Evaluation of district heating potential at the territorial scale: validation of the BRUSA model

Energy 330 (2025) 136828

Contents lists available at ScienceDirect

Energy

journal homepage: www.elsevier.com/locate/energy

Evaluation of district heating potential at the territorial scale: validation of the BRUSA model

Chiara Monzani *, Giulio Cerino Abdin, Alberto Poggio, Giulia Montanari

Department of Energy, Politecnico di Torino, Torino, Italy

ARTICLE INFO

Keywords:
Building energy modelling
Decarbonization
District heating system
Spatial energy planning
Thermal demand estimation

ABSTRACT

The study presents the BRUSA model, a scalable and replicable tool for estimating the annual heat demand of larger residential buildings stock using national census data. Unlike traditional bottom-up models, it calculates energy demand at the individual building level without relying on archetypes. The model incorporates specific details about building geometry, wall construction, heating systems and energy performance assumptions based on building construction periods and applicable regulations. This methodology ensures a simple yet efficient representation of energy demand, making large-scale energy planning more practical.

The paper details the model's construction and validation using 170 buildings' annual thermal consumption data from eight heating seasons in Turin. The model has been validated at individual building, census section, and building aggregate levels, with a Mode of Percentage Error ranging from −1 % to 14 % at building level and a Mean Absolute Percentage Value of approximately 15 % at aggregate level. By overcoming common limitations of archetype-based and high-data-requirement models, BRUSA offers a versatile tool for spatial energy planning.

The paper presents a case study that uses the BRUSA model to assess the feasibility of developing a district heating system in an urban area, highlighting district heating systems' potential to support the energy transition.

Nomenclature

Acronyms		
CD	–	Census Database
CHP	–	Combined Heat and Power unit
BIO	–	Biomass Boiler (wood chip)
DHC	–	District Heating and Cooling System
HDD	°C	Heating Degree Days
IBB	–	Integration and Back-up Boiler
KDE	–	Karnel Density Estimation
MAPE	%	Mean Absolute Percentage Error
MoPE	%	Percentage Error Mode
VB	–	Validation Buildings database
Parameters		
$C_{d\ lim}$	W/m^3K	global thermal losses coefficient
η_c	%	control efficiency
η_d	%	distribution efficiency
η_e	%	emission efficiency
η_g	%	global efficiency
η_{Hgn}	%	utilisation factor
η_p	%	generation efficiency
U_{value}	W/m^2K	thermal transmittance
Variables		
b	–	building
d	–	dwelling
m	–	count of validation buildings
n	–	count of building dwellings
O_b	kWh/year	building annual thermal consumption
P_b	kWh/year	building annual thermal consumption model estimation
PE_b	%	Percentage Error
$Q_{Hnd\ b}$	kWh	building heat gain utilisation factor
$Q_{Ht\ d}$	kWh	dwelling primary energy needs
Q_{Htr}	kWh	transmission heat transfer for the heating mode
Q_{Hve}	kWh	ventilation heat transfer
Q_{int}	kWh	internal load
Q_{sol}	kWh	solar radiation load
S_B	m^2	base surface
S_D	m^2	building envelope surface
S_O	m^2	opaque surface
S_R	m^2	roof surface

(continued on next page)

This article is part of a special issue entitled: SDEWES 2024 published in Energy.

* Corresponding author.
E-mail addresses: chiara.monzani@polito.it (C. Monzani), giulio.cerino@polito.it (G. Cerino Abdin), alberto.poggio@polito.it (A. Poggio), giulia.montanari@polito.it (G. Montanari).

https://doi.org/10.1016/j.energy.2025.136828
Received 26 November 2024; Received in revised form 12 March 2025; Accepted 25 May 2025
Available online 26 May 2025

(*continued*)

S_T	m^2	total floor surface
S_w	m^2	glazed surface
T_0	°C	building set point temperature
T_m	°C	daily mean outside temperature
V	m^3	building volume

1. Introduction

The energy efficiency of buildings is increasingly identified as a pivotal factor in the global effort to address climate change and reduce CO_2 emissions. In 2021, the residential building sector accounted for 27 % of final energy consumption in Europe, with heating accounting for approximately 64 % of the total [1]. In this context, the European Union has set ambitious decarbonization targets, outlined in two key directives: the Renewable Energy Directive (RED III) and the Energy Performance of Buildings Directive (EPBD). The RED III calls for an annual increase in the share of renewable energy used for heating and cooling, aiming to reach 49 % by 2030 [2]. Concurrently, the EPBD aims to transform the existing building stock into zero-emission buildings (ZEB) by 2050 [3]. The EPBD recognises efficient District Heating and Cooling systems (DHCs) [4] as a key technology for achieving ZEB qualification. Therefore, DHCs have a crucial role to play in the achievement of decarbonization targets and stand out for their ability to integrate renewable energy sources, especially in densely populated urban areas where space constraints limit the direct installation of such sources. However, the feasibility and enhancement of DHCs depend on local territorial characteristics and the spatial distribution of energy demand. Therefore, the adoption of advanced energy modelling tools is essential, not only to analyse building heat consumption and estimate potential energy savings but also to identify the most suitable areas for the development of new district heating systems or the potential extension of existing ones.

Spatial heat demand analysis is therefore a key element for energy planning and decarbonization of DHCs [5]. Recent studies emphasise the importance of integrating detailed building data and geospatial information within GIS platforms to improve the assessment of energy saving potential and the planning of DHCs. However, a major barrier is the scarcity of granular data, particularly in EU countries, which affects the reliability of spatial heat demand assessments and efficiency strategies [6]. According to Ref. [7], energy demand modelling for heating and cooling consumption can follow two main approaches: bottom-up and top-down. Among these, engineering-based models following a bottom-up approach are often regarded as more detailed and specific. These models rely on micro-level data (e.g., individual buildings or processes) and subsequently aggregate them to derive broader energy demand estimates. A recent literature review [8] analysing 419 studies on energy demand modelling published between 2015 and 2020 found that engineering-based models account for approximately 10 % of the analysed methodologies. These models are mainly used to forecast electricity and thermal energy demand, as well as fuel consumption, as indicated by the number of studies employing them. In recent years, several studies have developed bottom-up models to estimate the thermal demand of buildings at different spatial scales. A common approach is to use Archetype Building Energy Models (ABEMs) based on geometric characteristics, use and age of construction to attribute a normalized energy consumption (kWh/m^2/year). However, these models may introduce simplifications that limit their spatial accuracy, with the risk of underestimating the actual variability in consumption [9]. To obtain more accurate results, Dineen et al. [10] emphasised the importance of incorporating construction characteristics into energy models, but this often leads to a high computational cost.

In response to these challenges, this study introduces the BRUSA model, an innovative thermal demand estimation tool that combines a bottom-up approach with the use of detailed census data at the local level, with no need for archetypes. The BRUSA model represents an advancement of the E-SDOB model, previously developed at the Politecnico di Torino and described in Ref. [11]. While E-SDOB relies on aggregated census data, BRUSA adopts a bottom-up engineering approach, utilizing national census data at the individual dwelling level. Designed for application across the entire Piedmont Region (Italy), the BRUSA model can also be easily replicated at the national scale and in other regions or countries with comparable census data frameworks.

Previous studies have successfully used census data to develop electricity and gas consumption prediction models based on artificial intelligence algorithms [12] and allowing for high temporal resolution forecasts [13]. Another recently proposed approach exploits census data and geometric information of buildings from GIS databases to set up a detailed heat balance, without resorting to archetypes [14]. In this case, the thermal transmission coefficients of the dispersing surfaces are estimated based on EPC (Energy Performance Certificates) databases of nearby regions. Although this methodology improves the representation of the energy behaviour of buildings compared to archetypal models, it is affected by the limited availability of local data. The above-mentioned studies utilised census data through a simplified statistical approach, relying on raw information such as floor area and the number of dwellings. This approach is often overlooked, important construction and installation details, lacking deeper analysis or consideration of additional factors. To address this gap, BRUSA reprocesses census questionnaires to gather detailed information on heating systems and building characteristics incorporating specific details about wall construction, heating systems, and energy performance assumptions based on the construction periods of the buildings and regulations in effect in the analysed locations. This innovative methodology allows for a simplified yet computationally efficient representation of building energy demand. By avoiding the need for extensive individual building details or intensive computational resources, BRUSA makes comprehensive energy demand modelling and energy planning more practical and efficient at the local scale.

BRUSA has previously been validated at the municipal level [15]. This study differs from previous validations by evaluating the accuracy of the BRUSA model at the level of individual buildings and aggregations of buildings.

The paper outlines the methodology used to develop the model, which allows the thermal characteristics of the building envelope, the type of heating system used and the annual thermal energy requirement to be identified, all based on the climatic conditions of the specific year of analysis. The model was validated using thermal consumption data for approximately 170 buildings supplied by the District Heating System of Turin (DHS). The data is available for eight heating seasons. The model's robustness was tested at three levels: individual buildings, census sections, and the aggregation of all buildings. The results indicate that the model performs well at the individual building level, although there are some exceptions. The Mode Percentage Error at the building level varies between −1 % and 14 %. Performance at the section level does not deviate from that at the building level, while at the aggregate level better performance is achieved with Mean Absolute Percentage Error comparable to other studies that process thermal energy demand with alternative, but less computationally efficient, methodologies. At the aggregate level, the BRUSA model demonstrates superior performance, affirming its value as a tool for territorial energy planning.

Finally, this paper explores a practical application of the BRUSA model through an evaluation of the installation of DHCs in an area not yet served by DHCs. The potential for large-scale deployment of DHC to meet heat demand in the civil sector has been highlighted in previous studies [16]. In the proposed application, BRUSA highlights the importance of district heating as a strategy to reduce climate impacts within the European Union [17] by assessing the potential installation of a district heating system and estimating the impact on CO_2 emissions at the municipal level.

The remainder of this paper is organised as follows:

- Section 2 presents the methodology, detailing the data sources utilised and the structure of the model. Subsections within this section provide a deeper insight into specific aspects of BRUSA's architecture and outline the validation parameters used for performance assessment.
- Section 3 is dedicated to Results and Discussion, which presents the validation results and shows how the model performs at different scales. This section also illustrates the application of BRUSA in assessing the potential for installing a district heating system in a currently unserved area.
- Section 4 summarises the key findings and discusses the model's broader implications for energy planning and sustainability.

2. Methods

The proposed model was developed using dwelling-level data from the ISTAT 2011 national census [18], which represents the most detailed available dataset for residential buildings in Italy. Despite the data being of rather dated source, it constitutes the most extensive and detailed nationwide database currently available and may in future be replaced by other databases (e.g. thermal plant cadastre, energy performance certificate) which presently provide incomplete coverage of the territory. Previous studies have validated the performance of thermal demand forecasting at municipal level, using annual fuel consumption as the metric for evaluation [15]. The model was applied to the territorial planning of the use of wood chip biomass for heating residential buildings in some areas of the Piedmont Region [19].

In this study, dwelling-level details were processed in order to obtain building-level data. The buildings, their information and the results obtained by applying the BRUSA model are represented by the census database (CD). The buildings, their respective data, and the findings obtained through the application of the BRUSA model are represented in the census database (CD). The validation process was conducted at the individual building level. To validate the model, a database (VB) was utilised, providing data on the heat consumption of roughly 170 district heating substations in residential buildings supplied by Turin DHS (Italy).

2.1. Data sources

The following section describes the source databases used to build the model and validate it. The BRUSA model was implemented in MathWorks MATLAB to allow the processing of large amounts of data. Specifically, the input data to the models can be distinguished by the geometric and technical characteristics of the dwellings, the thermal plant information of the dwellings, and the climate data.

2.1.1. Census data (CD)

The data description refers to databases and information available in Italy and provided by ISTAT, which is the Italian National Institute of Statistics [18]. The database is available in an open data format [20] but is limited to a highly aggregated level (regional). However, more detailed data can be requested from public authorities. Application in other countries is strictly dependent on the availability of comparable detailed information.

The model currently covers the entire national territory, with details of individual dwellings. The database refers to individual dwellings and allows a detailed description of all their main geometric and technical characteristics. High level of data detail reduces the number of hypotheses needed in previous studies [11]. The data are organised into four main categories: (i) geographical data (position of dwellings in terms of building, census parcel, municipality, address); (ii) thermal plant description (type of plant/system, fuel); (iii) geometric data (surface, number of floors); (iv) other data (year of construction, tenure status).

The features are available in different data formats, as shown in Table A.1 in the appendix. Thermal plant types and fuels are described using boolean data. Geometric data are expressed as numerical values, while other information is available as range definitions (e.g., years of construction). The study also considers other information provided as aggregated values available at the municipal, provincial, or regional level.

2.1.2. Validation buildings (VB)

To validate the model, a database of heat consumption data from approximately 170 district heating substations serving residential buildings was used. A unique code and address were required to identify each building. The association between VB and CD was possible using the addresses available from the two databases by developing a fuzzy logic algorithm in a Python environment. By operating on a spectrum of similarity instead of binary logic, the algorithm facilitated the recognition and connection of similar addresses despite minor variations in details. The association between VB and CD makes it possible to obtain, by applying the BRUSA model, the values of the geometric and construction characteristics and, consequently, the estimated heat consumption for each building for each heating season.

The actual thermal consumption data was sampled at 5-min intervals from the 2013/2014 heating season through the 2020/2021 heating season, providing eight years of thermal consumption data. For each building, the data from each heating season was averaged on an hourly basis and then aggregated to determine daily, monthly, and finally annual thermal demand. The annual consumption value for each building was used to validate the model.

2.1.3. Climate data

Among climatic data, the outside temperature is the variable that most influences the building's thermal demand [21]. The availability of real mean external daily temperature (Tm) values is crucial for evaluating the model's thermal consumption. To evaluate winter thermal energy needs, a reliable value of Heating Degree Days (HDD) was calculated for the years of analysis, according to Equation (1) reported in UNI EN ISO 15927–6:2008 [22]:

$$HDD = \sum_{1}^{n} (T_0 - T_m) \tag{1}$$

Internal temperature T_0 was assumed to equal 20 °C according to national law standards [23]. T_m values were collected from weather stations located in the area under analysis.

2.2. Model structure

The BRUSA model was developed through a bottom-up engineering approach, involving a process of upgrading and deep refining the E-SDOB model [11]. The most substantial difference between the previous version and the upgraded version concerns the ability to assign to each dwelling the characteristics that have the most significant influence on the thermal energy demand during the heating season (e.g. dimensions, U-values, plant efficiencies), as well as the fuel (or fuels) used. The upgraded model performs analyses and evaluations of building stocks without the necessity of classifying buildings into categories, as was previously required. Instead, it integrates specific data from the national census survey at the dwelling and building level.

Its capability to describe individual dwelling features in detail allows for the estimation of annual thermal energy demand.

The schematic diagram of the model is shown in Fig. 1. The BRUSA model estimates the thermal energy demand and fuel consumption during the heating season by applying Equations (2) and (3), described in detail in section 2.2.1. The estimation process is based on various inputs derived from national census data and additional technical assumptions.

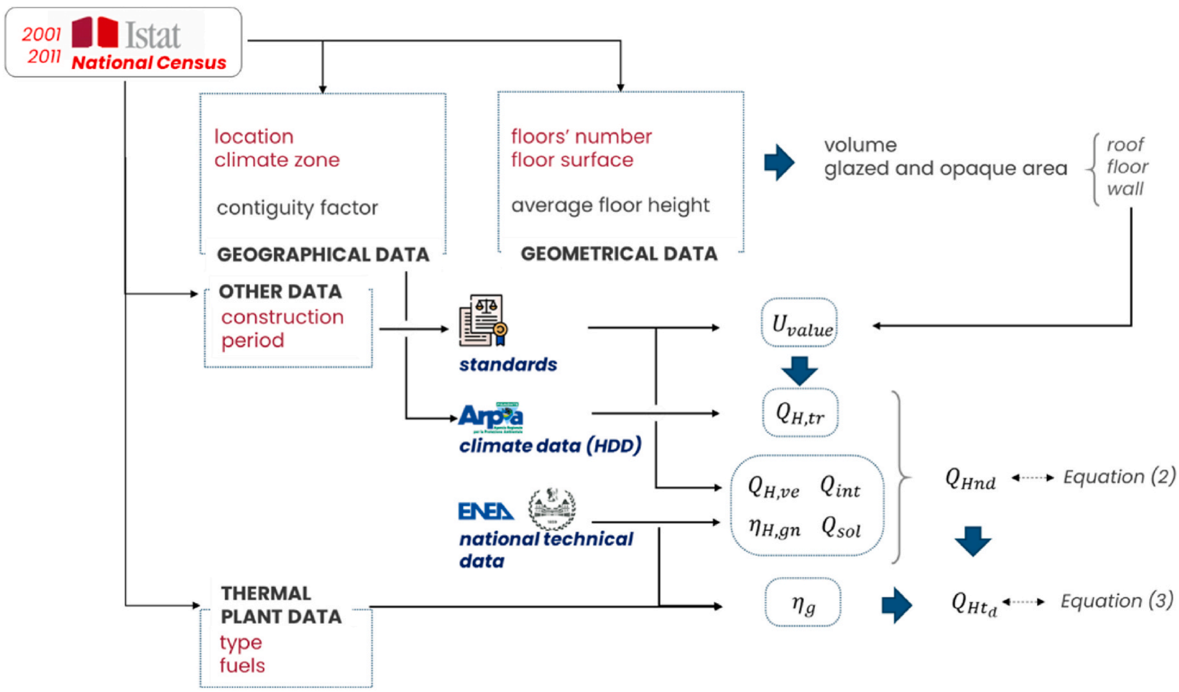


Fig. 1. Schematic representation of the data flow in the BRUSA model. The data from the national census (number of floors, floor surface area, location, year of construction, heating system data) are combined with measured climate data, the standards, and technical assumptions and to determine the parameters used in equations (2) and (3).

The terms of these equations are obtained as follows:

- the geometric characteristics of each building are obtained from the reprocessed census data. The methodology for this reprocessing is delineated in section 2.2.2;
- the construction characteristics are determined based on the geometric properties of the building, the period of construction, and the regulations in force at that time. This process is described in detail in section 2.2.3;
- the assumptions underlying the calculation of internal heat gain are delineated in section 2.2.4.

2.2.1. Structure and basis

Thermal energy and fuel consumption are evaluated by computing the thermal balance of each building, as given by Equation (2). For a given building (b), Equation (2) sums the contributions of the *n* dwellings (d) that comprise it, with each term defined using dwelling-level details:

$$Q_{Hnd_b} = \sum\nolimits_{d=1}^{n} \left(Q_{H,tr} - Q_{H,ve}\right)_d - \eta_{H,gn}\cdot\left(Q_{int} + Q_{sol}\right)_d \tag{2}$$

Each term of the equation is dependent on geometric characteristics, building construction, building materials, construction techniques, climatic data, and internal conditions as reported in Table A.2 in the appendix.

Subsequently, the primary energy needs of each dwelling (Q_{Ht}) are calculated by factoring in the global efficiency (η_g) of the thermal plant, which considers generation, distribution, emission, and control efficiencies (see Table A.3 in the appendix).

$$Q_{Ht_d} = \left(Q_{Hnd}/\eta_g\right)_d \tag{3}$$

$$\eta_g = \left(\eta_p\cdot\eta_d\cdot\eta_e\cdot\eta_c\right)_d \tag{4}$$

The thermal plant type, as well as allowing the estimation of generation efficiency, allows the identification of buildings with a centralised heating system. This is particularly interesting to evaluate the installation of district heating systems as detailed in section 3.2.1.

2.2.2. Geometric features (building level)

To evaluate each term in the thermal balance (2), certain geometric features must be defined for each building. Following the assumptions in the E-SDOB application [11], the model derives:

- total floor surface (S_T);
- glazed area (S_W).

Other geometric parameters are then computed as follows:

- the internal storey height is contingent upon the area under study and the year of construction;
- the total story height is calculated under the assumption that the slab thickness is equivalent to 30 cm;
- the calculation of building volume (V) is derived from the total floor surface area, the number of floors in the structure, and the storey height;
- base surface (S_B) and roof surface (S_R) are calculated as the ratio between the total floor surface (S_T) and the number of floors;
- the base shape is derived considering the square shape characteristic of buildings with up to two dwelling units. In the case of buildings comprising more than two dwellings, one side of the base is assumed to be equivalent to 9 m, and the second side is derived from the S_B value;
- the opaque surface (S_O) construction is defined by taking into account the external surfaces of walls, roofs, and basements. Subsequently, the process involves the subtraction of any adjacent walls, under the assumption of a contiguity factor. The evaluation of contiguity factor is derived from census data at the regional level [20];
- building envelope surface (S_D) is assumed equal to the sum of terms S_O and S_W;
- S_D/V factor is calculated as well.

2.2.3. Construction features evaluation (building level)

The evaluation of construction features, which focuses on thermal performance, concerns the U-value (U [W/m^{2}K]) which quantifies the heat transfer through each building envelope surface: glazed area, vertical opaque surfaces, roof, and basement. This value can be determined using different approaches, applied according to territorial analyses and standards [24,25]. In the case of buildings constructed before 1982, the average U-value of the walls is assumed for each dwelling, depending on the year of construction. The consideration of distinct U-values is contingent upon the building's climate zone [26].

For more recent buildings (built after 1982), the coming into force of National Laws 373/76 [27] and 10/91 [28] is taken into account by prescribing allowed values for building global thermal losses coefficient ($C_{d\ lim}$). According to national laws, the evaluation of $C_{d\ lim}$ is performed based on S_D/V factor value and HDD law value [26]; the U-values are then obtained individually for each building based on $C_{d\ lim}$ and hypotheses on the construction standards. For specific details, see Table A.4 in the appendix.

2.2.4. Indoor conditions (building level)

Indoor conditions are defined according to the E-SDOB model [11]. Internal heat gain is defined as the average electrical consumption during the heating season. The assessment is based on actual electricity consumption data for the defined area during the heating season. Solar heat gains are evaluated by considering the coverage of 10 % of the total net energy needs of each dwelling. This is particularly relevant for buildings located in urban areas, where higher shading effects related to high residential density must be taken into account. In non-urban areas, solar heat gains are estimated to account for 15 % of the total net energy demand.

Upgrades are implemented by differentiating between residential and holiday houses based on each dwelling's tenure status. It is estimated that the thermal energy demand for vacation homes is 15 % of the energy demand for residential homes. This difference assumes that vacation homes are mainly used during non-working days during the winter season.

2.3. Validation parameters

Two main parameters, percentage error (PE_b) and mean absolute percentage error (MAPE), were considered to validate the model and assess its performance at different levels of detail and scalability.

PE was calculated for each prediction to evaluate the model's performance at the level of individual buildings (b). PE represents the percentage difference between the observed data Ob and the data estimated by the BRUSA model Pb (Equation (5)):

$$PE_b = \frac{O_b - P_b}{O_b} \cdot 100\% \tag{5}$$

Subsequently, a statistical analysis of the distribution of PE_b was conducted. An approach based on non-parametric methods was adopted, namely Kernel Density Estimation (KDE). This method was selected for its ability to provide detailed information on the model's performance without relying on specific assumptions regarding the shape of the underlying distribution of the data. KDE was used to obtain a smooth and continuous representation of the percentage error distribution, offering an intuitive view of the general shape of the distribution, including modes. Finally, the error mode was calculated to obtain a reliable estimate of PEb (MoPE).

MAPE was considered to evaluate the model's overall performance. MAPE represents the average of the absolute percentage errors between the data estimated by the model and the observed data, and it is calculated using the following formula (Equation (6)), where m is the total number of validation buildings:

$$MAPE = 1 \Big/ m \cdot \sum\nolimits_{b=1}^{m} |PE_b| \tag{6}$$

The combined use of these parameters provides a comprehensive assessment of the model's accuracy, enabling the identification of its performance at the individual and overall building levels.

3. Result and discussion

This section presents the validation results and the application of the BRUSA model. First, the model performance is evaluated by comparing its outputs with actual consumption data, highlighting key sources of discrepancies. The model's ability to estimate thermal demand is assessed both at the individual building level and in aggregated form, showing how its accuracy improves with larger datasets. Following the validation, the model's practical applications are discussed, including its potential use for spatial energy planning and district heating installation assessments.

3.1. Model validation

The dataset used to validate the BRUSA model (VB) spans eight thermal seasons from 2014 to 2021. Integrating new buildings into the Turin DHS introduced variations in the analysis sample during this interval. The analysis focused on thermal seasons rather than calendar years to mitigate potential distortions in energy consumption data. This methodological choice avoids the partial inclusion of heating cycles, thereby preventing the erroneous underestimation of energy consumption in buildings connected during summer months. For each thermal season, HDD were calculated based on average daily temperature data recorded by meteorological stations near the buildings used for validation (Table 1).

Table A.5 of the appendix shows the number of VB for each thermal season analysed for which the model was validated. The total heated volume is approximately 0.8 million m^3 and rises to approximately 0.9 million m^3 as of the 2016 season as a result of buildings connected to district heating throughout the years of analysis.

The model outputs are compared with the actual data below.

3.1.1. Model performances

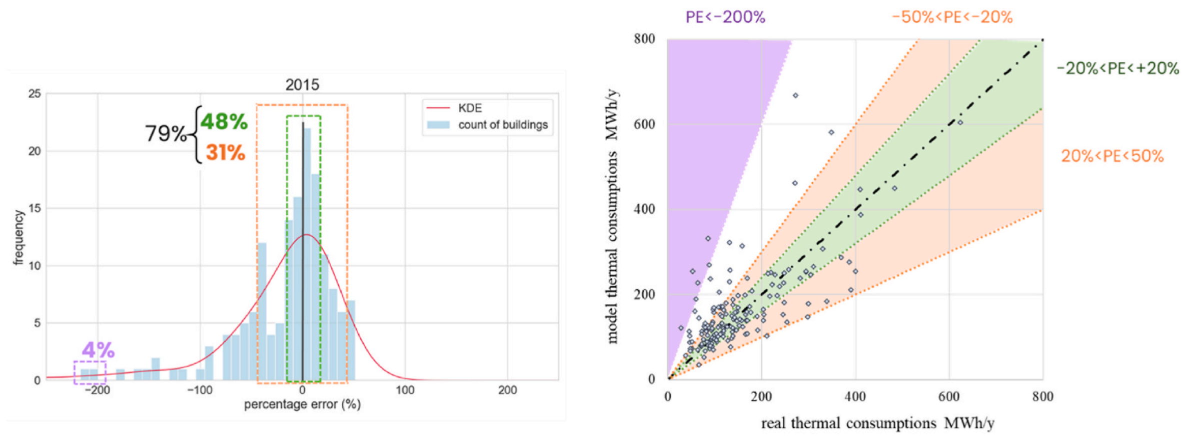
The thermal demand results of the BRUSA model were compared with actual consumption data, and the percentage error was calculated. The KDE, the MoPE, and MAPE were computed for each heating season. Findings reveal that approximately 27 % of the buildings show a MAPE of 10 %, while 60 % exhibit a MAPE of 30 %. For example, the KDE graph and the data's corresponding scatter plot are shown in Fig. 2. The percentage of buildings within the error range of ±20 %, ±50 %, and lower than −200 % are shown in the figure. The scatter plot shows that while the model performs well for many buildings, it tends to overestimate consumption for certain ones.

Four primary factors contributing to the discordances in individual buildings emerged:

- mismatch between the heated volume processed by the BRUSA model and the volume declared by the DHC operator: the heated volume represents a value that is not necessarily correct for either of the two input databases, as it is assumed from the building dimensions without considering any unheated spaces. 31 % of the buildings analysed show discrepancies between the volumes

Table 1
Heating Degree Days of seasons analysed.

Year	2014	2015	2016	2017	2018	2019	2020	2021
HDD	1960	2010	2080	2030	2310	2080	1980	2130



(a) (b)

Fig. 2. Season 2015: (a) in light blue the distribution of the number of buildings by percentage error and in red the KDE with respect to percentage error. 48 % of the buildings have a percentage error between ±20 % (green box) while 78 % of the buildings have a percentage error of ±50 % (orange box). 4 % of the buildings have a percentage error of more than 200 %; (b) scatter plot: relationship between annual thermal consumption estimated by the BRUSA model and actual annual thermal consumption.

assumed by the operator and those extrapolated from the model. This problem is particularly significant for buildings where the DHC substation may serve the whole building or only part of it. The association between the DHC substation and the model building is made on the basis of addresses. The discrepancy occurs when the BRUSA model considers each house number to be a separate part of the building, whereas the substation may serve multiple house numbers;

- the simplified geometric characteristics of the BRUSA model may not be perfectly aligned with the real building geometry, especially in densely urbanised areas such as Turin. The model assumes a degree of wall contiguity that varies according to the number of building units and their location (climate zone, urban area). Consequently, the model may overestimate the surface area dispersion in instances where there is no dispersion on the short sides of the building, provided that it is perfectly adjacent to contiguous blocks of flats. Conversely, the model may underestimate the surface area dispersion if the building is separated;
- presence of unoccupied dwellings: within the context of large apartment blocks in densely populated cities such as Turin, the presence of rented dwellings that are not constantly occupied may be relevant. A study estimated that 15 % of the urban volumes in the Turin city area are unoccupied [29]. As there is no evidence of this information, the model overestimates the heat demand compared to what occurred in the reference heating season;
- the behaviour of the occupants may deviate from the assumptions underpinning the normative standards applied in the study.

The KDE for each heating season of the validated buildings is shown in Fig. 3. The model demonstrated robust performance during the initial four-year period of analysis. However, beginning from the 2018 season, the BRUSA model exhibited a tendency to overestimate the annual thermal demand of the buildings. Potential causes for the model's overestimation, identifiable from a specific heating season onwards, include:

- installation of thermostatic valves: thermostatic valve installation became mandatory in 2017 [20], failure to install them by the building - unless justified by major technical problems - is subject to fines and penalties. According to studies carried out in the analysis area, the installation of thermostatic valves can reduce heat consumption by between 10 and 15 % [30];
- energy efficiency measures: building refurbishments with thermal insulation of opaque surfaces and/or replacement of windows result in a change in the thermal transmittance values of surfaces assumed by the model based on climatic zone and building construction period;

Since the analysis lacked information on specific energy efficiency measures implemented in the building sample, the only hypothesis that was introduced as of 2018 was the installation of thermostatic valves, which is mandatory by regulation. It is assumed that there has been a reduction in thermal demand of 12 %.

Table 2 shows the MoPE value for each heating season.

The heat demand forecast was also conducted at the census section scale and overall for the entire group of buildings analysed. A census section is a geographical unit used to collect and analyse demographic and socio-economic data, usually consisting of several buildings or housing units. In our study, the sample of buildings analysed was relatively small, including 170. Due to their geographical distribution, often only one or, at most, five buildings were included in each census section. Consequently, the model's performance at the census section level was similar to that expected for the individual building (see Fig. B.1. in the appendix). However, it was observed that the MAPE was drastically lower when estimating heat demand for the entire group of buildings (Fig. 4). This finding indicates that the model's sensitivity improves when applied to a more extensive sample of buildings, as the simplifications adopted, which represent the average of the buildings present, do not cause significant distortions in the results. A parallel analysis was conducted on the same sample of buildings, as described in Ref. [21]. In that study, heat demand was estimated using a tool based on the XGBoost machine learning model, which calculates the thermal energy demand at the building level on an hourly basis starting from the heating seasons of 2017. Aggregating the energy consumption of all buildings for each year and comparing these values with the actual consumption of users served by district heating resulted in a MAPE of approximately 12 %, a value comparable to that achieved by the BRUSA model. It is noteworthy that in both models, the MAPE decreases as the number of simulated buildings increases, due to the consequent reduction in the relative variability of the error.

3.2. Model application

The model is a simplified and easily replicable tool at a national level, and it is also suitable for use in other countries with data from

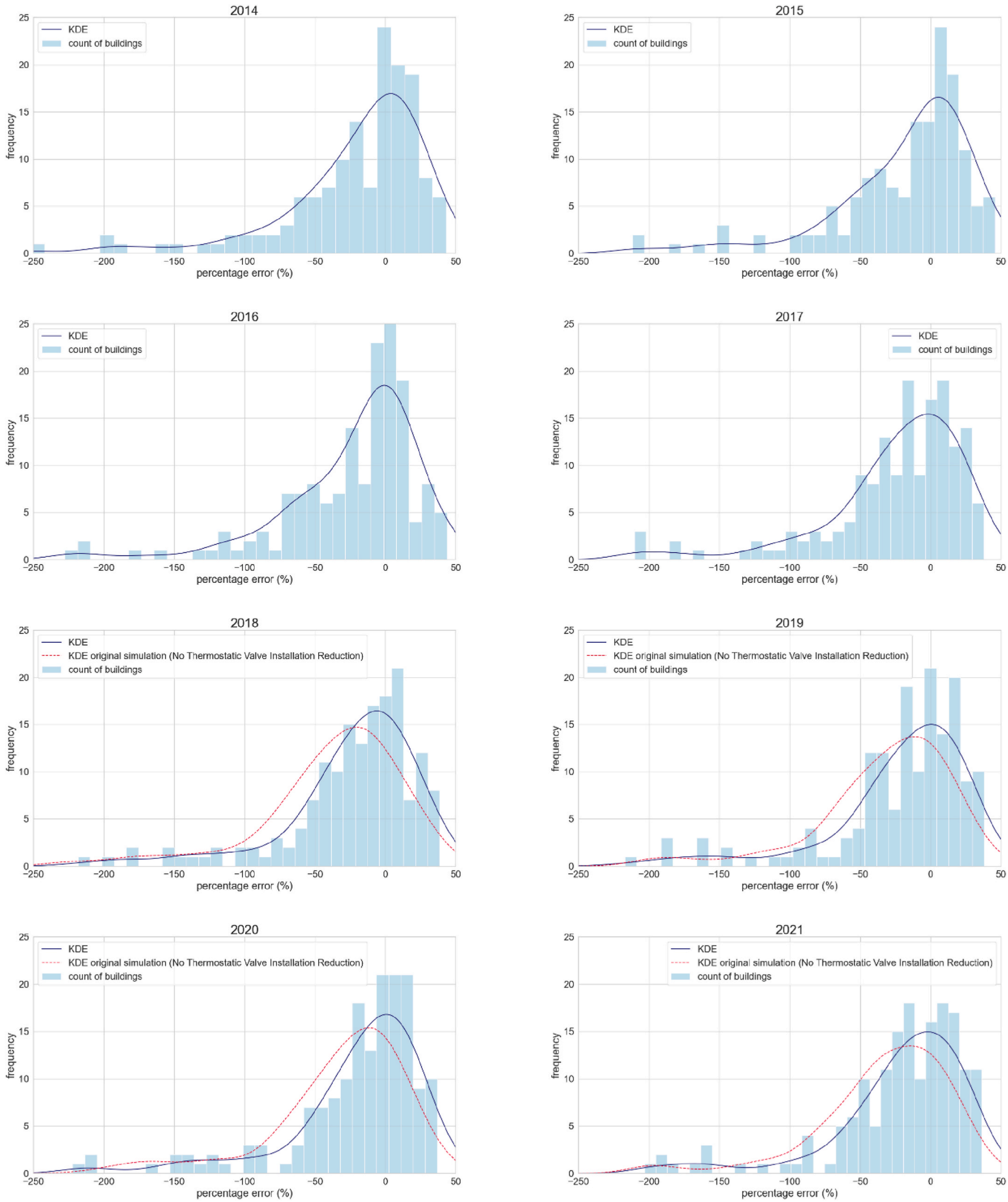


Fig. 3. KDE distribution at the building level for each thermal season. The red line represents the KDE without taking into account the reduction in heat demand achieved by installing thermal valves.

Table 2
Percentage error mode of the BRUSA model.

Year	2014	2015	2016	2017	2018	2019	2020	2021
MoPE	13 %	8 %	−1 %	5 %	6 %	14 %	1 %	8 %

statistical surveys or censuses similar to those conducted in Italy. This tool can accurately estimate thermal demand in spatially based energy planning contexts, providing a solid basis for various applications, including:

- modification of building thermal characteristics, such as thermal transmittance of opaque walls, roofs, basements, and windows, to evaluate the impact of energy efficiency measures on reducing energy consumption;
- quantification of primary energy and fuels needed to meet thermal demand following a shift in thermal energy production technologies;
- identification of potential areas for DHC implementation, taking into account existing heating system types (autonomous or centralised) and district heating volume thresholds;
- estimation of the reductions in CO_2 emissions achievable by decreasing energy demand and adopting more sustainable energy production technologies.

3.2.1. *Evaluation of district heating potential*

An illustrative application of the model focuses on assessing the potential for district heating implementation in a non-district-heated urban area located in the northern region of Italy's Po Valley. The BRUSA model was used to identify centralised heated residential buildings with a heated volume above the threshold value of 3000 m^3, aligning with typical values considered in the design of DHCs. The estimated volume is approximately 5 million m^3. In the preceding five heating seasons, a total of 2210° days have been recorded. Given these climatic conditions and an assumed reduction in consumption due to the installation of thermostatic valves, the seasonal thermal demand is estimated to be approximately 160 GWh/year. As illustrated in Fig. 5, each census section's potential volume and corresponding annual thermal energy needs are represented.

It is assumed that the DHC complies with the efficient district heating and cooling criteria [4]. The model assumes compliance with the 2035 targets, whereby at least 35 % of thermal energy is to be derived from

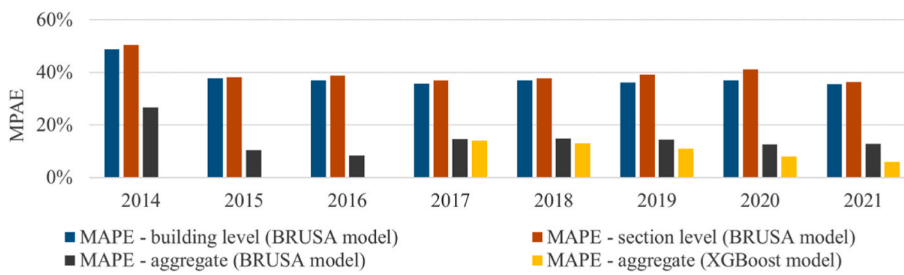


Fig. 4. MAPE values at the building, section, and aggregate level are compared with MAPE values obtained from the XGBoost model at aggregate level [21].

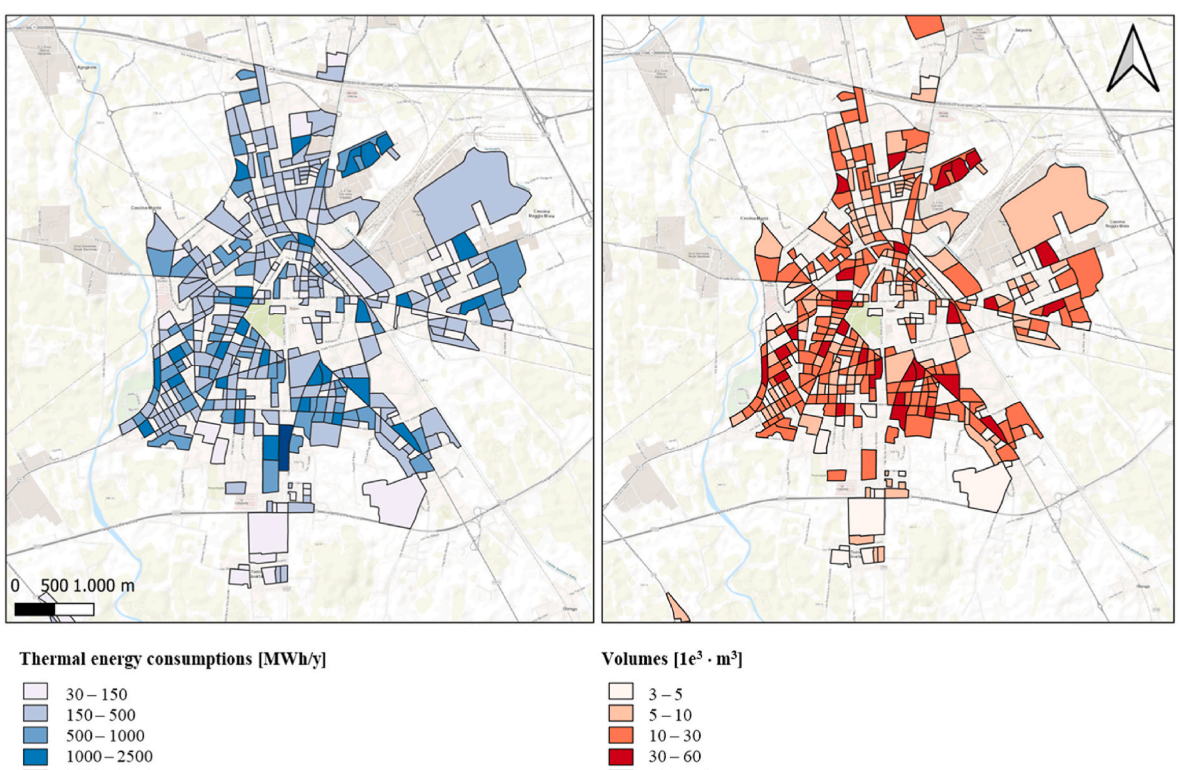


Fig. 5. Case study potential heating volumes and estimated annual thermal demand.

renewable sources, and up to 80 % can be generated from a combination of renewable sources, waste heat, and high-efficiency cogeneration. Woody biomass is considered to satisfy renewable energy requirements through the installation of wood chip boilers (BIO). The remaining 45 % is produced by a combined heat and power unit (CHP) through gas-fuelled internal combustion engines equipped with heat pumps for heat recovery. The remaining 20 % is produced by gas-fired integration and back-up boilers (IBB). The decision regarding the utilisation of a renewable energy source is contingent upon the seasonality of energy source availability, with the DHC being situated in a location that facilitates the exploitation of a local and sustainable supply chain of biomass products. The scenario under consideration is conservative in terms of CO_2 emissions. Based on the thermal energy required to satisfy the thermal demand of users, a heat loss rate of 15 % on the distribution network is assumed. The thermal energy produced by the generation plant is then converted into primary energy based on the average seasonal efficiencies of different technologies shown in Table B.1 in the appendix. Finally, the CO_2 emission contribution of the district heating system is calculated and compared with the current scenario in which all users supply their heating needs with natural gas boilers (seasonal efficiency 90 %). In the analysis, CHP-generated electricity is counted negatively regarding emissions because it avoids power generation from the electrical national grid. The calculation of emissions is performed by taking into account the electricity grid's emission factor, under the assumption that renewable sources contribute to 50 % of the national electrical energy production, as outlined in current national plans [31]. The assumed emission factor is, therefore, equal to 310 gCO_2/kWh. The emission factor for natural gas is equal to 202 gCO_2/kWh; biomass is a carbon-neutral fuel, meaning that the carbon emitted by biomass burning will not contribute to climate change if it is grown sustainably.

Fig. 6 shows the thermal and electrical energy produced by each generation plant component, the primary energy required, and the CO_2 emissions of the DHC scenario compared with the emissions of users currently served by natural gas boilers (current scenario). The data can be found in Table B.2 in the appendix. The DHC scenario would allow a 40 % reduction in CO_2 emissions.

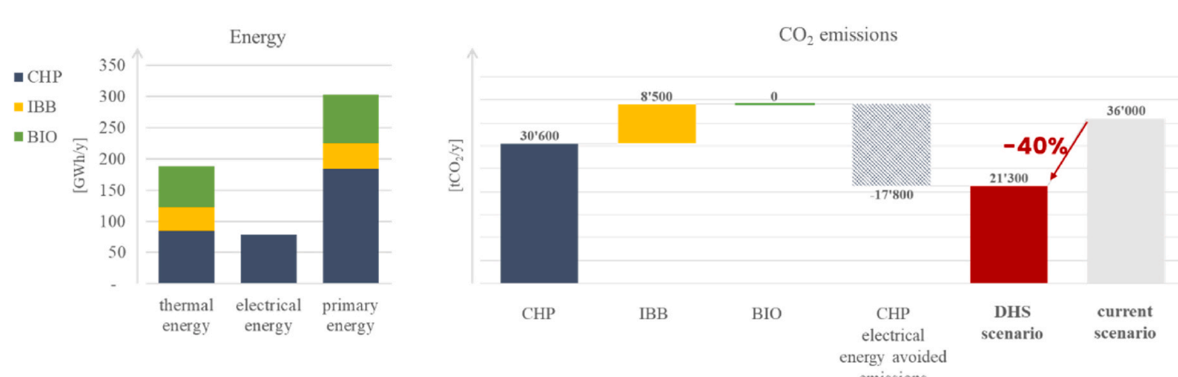
4. Conclusion

The present paper set forth the development, validation, and application of the BRUSA model, an estimation tool for thermal demand in the residential sector. The model employs a novel methodological approach that strikes a balance between computational simplification and analytical detail, rendering it applicable from individual building units to broader spatial scales. By leveraging data from national censuses, BRUSA exemplifies high scalability and adaptability, permitting its implementation in various territorial contexts, including international settings with statistical frameworks analogous to Italy's.

A distinguishing feature of the model is its independence from the application of archetype buildings; instead, reliance is placed on national census databases, allowing for detailed descriptions of all the main geometric and technical characteristics of individual dwellings. The processing of census data facilitates the incorporation of specific information regarding heating systems at the dwelling level, thereby expanding the model's scope of application. The dataset may in the future be updated and replaced by other databases (for example, plant cadastre, energy performance certificate) which currently provide incomplete coverage of the territory.

The model's validation was conducted using real energy consumption data from 170 buildings supplied by the Turin district heating system over eight heating seasons. The findings indicated a substantial concurrence between the model's estimations and the observed actual consumption, with the mean percentage error (MoPE) ranging from −1 % to 14 %. Despite occasional overestimations at the individual building level, the MAPE was significantly reduced at the aggregated level, thereby substantiating the model's resilience in large-scale energy planning applications. The BRUSA model's performance at the aggregate level is comparable to that achieved by an alternative approach that was explored in Ref. [21]. This model employs the XGBoost machine learning algorithm to estimate heat demand. The XGBoost-based approach yields comparable accuracy in aggregated demand estimation; nevertheless, it necessitates detailed building-specific information and elevated computational costs, rendering it more time-consuming. In contrast, the BRUSA model offers a more efficient and scalable solution, leveraging simplified assumptions while maintaining high accuracy in large-scale applications. This underscores the effectiveness of the BRUSA model in producing reliable projections of aggregated thermal demand, thus confirming its value as a critical tool in the field of spatial energy planning.

Beyond validation, the BRUSA model functions as a versatile instrument for evaluating energy efficiency measures. The model employs geometric and construction data from census processing to estimate the thermal performance of building elements, including walls, windows, basements, and roofs. This facilitates the evaluation of the impact of retrofitting interventions on heat demand. Furthermore, the model enables scenario analyses to assess policy-driven energy demand reductions, thereby facilitating strategic planning. Furthermore, the model fulfils a strategic function in the transition towards low-carbon local energy systems. It provides a comprehensive understanding of the building stock, integrating geometric and construction features with heating system data. This capacity facilitates the assessment of alternative energy technologies, thereby enabling the estimation of their impact on primary energy consumption, fuel demand, and greenhouse gas emissions.



(a) (b)

Fig. 6. (a) Thermal and electrical annual energy production and primary annual energy consumption of DHC scenario; (b) comparison of CO_2 emissions between current scenario and DHC scenario.

A case study was conducted to explore the feasibility of district heating implementation in a non-district-heated urban area in northern Italy. The results indicate that integrating an efficient district heating system, with at least 35 % of thermal energy sourced from renewables, could lead to a 40 % reduction in CO_2 emissions. The model's flexibility suggests that it could be applied to similar scenarios in different geographical areas, supporting the identification of optimal locations for district heating expansion and evaluating the benefits of integrating renewable energy sources. The incorporation of additional data sources, such as detailed information on recent building renovations, could lead to further refinement of the BRUSA model in future research. In summary, the BRUSA model is a versatile instrument for spatial energy planning, with the capacity to provide reliable thermal demand, making it particularly useful for guiding energy efficiency policies, designing sustainable heating solutions, and fostering the transition to low-carbon energy systems.

CRediT authorship contribution statement

Chiara Monzani: Writing – review & editing, Writing – original draft, Visualization, Validation, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Giulio Cerino Abdin:** Writing – review & editing, Visualization, Software, Methodology, Conceptualization. **Alberto Poggio:** Writing – review & editing, Supervision, Methodology, Conceptualization. **Giulia Montanari:** Writing – review & editing, Visualization, Investigation.

Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this work the authors used Grammarly and Chat GPT in order to proofread the text and correct grammar and syntax errors. After using this tool/service, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

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.

Acknowledgments

The authors gratefully acknowledge Michela Bevione and Andrea Crocetta for their valuable contribution to the development of the methodology underlying the BRUSA model.

Appendix A

Table A.1
Individual dwelling's features

	Sources	Data type
Geographical data	Municipality (scale 1:25,000 ÷ 1:100,000)	Geocode
	Census Parcel (scale 1:500 ÷ 1:10,000)	Geocode
	Building	Geocode
Thermal Plant: type	Central heating	Boolean
	Independent heating	Boolean
	Appliances in each room of dwellings	Boolean
	Appliances limited to some rooms of dwellings	Boolean
	No heating	Boolean
Thermal Plant: fuels	Central heating	Boolean
	Light fuel oil	Boolean
	LPG	Boolean
	Wood	Boolean
	Electricity	Boolean
	Fuel oil	Boolean
	Coal	Boolean
	Solar energy	Boolean
	Others (District heating, …)	Boolean
Geometrical data	Floors	Value
	Floor area	Value
Other	Years of construction	Classes
	Tenure status	Classes

Table A.2
Factors influencing buildings' thermal balance

	$Q_{H,tr}$	$Q_{H,ve}$	$\eta_{H,gn}$	Q_{int}	Q_{sol}
Geometrical features	X	X	X		
Materials/Construction features	X		X		
Climate data	X	X			X
Internal conditions				X	X

Table A.3
Efficiency's values

Efficiency	η_p	η_d	η_e	η_c	η_g
Natural gas – central heating	85 %	95 %	94 %	96 %	73 %
Natural gas – independent heating	80 %	99 %	99 %	96 %	75 %
Light fuel oil	83 %	95 %	94 %	96 %	71 %
District Heating system	100 %	95 %	94 %	96 %	86 %

Table A.4
U value and Cd values

	U [W/m^{2}K]								Cd [W/m^{3}K]
	External walls		Roof		Basement	Glazed surface			
	E	F	E	F		F	Independent Heating system	Central Heating system	
Before 1981	1.10	1.75	1.17	0.70	0.75	3.20	3.70	5.00	–
1982–1991	–	–	–	–	–	–	–	–	N.L. 373/76
After 1991	–	–	–	–	–	–	–	–	N.L. 10/91

Table A.5
count of Validation Buildings (VB) for each season

2014	2015	2016	2017	2018	2019	2020	2021
154	159	169	171	172	168	175	178

Appendix B

Table B.1
plant generators' efficiency

CHP	Thermal efficiency	56 %
	Electrical efficiency	41 %
IBB	Thermal efficiency	90 %
BIO	Thermal efficiency	85 %
User's gas boiler	Thermal efficiency	90 %

Table B.2
case study application energy data

Users' annual thermal demand		GWh/y	159.85
Users' natural gas boiler annual thermal energy produced		GWh/y	159.85
Users' natural gas boiler annual primary energy		GWh/y	177.61
Users' natural gas boiler annual CO2 emission		kt/y	36.02
DHC annual thermal energy produced		GWh/y	188.06
	by IBB	*GWh/y*	*37.61*
	by RES	*GWh/y*	*65.82*
	by CHP	*GWh/y*	*84.63*
DHC annual electrical energy produced		GWh/y	60.45
DHC annual electrical energy delivered to the grid		GWh/y	57.43
DHC annual primary energy		GWh/y	270.35
	by IBB	*GWh/y*	*41.79*
	by RES	*GWh/y*	*77.44*
	by CHP	*GWh/y*	*151.12*
DHC generation annual CO2 emission		kt/y	39.12
DHC avoided electrical CO2 emission on national grid		kt/y	−17.80
DHC annual CO2 emission		kt/y	21.32
CO2 emissions balance		kt/y	14.70
CO2 reduction		%	41 %

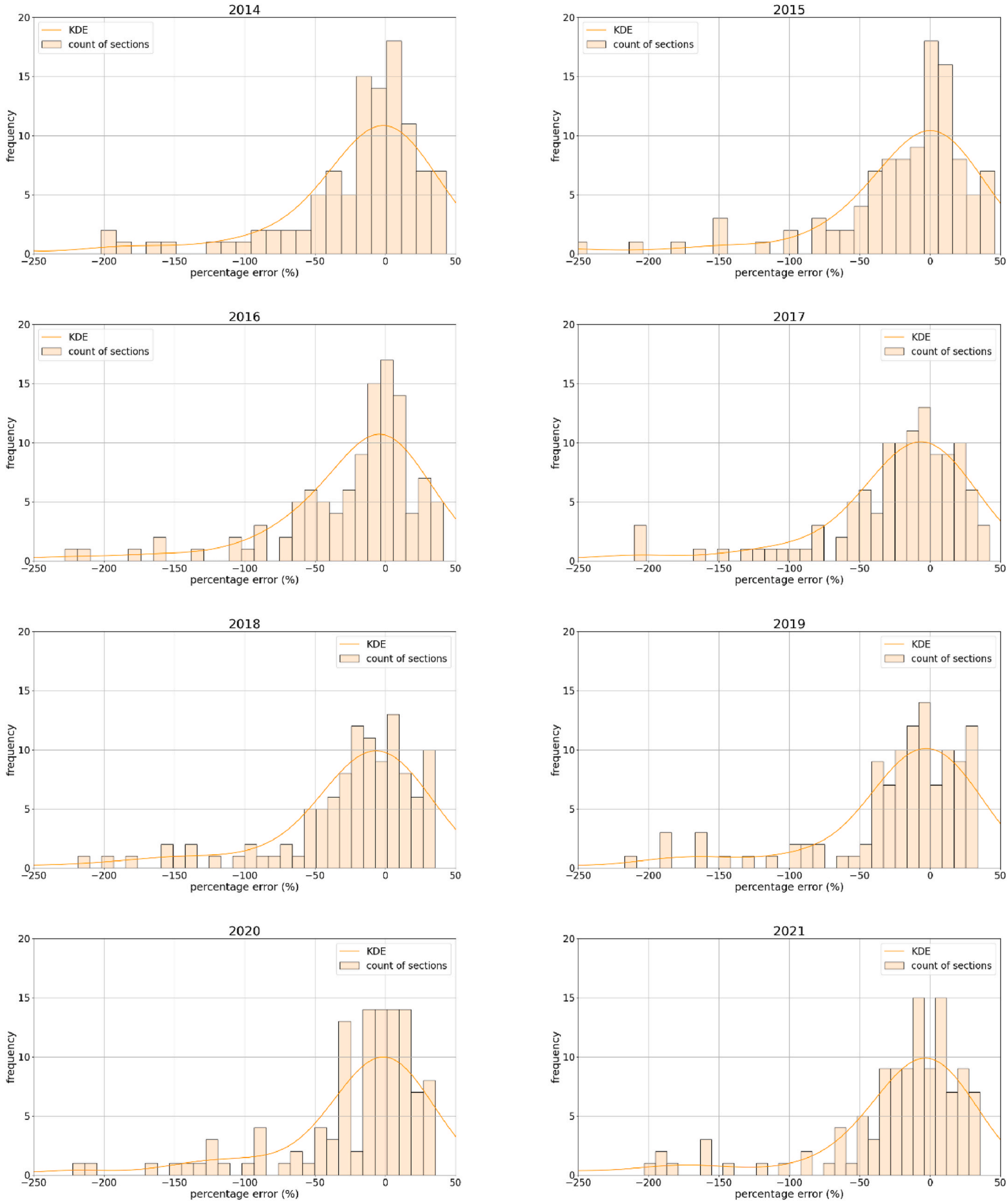


Fig. B.1. KDE distribution at section level for each thermal seasons.

Data availability

The data that has been used is confidential.

References

[1] Eurostat, Statistics Explained. Energy consumption in households 2021 [Online]. Available: https://ec.europa.eu/eurostat/statistics-explained/index.php?title=Energy_consumption_in_households; 2024.

[2] European Parliament and Council, Directive (EU) 2023/2413 of 18 October 2023 amending Directive (EU) 2018/2001. Regulation (EU) 2018/1999 and directive 98/70/EC as regards the promotion of energy from renewable sources, and repealing council directive (EU) 2015/652. 2023.

[3] European Parliament and Council. Directive (EU) 2024/1275 of 24 April 2024 on the energy performance of buildings. recast); 2024.

[4] European Parliament and Council. Directive (EU) 2023/1791 of the European parliament and of the council of 13 September 2023 on energy efficiency and amending regulation (EU) 2023/955. 2023.

[5] Meha D, Novosel T, Duić N. Bottom-Up and top-down heat demand mapping methods for small municipalities, case gllogoc. Energy (Calg) 2020;199:117429. https://doi.org/10.1016/j.energy.2020.117429.

[6] Meha D, Dragusha B, Thakur J, Novosel T, Duić N. A novel spatial based approach for estimation of space heating demand saving potential and CO2 emissions reduction in urban areas. Energy (Calg) 2021;225:120251. https://doi.org/10.1016/j.energy.2021.120251.

[7] Yu D. Two-step approach to forecasting city-wide building energy demand. Energy Build 2018;160:1–9. https://doi.org/10.1016/j.enbuild.2017.11.063.

[8] Verwiebe PA, Seim S, Burges S, Schulz L, Müller-Kirchenbauer J. Modeling energy Demand—ASystematic literature review. Energies 2021;14(7859).

[9] Shen P, Wang H. Archetype building energy modeling approaches and applications: a review. Renew Sustain Energy Rev 2024;199:114478. https://doi.org/10.1016/j.rser.2024.114478.

[10] Dineen D, Rogan F, Ó Gallachóir BP. Improved modelling of thermal energy savings potential in the existing residential stock using a newly available data source. Energy (Calg) 2015:759–67. https://doi.org/10.1016/j.energy.2015.07.105.

[11] Fracastoro GV, Serraino M. A methodology for assessing the energy performance of large scale building stocks and possible applications. Energy Build 2011;43: 844–52. https://doi.org/10.1016/j.enbuild.2010.12.004.

[12] Kim S, Yun GY, Ahmed Gassar AA. Data-driven approach to prediction of residential energy consumption at urban scales in London. Energy (Calg) 2019;187. https://doi.org/10.1016/j.energy.2019.115973.

[13] Xu W, Tu J, Xu N, Liu Z. Predicting daily heating energy consumption in residential buildings through integration of random forest model and meta-heuristic algorithms. Energy (Calg) 2014;301. https://doi.org/10.1016/j.energy.2024.131726.

[14] D'Alonzo V, Novelli A, Vaccaro R, Vettorato D, Albatici R, Diamantini C, Zambelli P. A Bottom-Up spatially explicit methodology to estimate the space heating demand of the building stock at regional scale. Energy Build 2020;206: 109581. https://doi.org/10.1016/j.enbuild.2019.109581.

[15] Piemonte Regione. Piano Regionale di Qualità dell'Aria (PRQA) - allegato C - analisi dei consumi energetici e riduzioni emissive ottenibili. 2019.

[16] Spirito G, Dénarié A, Fattori F, Muliere G, Motta M, Persson U. Assessing district heating potential at large scale: presentation and application of a spatially-detailed model to optimally match heat sources and demands. Appl Energy 2024;372. https://doi.org/10.1016/j.apenergy.2024.123844.

[17] Nielsen S. A geographic method for high resolution spatial heat planning, vol. 67; 2014. p. 351–62. https://doi.org/10.1016/j.energy.2013.12.011.

[18] ISTAT. XIV Censimento Generale della Popolazione e delle Abitazioni. 2011.

[19] Cerino Abdin G. Modelli per la pianificazione locale di filiere energetiche da biomassa forestale. 2015. Doctoral Thesis.

[20] Istat [Online]. Available: http://dawinci.istat.it/; 2011. June 2023.

[21] Monzani C, Cerino Abdin G, Poggio A, Montanari G. Modelling hourly thermal energy demand: a machine learning approach of residential district heating substations in turin. Renewable Energies and Power Quality (ICREPQ'24) 2024;22. https://doi.org/10.52152/4003.

[22] UNI, UNI EN ISO 15927-6. Prestazione termoigrometrica degli edifici - Calcolo e presentazione dei dati climatici - parte 6: Differenze di temperatura cumulate (gradi giorno). 2008.

[23] UNI. UNI/TS 11300-2 energy performance of buildings part 2: evaluation of primary energy need and of system efficiencies for space heating and domestic hot water production. 2008.

[24] CTI, CTI - R 3/2003 - Raccomandazione CTI: Prestazioni energetiche degli edifici. Climatizzazione invernale e preparazione acqua calda per usi igienico-sanitari. 2003.

[25] UNI. UNI/TS 11300-1 energy performance of buildings part 1: evaluation of energy need for space heating and cooling. 2008.

[26] D.P.R. 26 agosto 1993 n.412. "Regolamento recante norme per la progettazione, l'installazione, l'esercizio e la manutenzione degli impianti termici degli edifici ai fini del contenimento dei consumi di energia. 1993. p. 10. in attuazione dell'art. 4, comma 4, della L. 9 gennaio 1991.

[27] Legislative Decree N. 20 of April 1976. Norme per il contenimento del consumo energetico per usi termici negli edifici. 1976. p. 373.

[28] Legislative Decree No. 10 of January 1991. Norme in material di uso razionale dell'energia, di risparmio energetic e di sviluppo delle fonti rinnovabili di energia. 1991. p. 10.

[29] Casalengo M, Sanatangelo M. Il patrimonio abitativo inutilizzato: metodologie di analisi e ipotesi per il caso di Torino. Master Degree from Politecnico di Torino 2019.

[30] Monetti V, Fabrizi E, Filippi M. Impact of low investment strategies for space heating control: application of thermostatic radiators valves to an old residential building. Energy Build 2015. https://doi.org/10.1016/j.enbuild.2015.01.001.

[31] MASE. ma. PNIEC - piano Nazionale Integrato per l'Energia e il Cli. 2019.