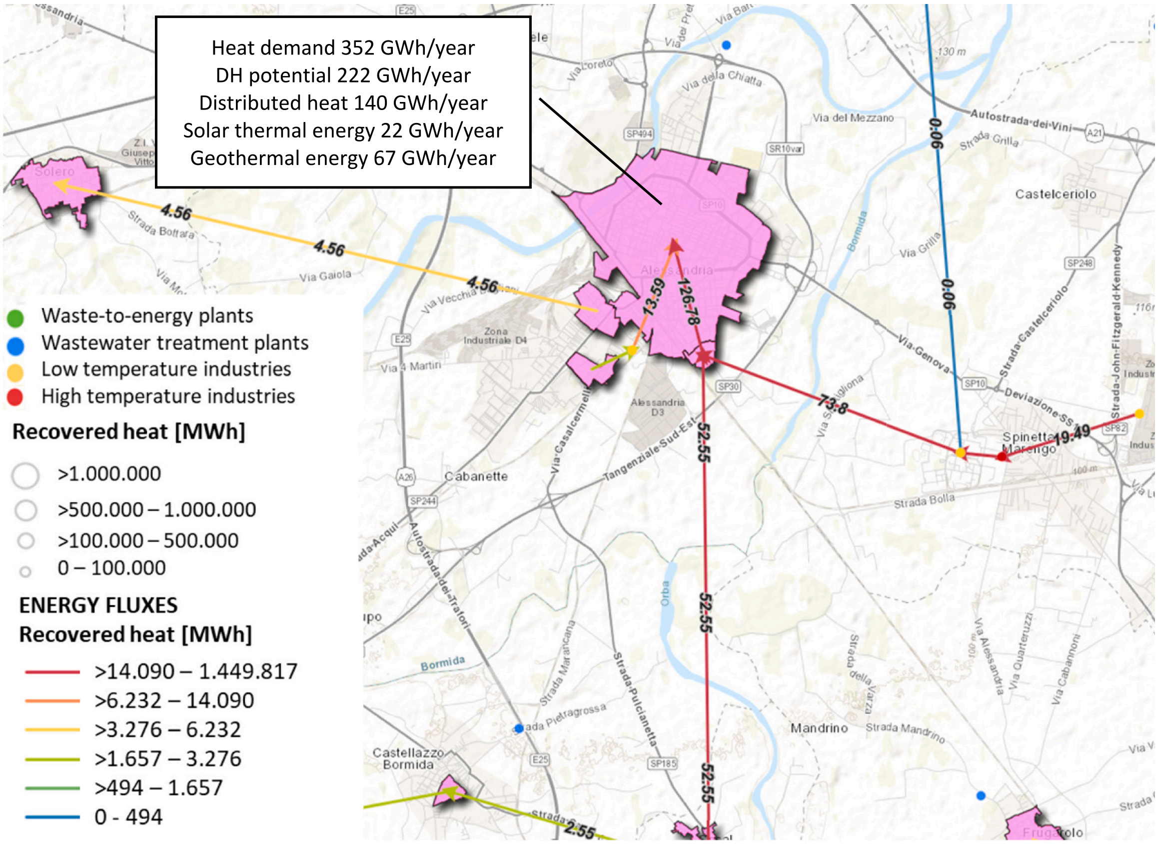

Fig. 16. Zoom on a cluster where >60% of the heat demand is met by DH. Energy flow values indicate the amount of distributed heat in GWh.

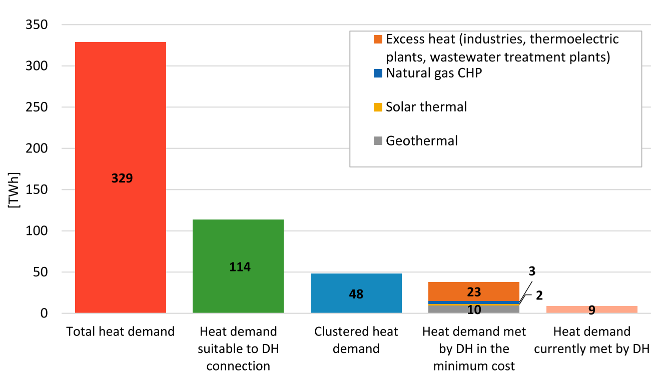

Fig. 17. Estimated DH potential in Italy in terms of covered heat demand.

considerations to be done according to the increasing decarbonization and the more and more binding limits on emissions.

Regarding the spatial distribution of the heat provided by DH, in Fig. 18 the 107 Italian Provinces (a) and the 7899 Italian Municipalities (b) are respectively reported. The heat delivered is mapped in absolute terms as [GWh/year].

Referring to Fig. 18(a) it is possible to highlight the predominance of Northern provinces. However, the province of Rome holds the record and Naples and Lecce stand out in South.

The potential seen at municipal level (b) confirms the predominance of Northern Italy in absolute terms. However, the distribution is not so homogeneous as it appears for example in Puglia and in Sicily. There are indeed few Municipalities with very high values of delivered heat, surrounded by municipalities that in some cases shows a null value. That is due to the optimization logic of the model which looks for the contemporary presence of high heat demand and heat sources at affordable cost, and which distribute the available heat to the most appropriate location. A wider range of possibilities in terms of renewable sources and excess heat recovery technologies would certainly increase the overall DH potential over the Country, together with its homogeneity.

What can be seen in Fig. 18 is confirmed in Fig. 19, where DH potential is shown in intervals of values referring to the amount of delivered heat. For each of these intervals, the overall amount of delivered heat in GWh and the number of municipalities within that range are reported. Over 40% of the total DH potential, equal to 38 TWh, is located in 4258 municipalities as shown by the green columns. 20% is located in 174 municipalities with values of delivered heat between 20 and 110 GWh/year, as shown in the red columns. The remaining 40% refers to 31 municipalities with values in between 200 and 4630 GWh/year (blue columns). It means that the same DH potential that is resulting from the aggregation of thousands of municipalities is found by the aggregation of only 31 big municipalities.

These first 30 municipalities in terms of DH delivered heat are reported in Fig. 20 in descending order. Rome, Milan and Turin alone make for 25% of the identified DH potential in Italy.

How this amount of heat is supplied to DH systems can be seen in Fig. 21, where the percentage share given by each renewable and excess heat source is given over the Italian provinces. Excess heat, that is the major contributor in the overall DH potential, is mapped in Fig. 21(a). It mainly covers the Northern area of the Country, but also an area overlapping Lazio and Campania and most of Puglia. Geothermal energy represents the second source making up the overall potential and, as illustrated in Fig. 21(b), it is mainly concentrated in the Tyrrhenian areas in the central part of Italy, i.e. Tuscany, Lazio and Sardinia. Besides these areas where there is availability of deep geothermal, we can highlight that interesting shares can be found also in the rest of Central

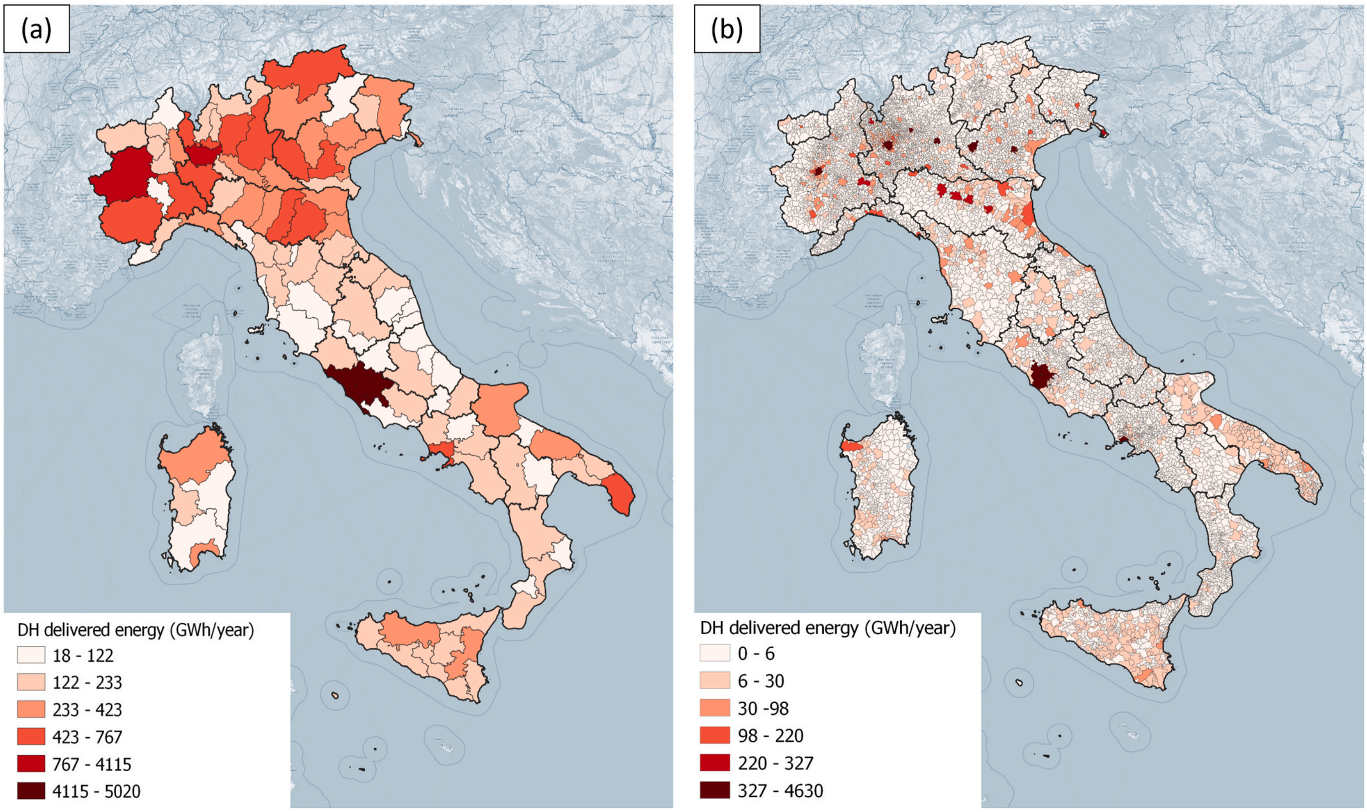

Fig. 18. Spatial distribution of DH potential over the Italian provinces (a) and municipalities (b).

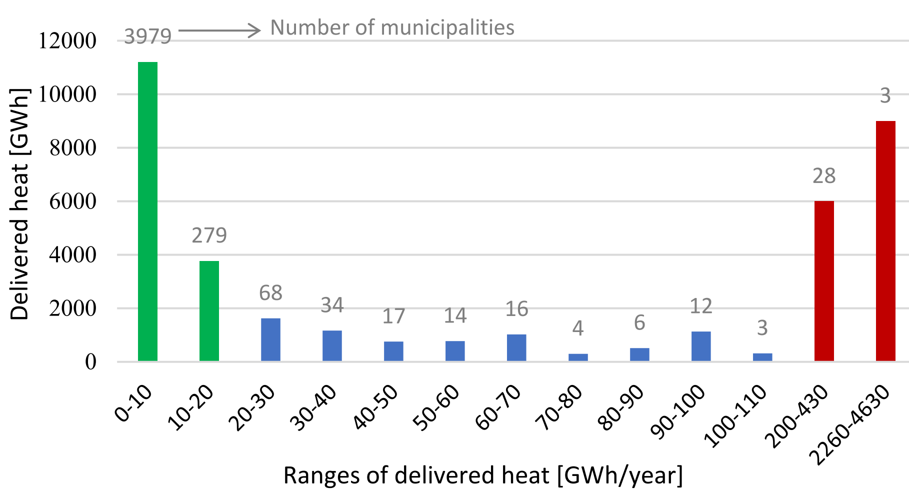

Fig. 19. Comparative analysis of municipal weights in the construction of the national efficient district heating potential.

Italy, in Sicily and in some areas over the Po Valley, in the North. There, mainly shallow geothermal is available.

Solar thermal energy, in Fig. 21(c), and natural gas-based cogeneration, in Fig. 21(d), are responsible for almost the same amount of DH potential in Italy. The first one does not show a particular trend in the spatial distribution, while the second one is mostly located in Sicily, over the Apennines in Central and Southern Italy and in some mountainous provinces along the Alps. However, for what concerns solar thermal energy, a not homogeneous spatial distribution would propably be obtained if a proper approach is introduced to identify the most suitable areas for this technology. This is an important aspect to be furtherly explored since the obtained potential of 2 TWh/year of solar thermal energy can be translated into an indicative needed surface of 1km^2.

5. Discussions

The authors of this paper developed a model for assessing DH potential at large-scale level, based on open-source modelling framework and based on geographic information systems. The main novelty stands in the high geographic resolution of the model with which is possible to connect heat sources and heat demands with a virtual energy graph. Based on it, with the aim to maintain the overall heat supply cost at its minimum, an optimizer enables the definition of the heat sources and of the network paths required to cover the heat demand of those aggregates that can be considered suitable from a technical and economic perspective.

This chapter attempts to critically comment on the results and on the

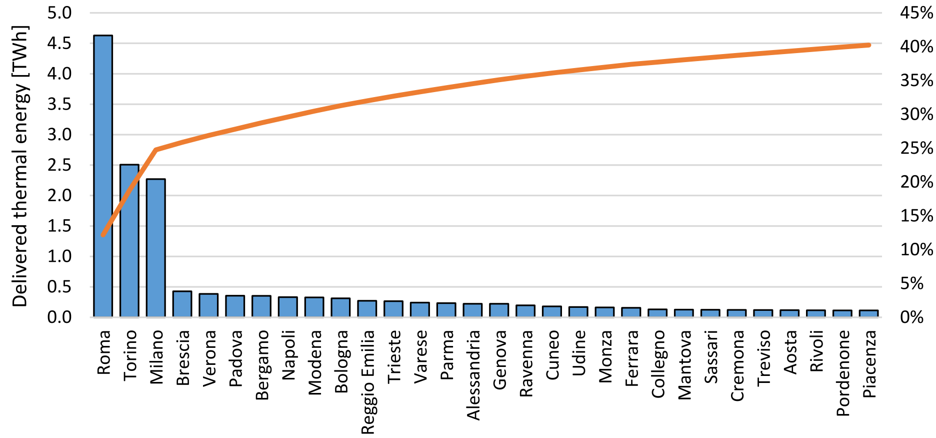

Fig. 20. Overview of the first 30 biggest cities in terms of amount of delivered thermal energy.

developed model. The aim is to compare the outcomes with similar DH potential assessment studies conducted in Italy and in other Countries, and to discuss the limits and simplifications introduced in the model. Possible future improvements are eventually outlined.

First, the numerical results are compared with the outcomes obtained from similar studies. The derived potential of DH in Italy lies within a range of values defined by previous studies, where the amplitude of this range is the result of different objectives, time, contexts, input data and approaches. These differences make their results hardly exactly comparable. However, it is possible to state that the results here obtained prove their robustness when compared with other studies, such as the very recent one conducted at European level by Fallahnejad et al. in. [13]. Even though in this study a higher DH market share is estimated in Italy in 2020, equal to 20%, a four-fold expansion is foreseen by 2050, with 70% of realizable market share. The overall heat demand is in the same order of magnitude: 383.4 TWh in [13] while it's here estimated to be 329 TWh. The same can be said about the estimated DH potential, which here amounts to 38 TWh while in Ref. [13] is equal to 27.2 TWh for Italy in 2020 and 62 TWh in 2050. The magnitude of heat demand and DH potential, together with their future evolution trend are therefore comparable. It is worth mentioning that the most recent estimation of DH potential in the EU-27 illustrated in [13] presents an updated and scaled-down result compared to the first estimates of DH potential diffusion in Europe presented by the Heat Roadmap Europe project [15], which for example estimated a 85% DH potential in Italy equivalent to over 250 TWh. On the other side this study highlights a higher expansion margin of DH technology with respect to the national estimation presented in [63] where the potential diffusion for DH in 2020 amounts to 20.9 TWh.

As already mentioned, one of the main advantages introduced in the presented model with respect to others that can be found in literature is that the potential expansion of DH is not limited by thresholds imposed upstream of the analysis. For example in the Italian study conducted by GSE [63], 67 TWh is the amount of excess heat that is estimated to be recoverable in DH networks in Italy in 2030, but only 6 TWh of it can be effectively distributed according to the authors of the study. This value has been obtained by considering for each excess heat source mapped a maximum of 5 municipalities to be served in a radius of 15 km. These constraints were set in order to limit the length, and therefore the costs, of the required transport networks. The impact of this constraint is however very relevant on the results. Differently from what is done there, the authors of the present paper let the optimizer choose how to distribute the available amount of heat from each source. It means that, based on the virtual energy graph created with triangulation and routing algorithms, the optimizer is able to select any paths for which the heat demand of the neighboring clusters is met and the overall supply cost maintained at his minimum level. Therefore, the model is not limited a priori but it takes the most promising solutions based on the entire overall heat delivery cost. Other approaches that uses thresholds can be found in [7,13], where thresholds are imposed on a minimum annual DH demand and a maximum heat distribution costs as criteria for identifying DH areas. Moreover, the hypothesis of uniform DH market share evolution for all hectare cells of each country is made.

Nevertheless, some simplifications have been introduced also in the hot-SPOT model here presented. These aspects have an influence on the results and their sensitivity is investigated in parallel ongoing research. The most impacting approach choice in terms of spatial resolution is the application of a density-based clustering algorithm to aggregate heat demands and reduce computational effort. This aggregation reduces the heat demand considered feasible to be connected to DH from 114 TWh to 48 TWh and it is therefore a relevant step in the analysis. Fundamental is the proper setting of the clustering parameters: given a point of heat demand, these parameters identify the radius of research and the minimum number of points to be included in it. More details are given in Ref. [34]. The authors of this paper are working on furtherly exploring them with the intention to absorb improvements in the future version of the model.

Future efforts are also aimed at increasing the temporal resolution of the model which currently simulates the energy system on annual basis, in a one-timestep simulation. This choice has been taken so to focus on spatial detail more then on temporal resolution. The demand and load profiles, together with heat storages to balance them, will be introduced in future research. Moreover, the current simplification at temporal level also implies that the capacities of the plants are not estimated based on the contemporaneity between the supply and the heat demands to be served, but on average equivalent hours in a year. This simplification reflects also on levelized costs that are not capacity dependent but based on average full equivalent hours. Improvements will be made also in this sense, so that investment costs may be defined according to the installed capacity, sized according to the peak demand to be covered.

As is done in [13], efforts of future research will be also aimed at making the model sensitive to variations in market prices, in CO_2 emissions constraints and in legislative frameworks. The adaptability of the oemof framework would enable the integration of all these improvements in the model, i.e. introducing a higher temporal resolution, enlarging the analysis perspective in long-term scenarios, and adding constraints on the emissions impact of the result.

Eventually, the aim is to extend the range of considered heat sources, for example by considering heat recovery from water basins through heat pumps, and to improve the estimation of solar thermal potential starting from space availability and solar irradiation. Indeed, in the current model solar potential is defined as a fraction of the overall heat demand.

Another improvement that can be introduced in the model concerns

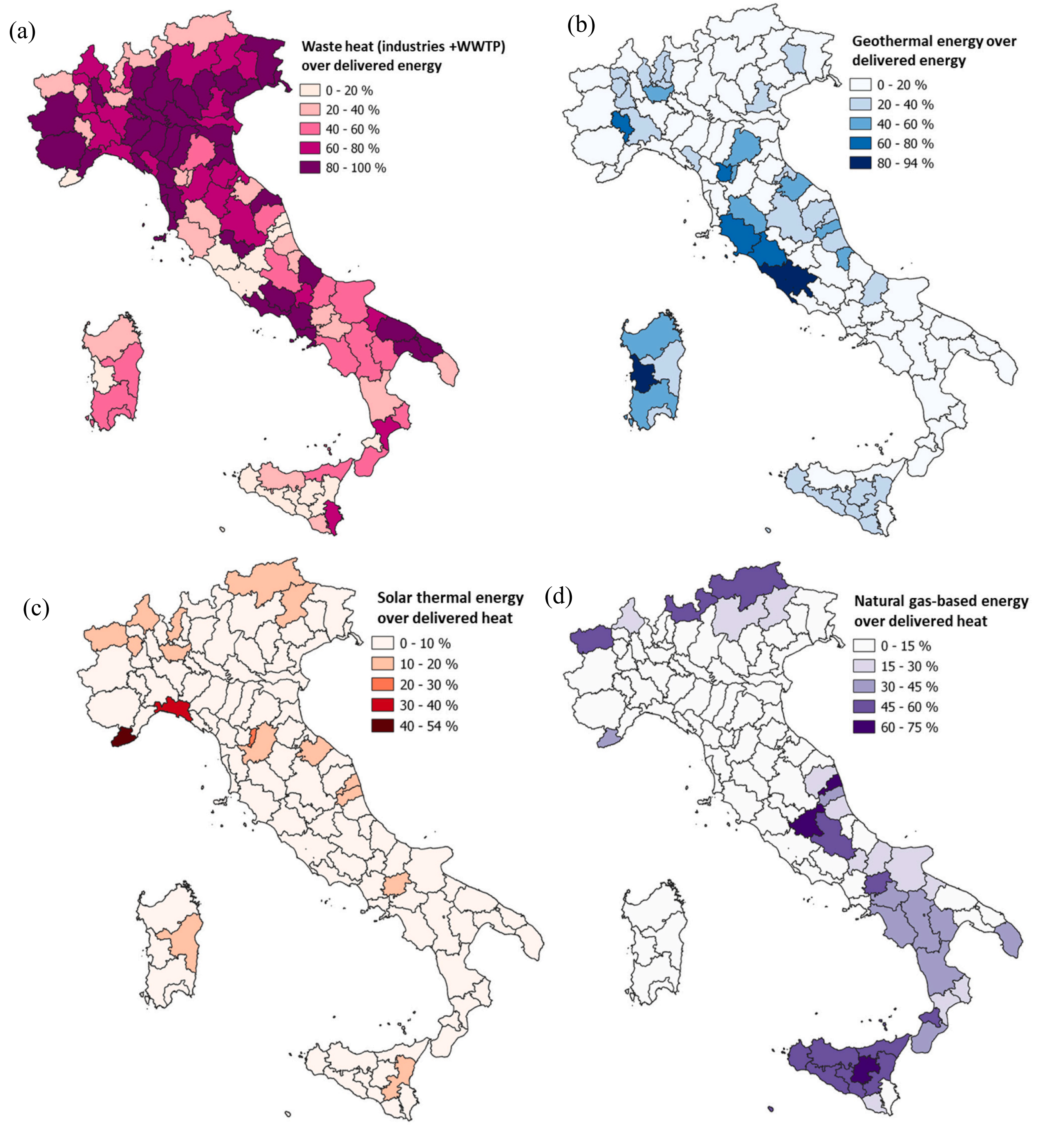

Fig. 21. Percentage shares, over the Italian provinces, of the heat delivered in DH networks by different sources. (a) Waste heat, i.e. industries and wastewater treatment plants; (b) Geothermal energy; (c) Solar thermal energy; (d) Natural-gas CHP plants.

the back-up solutions whose integration in this study has been considered in terms of cost only. The cost required for their installation has been indeed spread on all the considered technologies by increasing their total cost of 5 €/MWh. The impact of auxiliary plants on the whole energy system could be estimated also in terms of associated CO_2 emissions.

6. Conclusions

The developed methodology enables the assessment of DH potential on a large-scale level, as for the whole Italy, but with a significant spatial detail at neighborhood level, with a computational effort that can be addressed by an average computer and by considering the magnitude, the location and the costs of all the elements constituting the energy system. The used input data come from publicly available database. The result of DH diffusion potential derives from an optimization algorithm, which identifies the optimal option for each heat demand aggregate minimizing the cost of the heat delivered choosing among DH and the representative individual solution. Unlike most of the methods found in the literature, the potential is not calculated by inserting a priori thresholds on any components, e.g. heat demand density, cost of distribution networks, distances from energy sources, but considering the overall annualized cost of delivering heat via DH with local sources in comparison with the individual technological alternative available to the end user, case by case.

The outcome of the optimization problem can provide a reliable starting point for energy planners, local authorities, DH operators and policy makers.

To facilitate replicability and applications to other contexts, the model is built by using open-source software, such as Python and QGIS, and by exploiting public common input data. In this way, by simply feeding the model with different available databases, the study can be replicated in different and multiple geographic contexts.

The result of the application of the model in Italy shows a potential for DH based on renewables and waste heat of 38 TWh, corresponding to a four-fold expansion of the current DH diffusion equivalent to 12% of the civil sector heat demand.

Credit authorship contribution statement

G. Spirito: Writing – original draft, Visualization, Software, Investigation, Data curation. **A. Dénarié:** Writing – review & editing, Writing – original draft, Validation, Methodology, Formal analysis, Conceptualization. **F. Fattori:** Writing – review & editing, Writing – original draft, Supervision, Methodology, Investigation, Formal analysis, Conceptualization. **G. Muliere:** Visualization, Software, Formal analysis, Data curation. **M. Motta:** Writing – review & editing, Resources, Project administration, Funding acquisition. **U. Persson:** Writing – review & editing, Supervision, Resources, Methodology, Formal analysis.

Declaration of competing interest

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

Data availability

Data will be made available on request.

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