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# Generation of heat and electricity load profiles with high temporal resolution for Urban Energy Units using open geodata

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ABSTRACT

Urban areas account for up to 87% of global energy consumption, with around a third of $CO_2$ emissions from the building sector. Germany recently enacted a law targeting carbon neutrality in heating by 2045, requiring all municipalities to submit transformation plans for their heating infrastructure. Many are in early stages and need innovative methods to achieve these goals. This study proposes an automated GIS-based approach to generate heat and electricity load profiles for geographically referenced residential buildings and districts in Germany, using only open data. The methodology offers hourly temporal resolution and spatial detail from individual buildings to Urban Energy Units (UEUs), a concept introduced in prior studies. Nine distinct heating load profiles and nine electricity load profiles were identified. These profiles can adapt to different weather datasets and to three building refurbishment scenarios. The methodology and energy analysis were applied to a district in Oldenburg, Germany, demonstrating the model's flexibility under varying boundary conditions. For this district, the analysis revealed a total heat demand of $9.9 \pm 7$ GWh/a and an electricity demand of $2.3 \pm 0.126$ GWh/a, with respective errors of 45% and 39% when compared to other local data, this demand is presented in both yearly and hourly resolutions. This methodology intends to support German municipalities by accelerating the initial phases of the municipal heating plans and deliver high-quality data on building heat and electricity demand.

## 1. Introduction

Urban areas account for as much as 87% of global energy use, with roughly a third of greenhouse gas (GHG) emissions coming from buildings (DESA, 2019; IEA, 2021, 2023; Umweltbundesamt, 2023). Reducing energy consumption in cities and related $CO_2$ emissions significantly involves addressing this sector. Around 80% of the German residential energy consumption is attributed to heating and hot water systems (IEA, 2020; Umweltbundesamt, 2023), contributing notably to GHG emissions as displayed in Fig. 1.

Germany has enacted new legislation aiming for heating sector neutrality by 2045 (BMWK, 2020; BMWSB, 2023). This law mandates that all municipalities develop and submit plans for transforming their heating infrastructure in four phases: inventory analysis, potential analysis, target scenario 2040, and implementation strategy. Many municipalities have not started with the task, being in need accurate and high-quality data on building energy demand (Deutscher Städtetag, 2023). In order to make this possible, specialized engineering firms need to design transformation plans, requiring precise data about the energy demand of the specific regions to avoid costly errors. Load profiles of heat and electricity demand are essential for energy system modeling and therefore, essential to create comprehensive transformation plans (Büttner, Amme, Endres, Malla, Schachler, & Cußmann, 2022). Public datasets often lack detailed building characteristics, previous studies like the ones from Blanco, Aditya, Schiricke, and Hoffschmidt (2023), Garbasevschi et al. (2021), Ponge et al. (2021), Wurm et al. (2021) and Blanco, Alhamwi, Schiricke, and Hoffschmidt (2024), have shown that high-quality data at the building level can be obtained using open data and machine learning (ML). Blanco et al. (2024), building on Dettmar, Drebes, and Sieber (2020), introduced a method for analyzing district-level regions cost-effectively, by identifying regions within a city which they labeled Urban Energy Units (UEUs).

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**Nomenclature**

**Abbreviations**

| | |
|---|---|
| AB | Apartment Block |
| ALKIS | German Official Cadastral Data (German: Amtliche Liegenschaftskatasterinformationssystem) |
| AMY | Actual Meteorological Year |
| ANN | Artificial Neural Network |
| BGW | German Gas and Water Association (German: *Bundesverband der deutschen Gas- und Wasserwirtschaft*) |
| CDS | Copernicus Climate Data Store |
| CHP | Combined Heat and Power |
| DHW | Domestic Hot Water |
| DT | Decision Tree |
| DWD | German Meteorological Service (German: *Deutscher Wetterdienst*) |
| GHG | Greenhouse Gas |
| GIS | Geographical Information System |
| HVAC | Heating, Ventilation and Air Conditioning |
| INSPIRE | Infrastructure for Spatial Information in the European Community |
| ISO | International Organization for Standardization |
| IWU | Institut Wohnen und Umwelt |
| JRC | Joint Research Centre |
| LoD | Level of Detail |
| MFH | Multifamily house |
| ML | Machine Learning |
| RF | Random Forest |
| SFH | Single-family house |
| SLP | Standard Load Profile |
| TABULA | Typology Approach for BUiLding stock energy Assessment |
| TH | Terraced house |
| TRY | Test Reference Year |
| UEU | Urban Energy Unit |
| VDI | Verein Deutscher Ingenieur |

**Symbols**

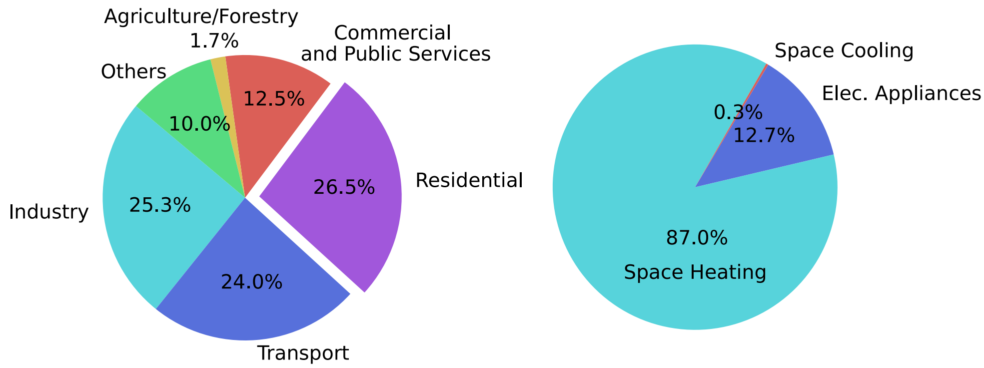
| | |
|---|---|
| $A$ | Sigmoid parameter $A$ |
| $A_{\mathrm{bp}}$ | Footprint area of a building part |
| $A_{\mathrm{f}}$ | Footprint area of the building |
| $A_{\mathrm{n}}$ | Total floor area of the building |
| $B$ | Sigmoid parameter $B$ |
| $b_{\mathrm{space}}$ | Interception of linear equation for space heat |
| $b_{\mathrm{water}}$ | Interception of linear equation for water heat |
| $C$ | Sigmoid parameter $C$ |
| $D$ | Linear parameter $D$ |
| $d$ | Day |
| $f_{d,l}$ | Nominated daily water heat quantity dependent on day ($d$) and location ($l$) |
| $h_{d,l}$ | Nominated daily heat quantity dependent on day ($d$) and location ($l$) |
| $l$ | Location |
| $m_{\mathrm{space}}$ | Slope of linear equation for space heat |
| $m_{\mathrm{water}}$ | Slope of linear equation for water heat |
| $n_f$ | Number of floors |
| $Q$ | Heat Demand |
| $Q''$ | Specific Heat Demand |
| $r_f$ | Roof type factor |
| $T$ | Temperature |
| $T_0$ | Temperature reference limit: 40 °C |

In their study, Blanco et al. (2024) developed a methodology that transitions from a building-oriented perspective to a more comprehensive district-level analysis by subdividing the urban fabric of a city into smaller units that can be better quantified and classified. This approach is based on the premise that the urban space of a city can be divided into morphological similar units (describing typical settlement patterns) that can be combined in a modular way for a holistic analysis of its structure and consequently its energy demand. Their methodology delineates pre-existing regions within a city and labels them as UEUs. Each UEU represents a specific geographical area with distinct building characteristics, settlement patterns, and energy demands. These units serve as modular building blocks for creating energy districts, as they can be combined to define larger geographical areas, or districts, each with its own unique geographic boundaries, features, and energy needs. By utilizing GIS-based and data-driven models, the subdivision of a city or region in Germany can be automated, standardizing the process while reducing both time and costs.

Blanco et al. (2024) were able to classify sixteen different UEU classes which represent urban regions with specific settlement patterns and energy demands. The authors developed an automatized process in order to take any given area in Germany and subdivided into regions that are later classified into one of the different UEU classes by utilizing only open geodata, hence the relationship with this study. This autotomized process was employed in the city of Oldenburg, Germany and provided a clear methodology in order to understand heat and electricity energy demand of the urban sector at a spatial resolution at the UEU level and yearly time resolution. This process and the different UEU classes can be seen both graphically and numerically and are explained in this paper in both Sections 3 and 4 as well as in the graphical abstract. While the previous methods offer high spatial resolution, it lacks the temporal dimension as it only provides annual demand values.

This study aims to enhance the temporal resolution of the model of Blanco et al. (2024) by generating heat and electricity demand curves with hourly resolution using open-access data, but maintaining at the same time the model's spatial resolution at the building and UEU levels. The goal is to develop a GIS-based method for creating load profiles for georeferenced residential and non-residential buildings in Germany. This model aims to support the creation of heating plans in Germany by providing detailed energy demand insights of their local energy demand. The study objectives include:

- Construct a building database for any given area using the model proposed by Blanco et al. (2024).
- Integrate specific localized weather data into the model.
- Generate heat and electricity demand curves for individual buildings in the study area for a reference year.
- Aggregate both energy demand curves into the study area's UEUs.
- Normalize and typify the aggregated demand curves for each UEU type.
- Assess the relevance of UEUs and their demand curves in real-world scenarios, particularly for Germany's municipal heating plans.




(a) Energy consumption by sector (b) Residential energy consumption by category

**Fig. 1.** Germany's final energy consumption by sector and final residential energy consumption by category in 2020. Data taken from IEA World statistics Germany (IEA, 2020).

## 2. Literature review

Urban energy planning focuses on creating synthetic heat and electricity load profiles for residential buildings to develop sustainable energy solutions Proedrou (2021), Schreiber et al. (2023). Transitioning from fossil fuel-based heating to electric or hydrogen systems requires estimating the energy demand of traditional systems Heitkoetter, Medjroubi, Vogt, and Agert (2020). As renewable energy replaces electricity for household needs, it is essential to analyze time-varying factors affecting building energy consumption. Accurate load profile generation is crucial for optimizing energy demand patterns, which is in itself a current challenge in energy analysis due to the fact that data such as user behavior or hourly consumption data is difficult to obtain because of factors such as unavailability of the data, data privacy laws compliancies and/or non-real time measure of consumption data. To address this need, this work applied the methodology developed by Blanco et al. (2024), creating a building-level resolution database using publicly available data and generating energy demand profiles (both heat and electricity) for individual buildings as well as for UEUs. This section provides a succinct summary of the literature currently available on methods for modeling heat and electricity load profiles, current approaches for typifying time-varying profiles, the importance of both heat and electricity load profiles in the new German legislation for municipal heating planning and the current challenges for municipalities and energy planners.

### *2.1. Load profile generation*

The classification of residential load profile models is multidimensional, encompassing methodological approaches, sampling rates, application domains, and statistical methods (Proedrou, 2021). Methodological approaches are typically categorized as bottom-up, top-down, or hybrid models. Sampling rates are classified into low-, middle-, or high-resolution models. These models serve various application domains such as demand-side management, control, design of energy systems, among others. Statistical methods include Markov chain modeling, statistical and probabilistic methods, and Monte-Carlo simulations, among others. However, the literature indicates the need for additional modeling parameters to comprehensively classify each model. These parameters include accessibility of the model and data for consultation by other researchers (Heitkoetter et al., 2020), the influence of household size and consumer behavior (Flett & Kelly, 2021), and the spatial resolution of the model (Fonseca & Schlueter, 2015).

This paper explores various authors' works concerning parameters crucial for generating and categorizing both heat and electricity load profiles in residential dwellings. Each parameter essential in the context of load profiles will be systematically addressed, establishing connections with aspects relevant to the present study.

**Type of load profile:** Some authors, such as Anvari et al. (2022), Flett and Kelly (2017), Idowu, Saguna, Å hlund, and Schelén (2016), have exclusively modeled either heat or electricity demand. Conversely, Fischer, Wolf, Scherer, and Wille-Haussmann (2016), Fonseca and Schlueter (2015), Lindberg, Bakker, and Sartori (2019), Penya, Borges, and Fernández (2011), Yao and Steemers (2005) have addressed the modeling of both heat and electricity demand. While concentrating on modeling a specific type of demand provides a detailed understanding of that load, the modeling of both demands presents a more holistic view of the overall energy demand in residential buildings.

**Method:** Heitkoetter et al. (2020), Labeeuw and Deconinck (2013) formulated a top-down model aimed at establishing a mathematical correlation between reported energy consumption and potential attributable energy consumption per household. On the other hand, both Anvari et al. (2022) and Penya et al. (2011) developed hybrid models. The former analyzed highly detailed residential electricity consumption data, proposing a broadly applicable, data-driven load model. The latter focused on non-residential buildings' load, constructing a model for short-term forecasting using ML algorithms and workday schedules as day-type classifiers. While capable of forecasting load profiles based on statistics, it falls short in generating profiles based on occupants' energy demand behavior. This distinction is crucial, as it enables bottom-up approaches to capture how occupants generate energy demand, allowing for aggregation at the neighborhood or city level for comparison with real energy consumption. In the case of electricity demand load profiles, Fischer, Härtl, and Wille-Haussmann (2015), Fischer et al. (2016) use a stochastic bottom-up approach for electrical loads, which is extended to include domestic hot water (DHW) and space heating demand. A behavioral model is used to determine DHW consumption, electrical appliance use and building temperature settings. For heat demand load profiles, Fonseca and Schlueter (2015) modeled building subsystems representing all possible heat flows, including heat losses due to ventilation and transmission, as well as internal heat gains due to occupancy, solar radiation, appliances and lighting. Mathematical and logical relationships between these variables were used then to estimate the net space heating, cooling and hot water demand. In all these cases, the unit of study (a household or a building) is first modeled based on variables such as household size, occupancy patterns, building characteristics and energy use habits. The modeled unit is then aggregated to estimate energy demand at the district or city level.

**Box-model:** In some prior research (Anvari et al., 2022; Heitkoetter et al., 2020; Kairisa et al., 2022; Pflugradt & Muntwyler, 2017; Staffell, Pfenninger, & Johnson, 2023), a white-box approach is employed, characterized by the use of open-source data, the publication of implemented code, and explicit explanations of mathematical relationships within the model. In contrast, the majority of authors, as in the case of Fischer et al. (2015), Fonseca and Schlueter (2015), Idowu et al. (2016), Yao and Steemers (2005) and others, adopt a grey box approach, providing details of their source code and using either public or non-public data, or providing general explanations of their modeling approach and the equations implemented in the methodology. Only Labeeuw and Deconinck (2013), Penya et al. (2011) can be categorized as adopting a black-box approach, as they do not substantially publish the equations used, the source code or the data used.

**Consumer behavior:** The studies made by Fischer et al. (2015, 2016), Nijhuis, Gibescu, and Cobben (2016), Pflugradt and Muntwyler (2017), Yao and Steemers (2005) focus on modeling building occupant behavior, detailing factors like illness periods, personal hobbies, and device ownership to simulate Domestic Hot Water (DHW) tapping, electric appliance use, and temperature settings. They employ statistical data or psychological models to represent occupants as desire-driven agents. While some consulted authors limit their definition to the number of occupants per building Heitkoetter et al. (2020), other authors like Anvari et al. (2022), Idowu et al. (2016), Labeeuw and Deconinck (2013), Lindberg et al. (2019), Penya et al. (2011), Sakkas and Abang (2022) either neglect consumer behavior or rely on standard load profiles (SLPs) or historical energy consumption statistics to generate future load profiles.

**Building details:** The authors Fischer et al. (2016), Fonseca and Schlueter (2015), Heitkoetter et al. (2020), Kairisa et al. (2022), Staffell et al. (2023) constructed models that incorporate highly detailed information about each modeled building. These models encompass crucial parameters such as the building's age, type, insulation based on energy class, household area, number of storeys, and heat interaction with neighboring buildings. This detailed information is particularly pertinent for models focused on defining heat demand load profiles. Given the strong correlation between heat demand and local weather conditions, local weather data is considered a significant input in these models. Conversely, some studies in the literature review only consider one or two of these parameters, resulting in less accurate heat load estimations. On the opposite end of the spectrum, certain papers, particularly those centered on data-driven machine-learning approaches, disregard building details as input variables.

**Spatial resolution:** Most bottom-up models can replicate energy load profiles at the building scale, but not all models generate reproducible load profiles for entire cities due to limitations in sourcing databases. Data-driven ML models developed by Anvari et al. (2022), Idowu et al. (2016), Lindberg et al. (2019), Sakkas and Abang (2022) reproduce building-scale profiles, but rely on past energy consumption data and cannot independently generate new data. Conversely, approaches by Fischer et al. (2016), Fonseca and Schlueter (2015), Labeeuw and Deconinck (2013), Staffell et al. (2023), Yao and Steemers (2005) are considered more powerful because they create profiles without historical data dependency and can be aggregated to higher resolutions such as administrative districts or municipalities. In terms of heat load results, the tool of medium to low spatial resolution is HOTMAPS from the European Union (Hotmaps, 2019) and developed by Pezzutto, Zambotti, et al. (2019), this tool provides an overview and rough estimate of the heating and cooling demand default data for EU28 at national and local level.

**Temporal resolution:** Temporal resolution models can be divided into low-, middle- and high-resolution models (Proedrou, 2021). A low resolution model has a sampling rate of fewer than 15 min (Fonseca & Schlueter, 2015; Lindberg et al., 2019; Penya et al., 2011; Sakkas & Abang, 2022; Staffell et al., 2023). Heating home appliances do not change instantly; therefore, models oriented to reproduce heat demand profiles have usually low resolution when compared to electricity profiles. Middle-resolution models such as those from Heitkoetter et al. (2020), Idowu et al. (2016), Labeeuw and Deconinck (2013), Nijhuis et al. (2016), Saloux and Candanedo (2018), contain a temporal resolution varying between one but no higher than fifteen minutes. High-resolution models have a temporal resolution equal or lower to one minute (Anvari et al., 2022; Fischer et al., 2015, 2016; Kairisa et al., 2022; Pflugradt & Muntwyler, 2017; Yao & Steemers, 2005). An interesting project which is worth-mention in this section is the project NOVAREF, which is discussed in Lange and Zobel (2017) and which conducted a detailed, high-frequency measurement of electricity consumption in single-family homes in Oldenburg, this reference and respective data will be used for the purpose of validating the present study, the objective of the study conducted by Lange and Zobel (2017) was to develop and validate new VDI reference load profiles, taking into account adjustments for heating limits and low-energy homes. Data were collected from 12 homes over a three-year period, demonstrating the existence of distinct morning, midday, and evening peaks. These peaks were influenced by both occupant behavior and appliance use.

**Modeling approach:** The literature review identifies three main modeling approaches in the context of energy demand. First, models utilize statistics and probabilities of energy demand, drawing on historical data or statistical sources to generate artificial load profiles (Anvari et al., 2022; Fischer et al., 2015, 2016; Fonseca & Schlueter, 2015; Heitkoetter et al., 2020; Idowu et al., 2016; Kairisa et al., 2022; Penya et al., 2011; Pflugradt & Muntwyler, 2017; Sakkas & Abang, 2022; Staffell et al., 2023). Second, models that employ Monte-Carlo simulation for repeated random sampling to produce numerical results Labeeuw and Deconinck (2013), Zhang (2021). Finally, the third approach involves Markov chains for developing a household occupancy model and for randomizing load profile behavior (Flett & Kelly, 2017; Labeeuw & Deconinck, 2013; Nijhuis et al., 2016). All the information and parameters discussed above are succinctly summarized in Table 1. Each study presented in this literature review has been classified according to the respective parameters. Last but not least, the last row, exemplifies where our research falls in this multidimensional space.

### 2.2. Current typification of load profiles for residential buildings

Different approaches are used to identify types of load profiles in neighborhoods, depending on the final objective of categorization. Some methods focus on identifying the main components that constitute the load profile. For instance, Buchhop and Ranganathan (2019) employed an artificial neural network (ANN) trained to identify four residential electricity load types: dishwashers, refrigerators, furnaces, and stoves. While the model successfully identified some loads, it did not recognize all. Other studies focus on clustering load curves. Adonias, Cavalcante, Fontes, and Marambio (2013) developed a method to select, typify, and cluster load curves, recognizing consumption patterns in the electricity sector. This method was effectively used to optimize energy consumption following the introduction of more efficient refrigerators in Brazilian homes.

Similarly, Akperi and Matthews (2014) applied ML clustering techniques to load profiles, finding that K-means clustering achieved the best performance in creating distinct, well-populated cluster groups. Gouveia and Seixas (2016) offered another example of a cluster approach, using a combination of high-resolution smart meters and detailed surveys in Portuguese households. They defined power consumption clusters using Ward's method of hierarchical clustering. Their findings indicated three primary factors for electricity usage segmentation: the structural attributes of a residence (notably its age and size), the presence and utilization of heating, ventilation, and air conditioning (HVAC) systems and fireplaces, and the characteristics of the occupants (primarily their numbers and monthly income).

Other concepts of load profile classifications are based on qualitative assessments. For example, Agbonaye, Keatley, Huang, Ademulegun, and Hewitt (2021) classified neighborhoods using metrics related to vulnerable consumer groups, such as income levels, the presence of older populations, access to gas, or areas with difficult access. This classification aimed to propose a flexibility prioritization model to ensure a fair distribution across various locations in Northern Ireland.

**Table 1**
Overview of selected studies concerning the nature of the load profiles, their model characteristics and classification. Annotations:+ = limited, ++ = medium, +++ = high, S&P = Statistical and probabilistic approach, MC = Monte-Carlo, MkCh = Markov Chain.

| Author | Load profile | Method | Box model | Consumer behavior | Building details | Temporal resolution | Spatial resolution | Approach |
|---|---|---|---|---|---|---|---|---|
| Yao and Steemers (2005) | H& E | Bottom-up | Grey | +++ | ++ | +++ | Building | S&P |
| Penya et al. (2011) | H & E | Hybrid | Black | + | + | + | Building | S&P |
| Labeeuw and Deconinck (2013) | E | Top-down | Black | + | + | ++ | Building | MC&MkCh |
| Fischer et al. (2015) | E | Bottom-up | Grey | +++ | ++ | +++ | Building | S&P |
| Fonseca and Schlueter (2015) | H & E | Bottom-up | Grey | ++ | +++ | + | Building | S&P |
| Pezzutto, Zambotti, et al. (2019) | H | Top-down | White | + | ++ | + | Regional, Adm. | S&P |
| Idowu et al. (2016) | H | Bottom-up | Grey | + | + | ++ | Building | S&P |
| Fischer et al. (2016) | H & E | Bottom-up | Grey | +++ | +++ | +++ | Building | S&P |
| Nijhuis et al. (2016) | E | Bottom-up | Grey | +++ | + | ++ | Building | MkCh |
| Pflugradt and Muntwyler (2017) | E | Bottom-up | White | +++ | + | +++ | Building | S&P |
| Flett and Kelly (2017) | E | Bottom-up | Black | ++ | ++ | +++ | Building | MkCh |
| Saloux and Candanedo (2018) | H | Bottom-up | Grey | ++ | ++ | ++ | Adm. District | S&P |
| Lindberg et al. (2019) | H & E | Bottom-up | Grey | + | ++ | + | Building | S&P |
| Heitkoetter et al. (2020) | H | Top-down | White | ++ | +++ | ++ | Adm. District | S&P |
| Kairisa et al. (2022) | E | Bottom-up | White | ++ | +++ | +++ | Building | S&P |
| Sakkas and Abang (2022) | H | Bottom-up | Grey | + | + | + | Adm. District | S&P |
| Anvari et al. (2022) | E | Hybrid | White | + | + | +++ | Building | S&P |
| Staffell et al. (2023) | H | Bottom-up | White | ++ | +++ | + | Building | S&P |
| Present study | H & E | Hybrid | Grey | +++ | +++ | +++ | Building | S&P |

### 2.3. Current challenges in artificial load profiles and municipal heating plans

The German law for heat planning and decarbonizing heat networks establishes a framework for comprehensive heat planning in Germany, aiming for greenhouse gas neutrality in the heat supply sector by 2045, in alignment with national climate protection goals (BMWSB, 2023). It mandates that states develop heat plans for municipal areas, ensuring that by June 30, 2026, regions with over 100,000 inhabitants, and by June 30, 2028, those with fewer than 100,000 inhabitants, have such plans in place. These plans, must be based on existing and potential local conditions, outline target scenarios and implementation strategies for cost-efficient, sustainable, and climate-neutral heat supply, embracing technology-neutral approaches like district heating and decentralized solutions such as heat pumps. Additionally, the law sets the target of 50% by 2030 for climate-neutral heat production, with specific renewable energy integration goals for heating networks by 2030 and 2040.

According to the German federal government on the heat planning act (Bundesregierung, 2024) the development of municipal heat plans involves four mandatory phases. The first phase (inventory analysis) evaluates the current state of the building stock, its energy demand, and the energy infrastructure. The second phase (potential analysis) explores the technical and economical options. The third phase (2040 target) establishes the local actions to take place in order to achieve local heat neutrality by 2040. The last phase (heat transition strategy) centers on implementation plans. However, the municipalities responsible for this planning, encounter different challenges, including the need for qualified personnel, the high costs involved, and the time-intensive nature of the projects. Consequently, many municipalities in Germany are either yet to begin or find themselves in the early phases of this assignment as previously explained by Blanco et al. (2024).

In order to properly manage energy consumption of the building sector and accelerate the creation of the municipality heating plans, practical models that incorporate large urban areas and their energy consumption patterns are essential. One major challenge in meeting the law's objectives is the need for accurate energy demand predictions and load profiling. Authors such as Blanco et al. (2024), Fischer et al. (2016) highlight the critical importance of understanding demand patterns to optimize the distribution of renewable energy systems. They discuss the shift toward thermal-electric systems like heat pumps, which require interconnected demand profiles for efficient grid and supply design, which is in itself a current challenge, not just because for coupling loads of power to heat but also because of the limitations of current methods in accounting for user behavior, technology diversity in both demand and generation, and the need of covering demand at high time resolution . Additionally, Fonseca and Schlueter (2015) emphasize the importance of characterizing energy services at the neighborhood level, which is crucial for implementing retrofit strategies and assessing technologies like heat pumps and distributed generation schemes. Understanding spatial and temporal variations in energy demand and supply is vital to ensuring the feasibility and effectiveness of climate-neutral heat supply solutions, as required by the law.

The literature review identified a lack of comprehensive, high-temporal resolution, building-level models that integrate both heat and electricity demand profiles for urban energy planning. Table 1 presents 18 related studies that were reviewed. It was found that existing models often focus on a single type of energy demand 13 of the studies did not generate both heat and electricity profiles. Additionally, eight studies exhibited limited spatial or temporal resolution, while seven studies lacked key parameters such as consumer behavior and detailed building information. The approach by Fischer et al. (2016) comes closest to achieving a similar scope, incorporating both heat and electricity demand simulation, but it requires extensive building parametrization, making it time-intensive.

Moreover, the literature review conducted in Section 2.2 reveals a potential avenue for further investigation into comprehensive approaches that integrate quantitative and qualitative elements to develop precise, comprehensive load profiles for neighborhoods. The existing methods, as exemplified by the works of Buchhop and Ranganathan (2019), Adonias et al. (2013), Akperi and Matthews (2014), and Agbonaye et al. (2021), concentrate on particular load components, clustering techniques, or qualitative classifications. However, there is no unified model that integrates both high-resolution quantitative data (e.g. appliance use, occupancy, as discussed by Buchhop and Ranganathan (2019) and Gouveia and Seixas (2016)) and qualitative metrics (e.g. socioeconomic factors and vulnerability, as in Agbonaye et al. (2021)) to create a comprehensive energy demand profile that addresses diverse neighborhood characteristics.

Overall, while the law provides a legislative framework for transitioning Germany's heat supply to carbon neutrality, addressing challenges such as accurate load profiling, integrating diverse energy sources, and understanding spatial and temporal energy demand variations is essential for its successful implementation. For this reason, this study focuses on answering the following research questions:

- Can new data-driven approaches accelerate the initial inventory and potential analysis phases of municipal heating plans in Germany?
- Is it possible to develop a model using open data that provides hourly energy demand estimates, and if so, how accurate can these estimates be?
- Can demand curves be standardized and typified for energy analysis at a district level, rather than just at a building level?

Hence, the following methodology tries to fulfill the research gap and answer the research questions by generating typical heat and electricity load profiles tailored to various urban spaces, designed to be an essential resource for the initial phases of municipal heating plans in Germany. Given the challenges municipalities face—such as limited detailed building data, shortages of qualified personnel, constrained resources, and stringent data protection laws—this approach provides a valuable new tool for accurately assessing energy needs within the building sector. By addressing these barriers, the methodology supports municipalities in creating effective, data-informed heating plans despite limited resources.

## 3. Methodology

### 3.1. Selection of the study area

The initial step involves selecting the study area, which can encompass any specific region within Germany. For this research, the focus is on the city of Oldenburg, Germany. The city is located in the north of the state of Lower Saxony, Germany with a total area of 103.09 $km^2$ and a total population of 174 629 as of 2022. This city was chosen based on previous studies conducted by Blanco et al. (2024) and explained in the introduction. Fig. 2 shows a graphical representation of the subdivision of Oldenburg into UEUs as done previously by Blanco et al. (2024), showing the subdivision of the city center into the different UEU classes, which are also explained in detail in Section 3.2.2. Subsequent subsections introduce the collected datasets for the study area and for the general model.

### 3.2. Data collection

The process of gathering accurate and relevant data is crucial for ensuring the validity and reliability of our study. As mentioned previously, our research builds upon the work of Blanco et al. (2024), and thus, the data employed in this study are the same, namely: 3D CityGML–LoD2 Building models, census data, and cadastral data. Additionally, weather data for the study area and statistical information about energy demand parameters based on building types have been acquired. The subsequent paragraphs provide a detailed explanation for each data type obtained for this study and their respective sources.

#### 3.2.1. Building stock database

This study applies the building stock database of Oldenburg, as employed in Blanco et al. (2023, 2024), because it contains key information at the building level about the age of the buildings and other crucial parameters such as building type, use, height, roof type, etc. The model developed by Blanco et al. (2024) combines 3D CityGML information Models of Germany and Germany's 2011 census, sourced from Lower Saxony's data portal (LGLN, 2021), and the Statistical Office of the Federal Government (Statistische Ämter des Bundes und der Länder, 2011) respectively, in order to create a complete database, which includes 28 parameters for 56,749 buildings in Oldenburg, with 80% residential buildings and 20% with non-residential purposes. Table 2 summarizes the parameters derived from this model.

A particularity of the study of Blanco et al. (2024) is the fact that it uses a Random Forest (RF)-model to disaggregate the census information regarding building age (categorized into ten construction year intervals) because of the fact that Germany's 2011 census data are publicly available in a 100 m×100 m grid format, with values aggregated according to the Infrastructure for Spatial Information in the European Community (INSPIRE) guidelines (BKG, 2019; INSPIRE, 2017; Statistische Ämter des Bundes und der Länder, 2011). This is the official and only dataset of the country about the year of construction of buildings.

#### 3.2.2. UEU classes and database

In their study, Blanco et al. (2024) developed a GIS-based model to categorize urban regions into 16 distinct morphological units, termed by the authors as UEUs. These units are defined based on local building parameters, settlement patterns, and energy demands specific to the German building stock. Based upon the previously mentioned data sources, the authors implemented the classification of UEUs in the city of Oldenburg, resulting in the division of the area into 8249 unique UEUs. Each UEU was classified by the authors into one of the 16 categories employing a Decision Tree (DT) model. Table 3 gives a brief description of this 16 categories, the percentage of area they cover in Oldenburg, and sample data on heat and electricity demand considering no refurbishment of the building stock. More detailed information, for other refurbishment scenarios and building ages, is available in Blanco et al. (2024). A geographical representation of the UEUs is displayed in Fig. 2.

#### 3.2.3. TABULA database

A significant source of information regarding the energy and architectural characteristics of the German building stock comes from a report by Loga, Stein, Diefenbach, and Born (2015), part of the Typology Approach for BUiLding stock energy Assessment (TABULA) project under the European Commission and coordinated by the Institut Wohnen und Umwelt (IWU), Germany. The TABULA project aimed to support the energy efficiency and retrofit objectives of the European Union by establishing a comprehensive framework for assessing the energy demand of national residential building stocks. Each participating country, including Germany, developed a classification system to categorize its diverse building stock.

According to Loga et al. (2015), the German residential building stock is categorized into various age and size classes based on energy-relevant characteristics. Building age is particularly crucial as construction methods in different eras affect components such as window sizes, significantly influencing U-values and overall heating demand. Therefore, the TABULA project identified 12 building age classes based on historical data, survey dates, and relevant changes in building regulations related to thermal engineering. The construction types in the German building stock were classified into four categories: Single-family house (SFH), multifamily house (MFH), terraced house (TH), and apartment block (AB). Typical total heating specific demands were calculated and presented in $kWh/(m^2a)$ for each construction type and building age class. The TABULA database is currently the most detailed and officially recognized source on the refurbishment status and typical heating demand values of the German building stock. For summarized information, refer to Table 4; for further details, consult Loga et al. (2015).

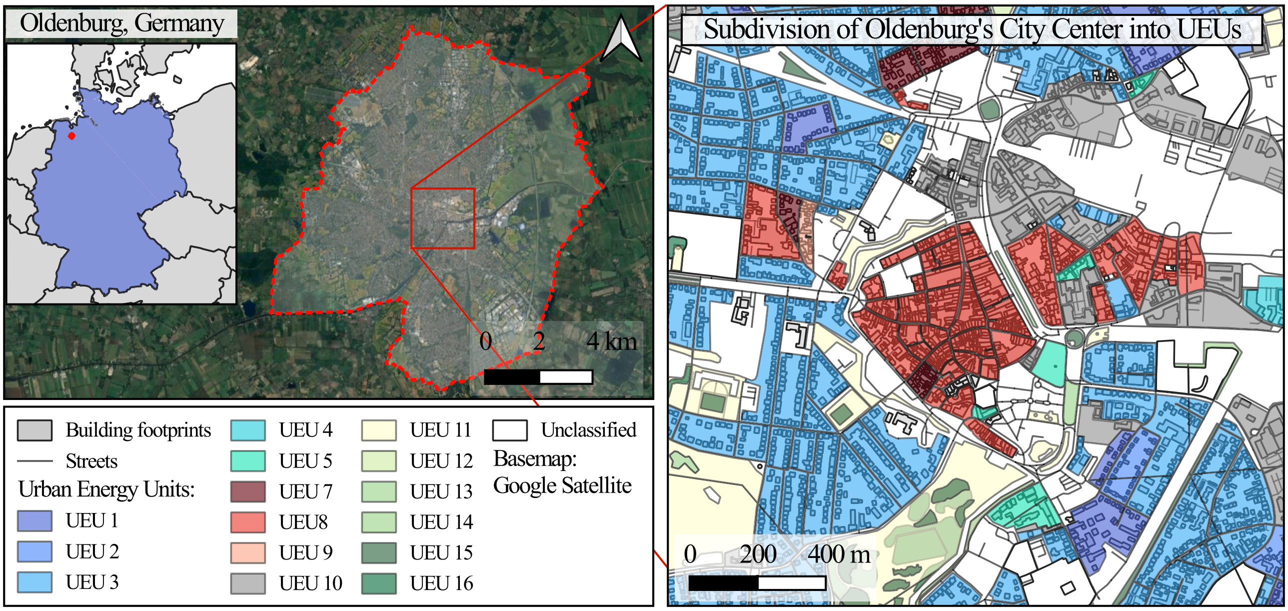



**Fig. 2.** Study Area: Oldenburg, Germany. (Left) Map showing the location of Oldenburg within Germany and its administrative boundaries. (Right) Detailed division of Oldenburg's city center into 16 distinct UEUs, labeled UEU 1–16.
*Source:* Adapted from: Blanco et al. (2024).

**Table 2**
Building parameters of the database for the city of Oldenburg.

| Parameter | Units | Description |
|---|---|---|
| Building ID | – | Identification sequence of the building |
| Municipality key | – | Key of the municipality where the building is located |
| Address | – | Address of the building |
| Measured height | m | Height measured from the topmost point of the building |
| Function | – | Functional use of the building given in CityGML numerical code |
| Type | – | Detached, semi-detached, terraced, multi-family |
| Area | m$^2$ | Footprint's area |
| Perimeter | m | Footprint's perimeter |
| Absolute Height | m | Height measured from sea level |
| Roof type | class | Standardized CityGML roof type |
| Roof height | m | Distance measured from the middle eave until the highest roof's point |
| No. of storeys | – | Approximate number of storeys of the building with 3.5 m story height |
| No. of apartments | – | Approximate number of apartments of the building |
| Neighbors IDs | – | Identification sequence of all the adjacent buildings |
| No. of neighbors | – | Number of all the adjacent buildings |
| Shared perimeter | m | Sum of all the perimeter shared with adjacent buildings |
| Volume | m$^3$ | Volume od the building |
| 2D shape index | – | Shape smoothness index, expressed as $\frac{p}{4\sqrt{A}}$ |
| Height-Area ratio | m$^{-1}$ | Building height to footprint area's ratio |
| Shape compactness | – | Exposed surface area per unit of volume, expressed as $V^2/V^3$ |
| Floor areas | m$^2$ | Sum of all floor areas |
| Surface area | m$^2$ | Sum of all surface areas |
| Perimeter index | – | Building footprint index, expressed as $\frac{2\sqrt{\pi A}}{p}$ |
| Roof pitch angle | ° | Angle with the horizontal of the buildings roof |
| Roof surface area | m$^2$ | Surface area of the building's roof |
| A/V | m$^{-1}$ | ratio between the envelope area and the buildings volume |
| Building age | class | Predicted building age categorized into 10 groups based on German census. |
| Centroid | – | X, Y and Z Coordinates of the building's centroid |

### 3.2.4. Weather data

In addition to the building stock database, our model integrates time series data on local weather conditions. Weather data is necessary because it directly influences calculations of heat demand. Factors like environmental temperature and wind conditions faced by the buildings play a significant role in determining the total heat demand.

To obtain this time series data, the model is able to integrate two different databases, German Meteorological Service, known as DWD (Deutscher Wetterdienst) and Copernicus Climate Data Store (CDS). Weather data from the DWD provides precise Test Reference Years (TRY) for specific areas in Germany, including average years, extreme winters, and extreme summers for 2015 and 2045. These datasets include hourly values for temperature, air pressure, wind speed, solar radiation, and other parameters. On the other hand, the Copernicus database, offers datasets for Actual Meteorological Years (AMY) from 2010 to 2020 including hourly values for temperature, wind speed, and solar radiation across an area of 464 square kilometers, covering the city of Oldenburg. While the analysis showed in this paper is based on the official TRY for the time period 1996–2015 from the DWD (referred to in this paper from now on as $TRY_{2015}$), our model is able to accommodate temperature and wind data for any year downloaded

**Table 3**
Brief description of UEU classes. Percentage of area covered in Oldenburg by each type. Values for heat and electricity demand considering: **no refurbishment** and construction period of **1949–1978**. Demand values are expressed in MWh/(ha × a).
*Source:* Adapted from Blanco et al. (2024).

| UEU | Description | Percentage % | Heat demand | Electricity demand |
|---|---|---|---|---|
| | | Predominant residential use | | |
| 1 | Single family housing | 14.7 | 433 | 78 |
| 2 | Terraced house development | 2.2 | 1040 | 116 |
| 3 | Low to mid-rise row development | 3.9 | 1420 | 268 |
| 4 | Large-scale development | 0.2 | 1281 | 395 |
| 5 | Perimeter block development | 0.1 | 3243 | 694 |
| | | Predominant mix use | | |
| 6 | Village development | 0 | 1738 | 312 |
| 7 | Historic old town | 0.1 | 3126 | 751 |
| 8 | Inner city | 0.5 | 4924 | 693 |
| | | Administrative and commercial use | | |
| 9 | Business and offices | 0.1 | – | – |
| 10 | Industrial area | 7.4 | – | – |
| | | Open spaces | | |
| 11 | Public parks | 2.6 | – | – |
| 12 | Cemeteries | 0.3 | – | – |
| 13 | Allotment gardens | 0.4 | – | – |
| 14 | Arable land | 36.9 | – | – |
| 15 | Permanent grassland | 1.5 | – | – |
| 16 | Forest | 18.0 | – | – |
| Unclassified | – | 11.1 | – | – |

**Table 4**
Heating energy demand in kWh/($m^2$a) across construction types (SFH: single-family house, MFH: multifamily house, TH: terraced house, AB: apartment block), construction periods, and refurbishment levels (1: no refurbishment, 2: usual refurbishment, 3: advanced refurbishment). Data taken and adapted from: Loga, Stein, and Diefenbach (2016).

| Refurbishment state | | Construction type | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | SFH | | | MFH | | | TH | | | AB | | |
| | | 1 | 2 | 3 | 1 | 2 | 3 | 1 | 2 | 3 | 1 | 2 | 3 |
| Construction period | Before 1859 | 282.7 | 94.8 | 49.0 | 284.9 | 101.1 | 48.5 | – | – | – | – | – | – |
| | 1860–1918 | 269.7 | 98.5 | 57.5 | 172.5 | 80.0 | 40.8 | 199.5 | 94.8 | 51.8 | 134.5 | 70.4 | 36.5 |
| | 1919–1948 | 218.5 | 83.6 | 50.7 | 218.5 | 81.8 | 47.6 | 155.8 | 68.0 | 43.6 | 121.9 | 82.1 | 50.1 |
| | 1949–1957 | 272.9 | 119.2 | 61.4 | 193.7 | 78.5 | 48.4 | 193.4 | 81.1 | 51.7 | 164.0 | 68.1 | 41.8 |
| | 1958–1968 | 265.3 | 128.1 | 69.9 | 140.2 | 64.7 | 40.3 | 106.9 | 59.4 | 38.9 | 143.3 | 63.1 | 39.3 |
| | 1969–1978 | 195.3 | 91.5 | 58.5 | 147.9 | 72.6 | 45.3 | 137.6 | 72.4 | 47.2 | 121.7 | 59.3 | 37.3 |
| | 1979–1983 | 130.6 | 73.5 | 45.5 | 122.6 | 66.5 | 42.0 | 137.6 | 86.8 | 51.8 | – | – | – |
| | 1984–1994 | 151.7 | 96.5 | 57.2 | 127.6 | 70.5 | 44.0 | 95.4 | 70.3 | 43.2 | – | – | – |
| | 1995–2001 | 98.2 | 76.0 | 57.8 | 80.6 | 53.0 | 44.0 | 69.7 | 57.3 | 40.3 | – | – | – |
| | 2002–2009 | 70.1 | 61.3 | 55.0 | 49.9 | 44.9 | 41.3 | 62.0 | 59.2 | 50.7 | – | – | – |
| | 2010–2015 | 82.2 | 67.5 | 42.0 | 72.7 | 44.7 | 35.3 | 69.8 | 57.2 | 36.8 | – | – | – |
| | 2016 and after | 69.5 | 61.0 | 42.0 | 71.4 | 49.1 | 35.3 | 58.8 | 51.7 | 36.8 | – | – | – |

from the CDS, enhancing its flexibility. Fig. 3 shows DWD temperature and wind data for the $TRY_{2015}$ of the city of Oldenburg.

### 3.3. Calculation of heat load profiles

Three approaches to model energy demand in German households are proposed by Fischer et al. (2016) and Ruhnau, Hirth, and Praktiknjo (2019): using a standard load profile (SLP), adopting a reference load profile, or employing statistical data-driven methods. The heating demand in residential homes depends on weather conditions, building characteristics, and consumer behavior. By integrating these factors, a demand profile can be generated using any of these methodologies (Malla, 2021).

This study utilizes a hybrid approach that combines these methods. Specifically, the SLP method is employed hourly to generate heat demand profiles for individual residential buildings. Simultaneously, data-driven techniques are used to characterize reference load profiles customized for UEUs as defined by Blanco et al. (2024). This dual strategy offers a detailed temporal representation of heat demand for each UEU, while also providing specific information on heat demand for buildings within a large urban area.

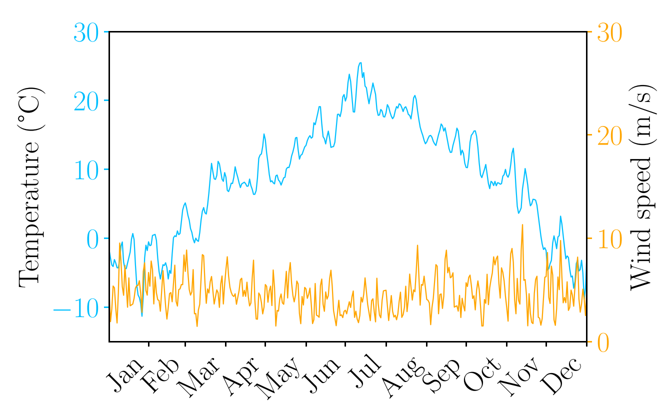



**Fig. 3.** DWD Weather data for the $TRY_{2015}$ of the city of Oldenburg. Temperature at 2 m above ground in Celsius and wind speed horizontal component at 10 m above ground in meters per second.

SLPs were initially introduced by the German Electricty Association (VDEW, 2000) for understanding the electricity market. Subsequently, the methodology for gas standard load profile was developed by the Technical University of Munich in collaboration with the German Gas and Water Association (BGW) (BGW, 2006; Hellwig, 2003). This method utilized a sigmoid function to model demand patterns for small customers in the liberalized gas market. Over time, 14 consumer load profiles were established, distinguishing between commercial, retail, service sectors, and households (single and multi-family houses). Challenges identified included low allocation at extreme temperatures, insufficient base load, high deviation rates, and seasonal inconsistencies. A status report by the German Association of Energy and Water Industries (BDEW), the Association of Municipal Enterprises (VKU), and the European Association of Independent Energy and Distribution Companies (GEODE) (BDEW, VKU and GEODE, 2016) recommended corrective measures such as partial linearization and date-dependent seasonal factors, resulting in a revised profile function called *SigLinDe*, which combines sigmoid and linear components. Partial linearization addresses under-allocation at very cold or warm temperatures, aligning the function with actual demand patterns.

SLPs are tailored to gas-dependent processes, where a flatter curve indicates consumers completely dependent on gas, while a steeper curve signifies households influenced by outdoor temperatures. The *SigLinDe* function is represented by Eq. (1), where $h_{d,l}$ denotes the daily heat quantity dependent on day ($d$) and location ($l$), with $T_0$ as the upper temperature reference limit set at $40\,°C$. The coefficients $A$, $B$, and $C$ are the sigmoidal of the equation, and $D$, $m_{\text{space,water}}$, and $b_{\text{space,water}}$ are the linear part refering to the heat coefficients for space and water, respectively.

To account for thermal inertia in buildings, the daily reference temperature $T^{\text{ref}}_{d,l}$ considers the weighted mean of ambient temperatures from the current day and the preceding three days, as described in Eq. (2).

$$h_{d,l} = \frac{A}{1+\left(\frac{B}{T^{\text{ref}}_{d,l}-T_0}\right)^C} + D + \max\left\{\begin{matrix} m_{\text{space}}(T^{\text{ref}}_{d,l}-T_0)+b_{\text{space}} \\ m_{\text{water}}(T^{\text{ref}}_{d,l}-T_0)+b_{\text{water}} \end{matrix}\right\} \tag{1}$$

$$T^{\text{ref}}_{d,l} = \frac{T^{\text{amb}}_{d,l}+0.5T^{\text{amb}}_{d-1,l}+0.25T^{\text{amb}}_{d-2,l}+0.125T^{\text{amb}}_{d-3,l}}{1+0.5+0.25+0.125} \tag{2}$$

In the report made by BDEW, VKU and GEODE (2016), the temperature independent component ($D$) and the linear function for water heating ($m_{\text{water}} \cdot T + b_{\text{water}}$) are correlated with gas consumption for water heating. Notably, the linear function for water heating is relevant only at temperatures above the linear space heating function. Specifically, this applies to temperatures exceeding the heating threshold of $15\,°C$. At temperatures above this threshold, it is assumed that the domestic hot water demand remains stable. As a result, the daily water heating demand ($f^{\text{water}}_{d,l}$) is determined for each location using Eq. (3):

$$f^{\text{water}}_{d,l} = \begin{cases} D + m_{\text{water}} \cdot T^{\text{ref}}_{d,l} + b_{\text{water}}, & T^{\text{ref}}_{d,l} > 15\,°C \\ D + m_{\text{water}} \cdot 15 + b_{\text{water}}, & T^{\text{ref}}_{d,l} \le 15\,°C \end{cases} \tag{3}$$

In the original method, hourly demand values are calculated for each location using hourly demand factors provided by the BGW for various building types and temperature ranges (BGW, 2006). These factors represent hourly proportions of daily demand, totaling 100% per day. For non-residential buildings the BGW (2006) provides a factor adjusting daily demand based on the day of the week but do not explicitly differentiate between space and water demand. Nevertheless, under the assumption that there is no need for space heating at elevated ambient air temperatures ($T^{amb}_{d,l} \ge 25\,°C$), the corresponding demand is associated just to water heating.

The space heating demand is therefore defined as the difference between the total heat demand and the domestic hot water demand. Negative values may appear for specific hours, specially in summer. These negative values are then adjusted to zero (Ruhnau et al., 2019). This method allows us to calculate an SLP for a specific building type in a given hour and location as long as a specific weather dataset is provided. By combining it with the building stock database, temperature and wind datasets of the city of Oldenburg, we are able to calculate a SLP for each individual building with the database in an hourly resolution. However these are normalized values, meaning that the total heat demand on a yearly basis still needs to be calculated in order to scale such profiles.

The next step is to calculate the total heat demand in a year of every single building within the study area in order to scale the respective SLP to have a building-specific heat load profile. In literature review various methods for calculating yearly heat demand values for buildings were shown, each with its own set of considerations. In our approach, we leverage a rapid and efficient methodology that takes into account the geometric properties of the buildings; nevertheless the proposed model can then later be adapted to use other calculation methods. The approach used to calculate the heating demand of buildings was adapted from prior studies by Dochev, Gorzalka, et al. (2020), Garbasevschi et al. (2021), Wurm et al. (2021). Initially, the method calculates the overall heated area of a building, considering factors such as constructed area, volume, building parts, roof type, and number of floors. Subsequently, the total heat demand is calculated by multiplying the respective heated area of the building with the specific reference heat demand value, expressed in watts per square meter per year. These reference values are tailored to account for all possible combinations of building age, type, and function. In the case of residential buildings, the reference heat demand values are taken from the TABULA database (see Table 4). In the case of buildings with a mixture of residential a non-residential use, the values are taken from the VDI 3807 report by the Association of German Engineers (VDI) (VDI, 2014) where more than 70 building functions were analyzed. The heat demand $Q$ is a function of the building's type, age, geometry and function. All of this can be summarized in Eqs. (4) and (5) taken from Dochev, Gorzalka, et al. (2020). The factor 0.8 is a factor considered in the standard DIN V 18599-1 to estimate the relationship between gross and actual residential floor area. The factor of 0.75 is used to prevent overestimating the area of a heated attic, as attics are not normally as large as a full story. It is important to note that the ALKIS cadastral system includes information on roof types, though the data availability can vary by region. Each building's SLP is then modified according to its annual heat demand. This adjustment ensures that an accurate heat load value is provided for each hour of the reference year for all buildings in the study area.

$$Q = A_{\text{n}}(0.8 \cdot Q''_{\text{TABULA}} \cdot r + Q''_{\text{VDI}}(1-r)) \tag{4}$$

$$A_{\text{n}} = A_{\text{f}}(n_{\text{f}} + 0.75 \cdot r_f) + \sum_{\text{bp}} A_{\text{bp}} \cdot \Delta n_{\text{bp}} \tag{5}$$

where: $Q$ is the heat demand of the building. $Q''_{TABULA}$ is the specific heat demand of the respective TABULA building typology and $Q''_{\text{VDI}}$ is the specific heat demand of the use type from VDI 3807. $A_{\text{n}}$ is the total floor area of building. $A_{\text{f}}$ is the footprint area. $A_{\text{bp}}$ is the footprint area of a building part (a part within the building's footprint that has a different number of stories). $n_{\text{f}}$ is the number of storeys. $r_f$ is the roof type factor (0 for flat roofs, 1 for the rest). $r$ is the share of residential area in the building. $\Delta n_{\text{bp}}$ is the difference in the number of stories between the main building and its sections as explained in Garbasevschi et al. (2021) and Dochev, Seller, and Peters (2020).

Last but not least, the different heat load profiles are then aggregated according to the UEUs in which the respective buildings are located. This is done via a geoprocessing method in which just the buildings located within the area of each UEU are extracted and their characteristics combined. By aggregating the different heat load profiles for each building within a UEU we get specific UEU heat load profiles which are dependent on their area and their respective building stock. Because we have also the architectural and structural properties of each UEU, we can then analyze the many profiles of the many UEUs and find common characteristics typifying the heat load profiles for large settlement areas and showing an effective way to quickly analyze communities and their heat demand.

### 3.4. Calculation of electricity load profiles

The software resLoadSIM is a stochastic simulation tool developed by the European Commission's Joint Research Centre (JRC) for predicting electricity load profiles for households (Estorff et al., 2022). Although the software is currently being improved, it stands as an open-source tool, readily accessible through the JRC's GitHub repository (JRC, 2019). resLoadSIM was selected for its ability to generate electricity load profiles for individual buildings with minute-level resolution. It adopts a bottom-up methodology, simulating energy consumption at the household level, while leveraging open-source data for detailed building characteristics and GIS information.

ResLoadSIM accurately models consumer behavior influenced by weather, the number of inhabitants per household, and appliance usage patterns, incorporating building details such as age, area and type. It offers flexible resolution settings for load profiles, providing high and medium resolution electricity profiles. The application of resLoadSIM's results aims to generate Residential Load Profiles, supporting planning authorities in making heating plans while respecting privacy data management requirements through its statistical and probabilistic building categorization approaches.

To begin generating electricity load profiles with resLoadSIM, it is essential to configure several parameters. These parameters govern the simulation's behavior, ensuring it accurately reflects the study's context. The simulation process requires five input data files each providing relevant information about the study area, building characteristics, and simulation settings.

Firstly, a GIS-based dataset containing the geographical limitations of the study area. Here, the UEUs database is imported. The dataset contains a total of 6746 UEUs, characterized by 48 variables and classified into 16 distinct UEU classes (Blanco et al., 2024). Due to the fact that 8 out of the 16 classes are non-residential (as seen in Table 3), and therefore resLoadSIM is not able to simulate them. This is probably the main setback in comparison with the heat load profiles where non-residential areas can be simulated. The remaining 8 residential UEU classes represent a total of 1923 GIS areas within the city of Oldenburg effectively simulated in this analysis.

Secondly, the simulation relies on a set of three configuration files. The first configuration file, holds parameters governing simulation behavior, such as irradiation data for photovoltaic energy generation, battery charging strategies, power flow specifications, consumer energy demand control, daylight saving time, and time resolution. The second file contains the country ISO codes, urban or rural designation, latitude, longitude, UTC offset, temperature, and irradiation data sourced from PVGIS (Barhdadi & Bennis, 2012). The third configuration file contains various factors influencing energy demand, such as laundry quantities, probabilities of owning additional appliances, and schedules for routine tasks. It also determines wake-up and bedtime schedules and resident presence at home throughout the day, providing crucial insights for energy demand simulation. This file also defines the population distribution among households per UEU, randomly allocating inhabitants based on the statistical distribution of households in Oldenburg from the census database, as outlined in Table 5. Moreover, resLoadSIM accounts for demographic factors like the prevalence of retirees in different household compositions, ensuring the simulated population distribution mirrors real-world demographics accurately. For example, a higher proportion of single-person households may be occupied by retirees. Finally, the last dataset needed for the calculation is: the time series containing weather data for the $TRY_{2015}$, including temperature, wind, and irradiation data.

**Table 5**
Assignment of family members per household to the proportion of the building stock in the city of Oldenburg. Distribution of inhabitants per buildings according to Statistische Ämter des Bundes und der Länder (2023b).

| Family members per household | Proportion of buildings |
|---|---|
| 1 | 41.0% |
| 2 | 33.0% |
| 3 | 11.0% |
| 4 | 13.0% |
| 5 | 1.5% |
| 6 | 0.5% |

In order to account for seasonal fluctuations and long-term energy consumption trends, the simulation was carried out over a period of 365 days. Furthermore, in order to maintain the population of the city of Oldenburg at a constant level throughout the simulations process, resLoadSIM was set to use a calculated number of households per building, derived from the Buildings Stock database (see Fig. 4 in the general methodology). The estimation of households per building is dependent on the type of buildings located within the UEU. Therefore, an UEU comprising detached or semi-detached houses is typically considered to contain SFHs or detached MFHs.

During the simulation, resLoadSIM generates electricity load profiles per household, each of which is identified by a unique code that allows the UEU to be identified. To ensure reproducibility and results validation, a random seed was defined equal to the order of the simulated household load profile as defined by the building stock database, allowing the simulation to be replicated and the results to be verified. These load profiles represent the energy demand patterns of the UEUs, including the activation of different household appliances at different times of the day. The generation of load profiles derives from probabilistic methods that predict the energy demand of household appliances built upon the behavior of the occupants throughout the year. Each household's load profile is determined by the simultaneous activation of different appliances during specific operating intervals, reflecting real world usage patterns. Once the load profiles for individual households have been generated, they are aggregated across each UEU to calculate the total electricity demand. This aggregation process provides a comprehensive picture of energy demand patterns at the UEU level, facilitating the analysis and typification of energy districts and residential areas.

### 3.5. General model and UEU-typical heat and electricity load profiles

The model outlined in this study generates a heat load profile for all buildings within the selected area using the methodology detailed in Section 3.3. Subsequently, these individual building profiles are combined based on the UEUs in which they are located, t o create a heat load profile for each UEU within the study area. The model also generates an electricity load profile for every UEU in the study area using the methodology detailed in Section 3.4. The heat as well as the electricity load profiles have an hourly resolution and are based the $TRY_{2015}$ for the city of Oldenburg, Germany. It is important to note that while both electricity and heat load profiles share the same units and time and spatial resolution, combining those two energy demand values directly is not feasible. This is primarily because heating and electrical systems operate on separate infrastructures and often rely on different energy sources. Heat load profiles are influenced by the efficiency and capacity of the chosen heating system, such as boilers, heat pumps, or district heating networks. As a result, a conversion between time series of heat and electricity profiles is not straightforward (Böttger, Götz, Lehr, Kondziella, & Bruckner, 2014; Jesper, Pag, Vajen, & Jordan, 2022) and it is out of the scope of this paper. For this reason, the analysis of heat and electricity heat load profiles in this study is treated

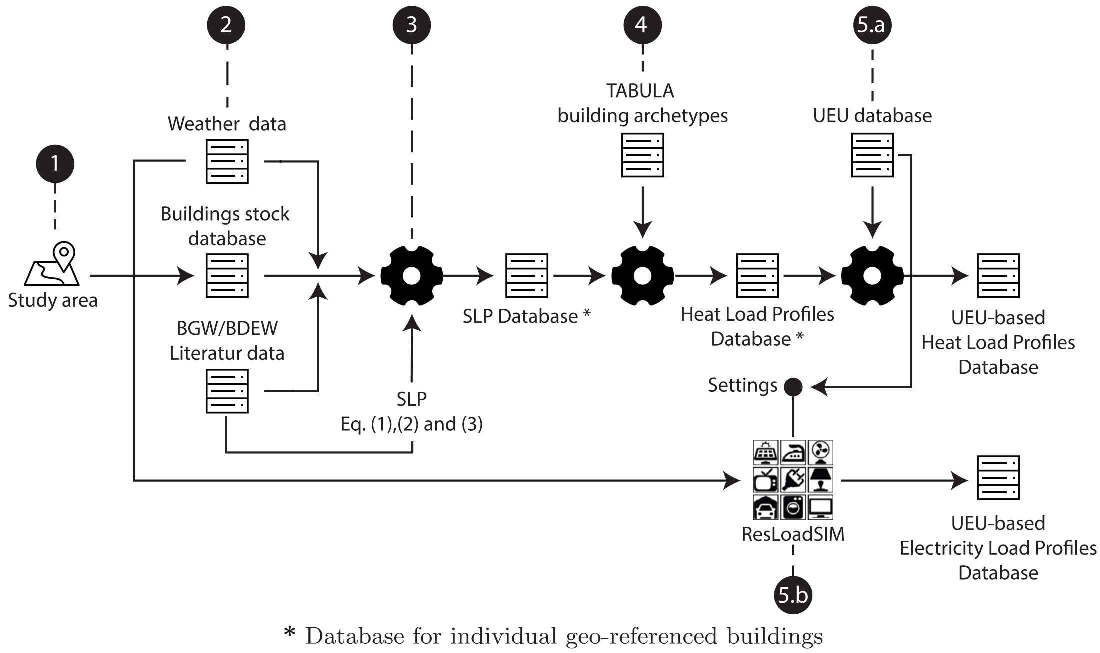



**Fig. 4.** General methodology for the generation of heat and electricity load profiles and their typification according to UEUs. **1:** Study area selection. **2:** Data collection and processing. **3:** Calculation of SLPs and generation of a database for individual geo-referenced buildings. **4:** Classification of the buildings database according to TABULA classes and generation of the Heat Load Profiles for individual geo-referenced buildings. **5.a:** Integration of the UEU database generated by Blanco et al. (2024) and data aggregation according to the geo-referenced UEUs. **5.b:** Integration of the UEU database into resLoadSIM and simulation run. The results are both heat and electricity load profiles for each geo-referenced UEU with hourly resolution.

separately to accurately analyze each side of the energy demand and develop effective energy management strategies. Last but not least, the validation of the model's results are going to be compared with two different tools, for the heat demand the comparison will be made with the tool HOTMAPS (Hotmaps, 2019; Pezzutto, Zambotti, et al., 2019), and the electricity demand wit the tool NOVAREF (Lange & Zobel, 2017), both of them previously described in the literature review.

When referring to the typification of load profiles, the term "typical" denotes a standardized representation of load profiles aligned with the aforementioned UEUs. Essentially, when using the term "typical load profile", it signifies a categorization or standardization of load profiles based on the characteristics and energy usage patterns observed within the UEUs. This approach to typification facilitates a systematic understanding and analysis of energy demand time-series patterns within urban areas. The methodology described above is succinctly presented in the workflow diagram, shown in Fig. 4. This workflow, illustrates the sequential procedure used to incorporate regional characteristics and district-level knowledge to model heat and electricity load profiles at larger urban scales with high spatio-temporal resolution and have a typical heat load distribution according to specific settlement patterns of the German urban matrix known as UEUs.

## 4. Results

The next section presents the study's results, based on the general model outlined in Fig. 4 and an energy analysis of a district in Oldenburg. Firstly, results for the generation of building-specific high-resolution heat load profiles and how these different profiles are matched with the building stock database previously employed by Blanco et al. (2024). Secondly it shows the methodology for generating electricity load profiles for the different UEUs. Thirdly it shows the normalization of both heat and electricity load profiles based on each UEU. Last but not least, an exemplary energy analysis of a randomly chosen district in Oldenburg showing the potentials of this methodology for quickly getting a high-resolution heat and electricity demand for any given region in Germany.

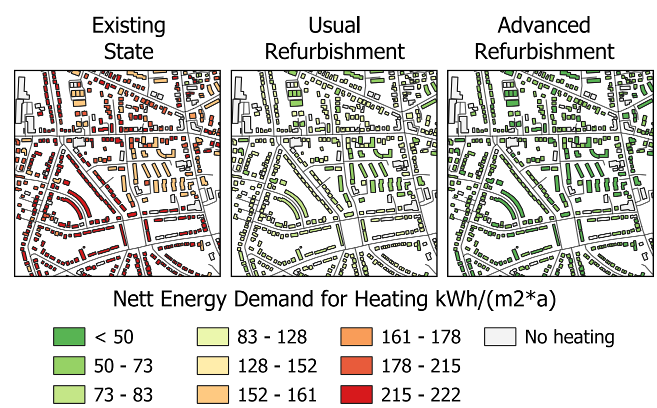
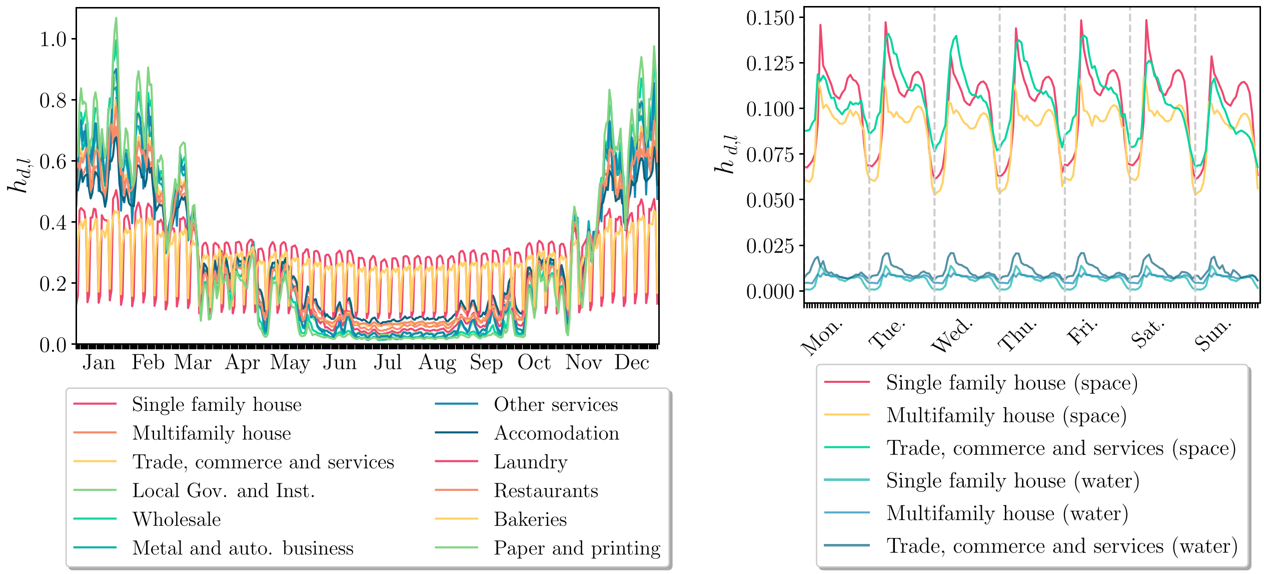



**Fig. 5.** Heating energy demand in kWh/($m^2$· a) for various building refurbishment scenarios.

### *4.1. Heat load profiles*

The building database used here includes a total of 56 749 buildings. According to the city's administration, there are approximately 45 438 and 2 956 residential and non-residential buildings respectively. The discrepancy in the number is attributed to individual structures like garages or garden sheds. For each building, the total annual heat demand was calculated as outlined in Section 3.3. The specific heat demands listed in Table 4 are matched with the construction period and building type characteristics of the building stock. This matching process allows for three potential scenarios for the total heat demand, based on the refurbishment states described by TABULA for the building stock. These scenarios are depicted in Fig. 5.

Fig. 6 illustrates the nominal heat quantity per hour during the $TRY_{2015}$ weather scenario, categorizing each profile into different building types and distinguishing between space and water demand. The sum of all values add up to 100%, providing a comprehensive




(a) Daily nominated heat quantity ($h_{d,l}$) variations across a year for different building functions and locations under $\mathrm{TRY}_{2015}$ typical weather

(b) Hourly nominated heat quantity ($h_{d,l}$) variations across a week for different building functions, space and water heating.

**Fig. 6.** Hourly and daily heat quantity ($h_{d,l}$) variations over a year, categorized by space and water heating and building types.

overview of the heat distribution throughout each day and the whole year. Every single building's total heat demand is matched with its corresponding profile, so this way each building has its own individual heat load profile for space and water heating.

### 4.2. Electricity load profiles

The explained approach at Section 3.4 to estimate the number of households yielded for the city of Oldenburg 100,219 households. The number of estimated inhabitants can be calculated by multiplying the number of households in each UEU by the distribution of inhabitants per household as showed in Table 5. This yields a total of 202,938 inhabitants, which represents a 15% increase compared to the actual population from Oldenburg of 175,878 people in 2024 (Stadt Oldenburg, 2024). The electricity demand simulation adheres to the guidelines outlined in the resLoadSIM user manual version 5.0, as referenced in the literature (Troyer, 2018).

The two main inputs to resLoadSIM were the 100,219 households and 365 days. These two variables, together with the configuration files, were used to simulate 1943 UEUs containing mainly residential buildings. Each UEU had a specific number of households and this specific number was passed to resLoadSIM to run the simulation. The UEUs containing residential buildings were UEU 1 to UEU 9, excluding UEU 6. Results of the simulation returned one file per UEU. Each file has six columns, each indicating load profiles of simulated instant power demand of household families with minute resolution during one year. To obtain the electricity demand of each specific geolocalized UEU, the load profiles of all types of households with different occupants within the UEU were summed and rearanged with an hourly resolution.

Fig. 7 presents an example of a simulated hourly power demand of one single household with 2 residents. It follows a standardized pattern of a family that start its activity at 5:00 a.m., with two peaks of electricity demand at 7:00 a.m. and at 6:00 pm. The load of this household is never zero, because there are home appliances that are continuously running, like refrigerators or lights.

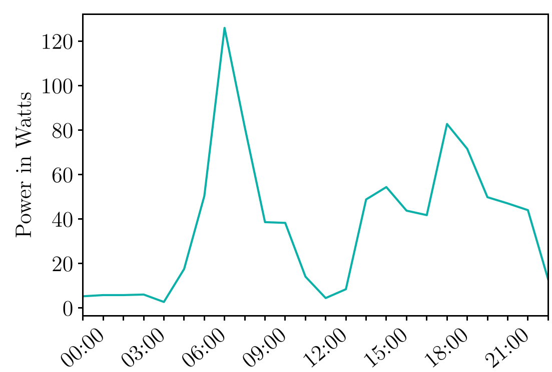



**Fig. 7.** Exemplary hourly power demand of a single family house with 2 members on a 24 h window of a weekday.

### 4.3. Normalization of heat and electricity load profiles at UEU level

The term *typical* is used to denote characteristics that are representative of a specific group, category, or standard. However, it is essential to note that *typical* does not imply exactness. With the introduction of the UEU methodology, urban spaces can now be classified into energy classes, providing a rapid assessment of their typical energy demand. Consequently, normalizing and standardizing heat and electricity load profiles has become feasible. We now have precise heat and electricity load profiles for various UEU classes. Focusing on residential UEU classes (1–9), we normalized their distinct load profiles based on total constructed area and energy demand using Eq. (6), resulting in typical load profiles for each class.

$$LP_{i,(heat,electricity)} = \frac{1}{N}\sum_{j=1}^{N}\frac{UEU_{i,j}}{A_j \times E_j} \quad |i = 1, 2, 3.. \tag{6}$$

Figs. 8 and 9 show the results of the normalization for both heat and electricity profiles for residential UEUs. The results have hourly resolution given in normalized percentage per constructed hectare. The profiles show also the variance of minimum and maximum possible values. The different typical normalized UEU-heat load profiles show

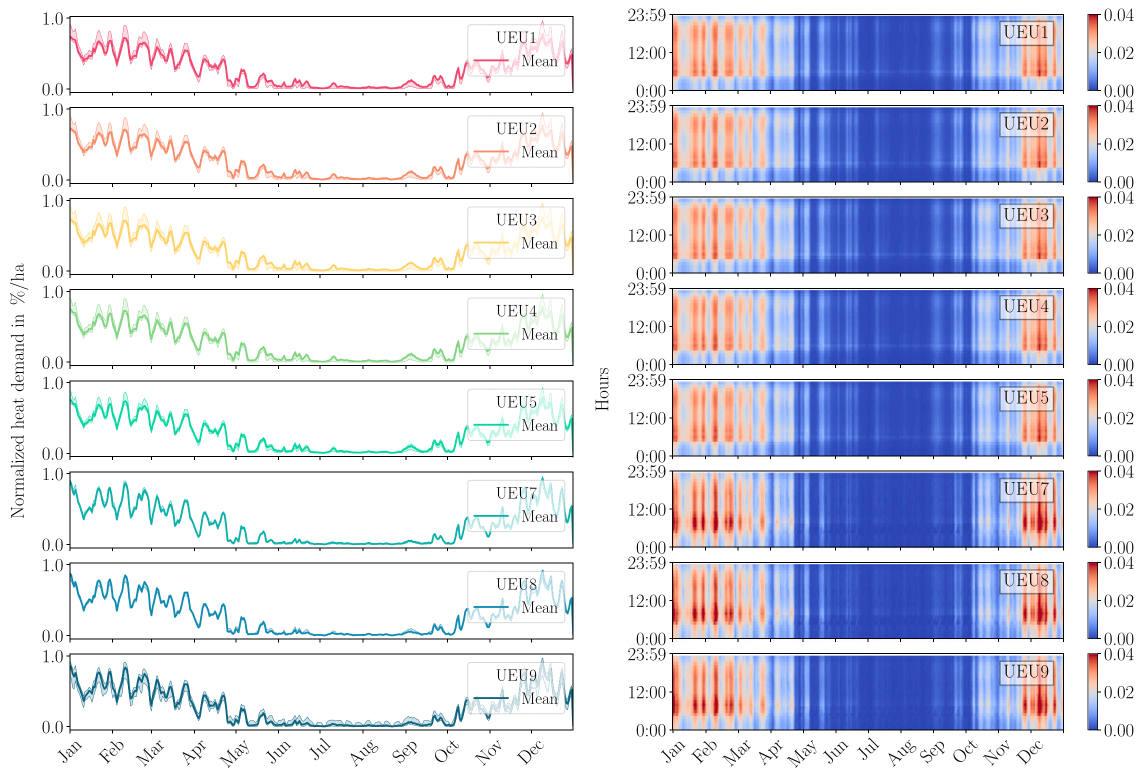



**Fig. 8.** Normalized and typified heat load profiles for each UEU type under $TRY_{2015}$ conditions, displayed as a profile for each day from minimum, mean and maximum possible values (left) and a heatmap (right) for each hour throughout the year in normalized heat percentage per constructed hectare.

a relative small difference between each other in terms of form, due to the fact that they are based on the specific weather conditions and SLPs. However, it can be observed that the higher the UEU-class, the higher the values on winter tend to be, this is due to the fact that the complexity of the building structures increment with the UEU-class (see Table 3). The maximal deviation of the profiles from the mean is 20% for the UEU 3, the general standard deviation accounts for 2%, in contrast with the electricity profiles which present a higher variance.

The heat and electricity typical normalized UEU profiles need to be analyzed separately to understand better their statistical distribution and level of confidence. To have a more detailed statistical description of the level of confidence of these normalized artificial profiles, the errors were calculated using the absolute difference of the maximum and minimum values divided by the mean value for every single hour along the reference year. A statistical examination of the heat profiles of Fig. 8 was conducted and the statistical mean, minimum, maximum, standard deviation and percentiles of the corresponding error were calculated for each UEU profile and are shown in Table 6. The results show the mean error of UEUs 1 to 5 to be around 60% while for UEUs 7 to 9 above 80%, this can be correlated firstly to the fact that UEUs 1 to 5 are settlement areas, meaning that the residential buildings are more studied and do not show as much variance as those of non-residential characteristics, which is the case for UEUs 7, 8, and 9. Secondly, the variation can be directly related to unknown refurbishment state of the building stock while for the non-residential UEUs the variance is due unknown process related and function related energy demand. Maximum values are found to be in the summer months meaning that there is zero space heat demand but constant DHW demand. Thus the high maximum differences. Nevertheless, the 75% is still around the 100% difference margin, which are the combination of maximal uncertainty on refurbishment status of the building stock, process related demand and high DHW demand in comparison with null space demand on the summer months.

Examination of the typical normalized UEU-electricity load profiles shows no significant differentiation among the absolute mean values for all UEUs (see Fig. 9). However, notable differences were identified in maximum and minimum values, as well as in the deviation from the mean. For instance, the maximum deviations from the mean in UEU 1 to 3 were found to be as high as 90%, while in UEU 5 and 9, deviations had a maximum of 48%. The high deviations observed in the typical electrical load profiles are due to the statistical approach employed by resLoadSIM in calculating the load profiles. Fig. 9 depicts the minimum, mean and maximum value that a typical UEU could take at any hour of a year. It means for instance, that at a given hour, while some population living at a given UEU 1 was sleeping or working and not consuming a lot of energy, in other specific apartments, there were residents actively living and operating different home appliances. Another reason that explains the different deviations among the UEUs is based on the number of simulated apartments per UEU. The greater the number of UEUs, the higher the deviation found, due to higher probabilities of having different demand behaviors of the residents in a given UEU.

Table 7 shows a statistical analysis of the absolute error for all the typical normalized UEU-electricity load profiles. The errors were calculated using the absolute difference of the maximum and minimum values divided by the mean value for every single hour along the reference year. The results show a contrast to the heat demand errors previously discussed. The UEUs 1 to 5 show the highest variances and UEUs 7, 8, and 9 show low variance. This can be attributed to a number of factors. First, the resLoadSIM model is stochastic, meaning that a random model is applied when simulating the turning on and off of electrical devices in a specific household, and the more simulations the more high data-points we can get, and there are more UEUs of residential areas in total as there are of non-residential. Second, residential areas show a high volatility and uncertainty in consumption because of user behavior in contrast to non-residential areas. Third and

**Table 6**
Summary Statistics for the absolute error of the typical normalized UEU-heat load profiles. All the values are given in % .

| Abs. Error | UEU 1 | UEU 2 | UEU 3 | UEU 4 | UEU 5 | UEU 7 | UEU 8 | UEU 9 |
|---|---|---|---|---|---|---|---|---|
| Mean | 66.34 | 54.92 | 68.06 | 63.22 | 49.10 | 82.71 | 91.23 | 194.51 |
| Std | 79.27 | 69.72 | 109.38 | 58.85 | 50.71 | 188.28 | 283.12 | 440.16 |
| Min | 0.51 | 0.51 | 3.37 | 0.51 | 0.11 | 0.05 | 0.00 | 4.93 |
| 25% | 21.72 | 18.75 | 23.56 | 20.04 | 14.26 | 7.60 | 6.67 | 30.80 |
| 50% | 43.68 | 39.32 | 44.50 | 42.99 | 35.08 | 20.20 | 15.51 | 51.62 |
| 75% | 108.22 | 78.56 | 104.87 | 111.80 | 78.38 | 108.15 | 42.75 | 256.89 |
| Max | 1441.35 | 1461.82 | 2873.94 | 1028.78 | 1300.00 | 2454.09 | 1800.00 | 13 540.51 |

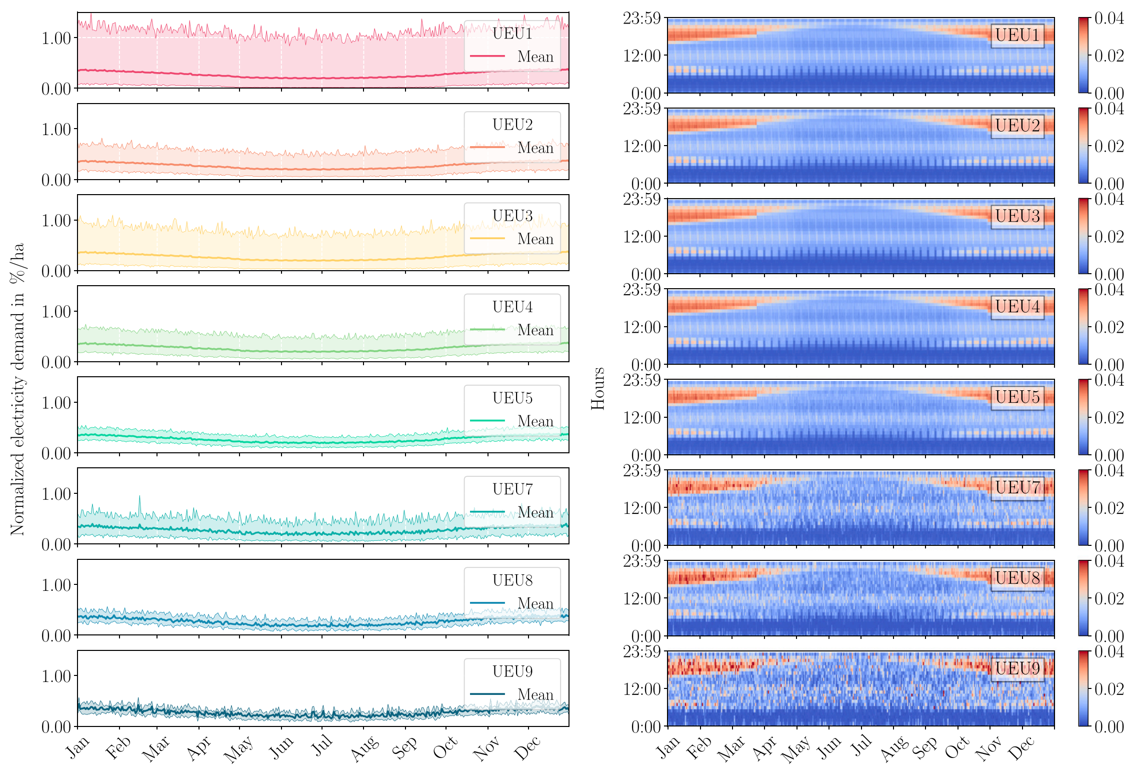



**Fig. 9.** Normalized and typified electricity load profiles for each UEU type under $TRY_{2015}$ conditions, displayed as a profile for each day from minimum, mean and maximum possible values (left) and a heatmap (right) for each hour throughout the year in normalized heat percentage per constructed hectare.

**Table 7**
Summary Statistics for the absolute error of the typical normalized UEU-electricity load profiles. All the values are given in %.

| Abs. Error | UEU 1 | UEU 2 | UEU 3 | UEU 4 | UEU 5 | UEU 7 | UEU 8 | UEU 9 |
|---|---|---|---|---|---|---|---|---|
| Mean | 484.26 | 210.32 | 326.17 | 194.20 | 93.32 | 153.57 | 87.40 | 63.89 |
| Std | 242.87 | 101.68 | 165.75 | 87.06 | 42.22 | 72.80 | 50.21 | 44.93 |
| Min | 97.95 | 39.41 | 70.83 | 34.86 | 15.37 | 7.91 | 2.13 | 0.00 |
| 25% | 332.52 | 152.21 | 228.79 | 142.33 | 63.928 | 100.86 | 47.80 | 27.59 |
| 50% | 427.81 | 191.89 | 289.21 | 179.53 | 88.712 | 143.69 | 80.82 | 53.43 |
| 75% | 574.31 | 244.54 | 378.76 | 229.22 | 114.73 | 190.65 | 118.43 | 95.25 |
| Max | 3097.18 | 2010.00 | 2180.31 | 987.42 | 396.365 | 591.40 | 316.94 | 187.72 |

last, there are less household related electrical appliances simulated in resLoadSIM for non-residential spaces such as offices.

In this study, we analyze typical electricity load profiles and observe their resemblance to electricity SLPs commonly used by utilities, as discussed in Fünfgeld and Tiedermann (2000), albeit with some discrepancies. Fig. 10 illustrates the variability among electricity SLPs, a typical load profile for UEU 1, and a specific load profile for a residential unit within UEU 1 with an annual demand of approximately 1 MWh, spanning from Friday to Monday. It is noteworthy that the selected comparison days reflect established findings in SLP research, showing distinct load profile differences between weekdays and weekends (Fischer et al., 2015). The highlighted UEU 1 example exhibits statistically random demand behavior, as described in Section 3.4 detailing how resLoadSIM conducts simulations, without following a discernible pattern. In contrast, the mean of all simulated UEU 1 load profiles in Oldenburg, represented as the typical UEU 1 profile in red, demonstrates behavior closely aligned with weekdays but diverges slightly on weekends. This mirrors observed patterns in electricity SLPs, where differences are more pronounced on weekdays compared to weekends. These variations are crucial given ongoing technological advancements in residential building operations. While residences predominantly used less efficient lighting and refrigerators two decades ago, modern homes are equipped with significantly more energy-efficient appliances. Additionally, the diverse range of appliances and consumption patterns today contribute to higher peaks in the typical UEU 1 load profile. These factors explain the observed lower minimum points and higher maximum values in the typical UEU 1 load profile compared to electricity SLPs.

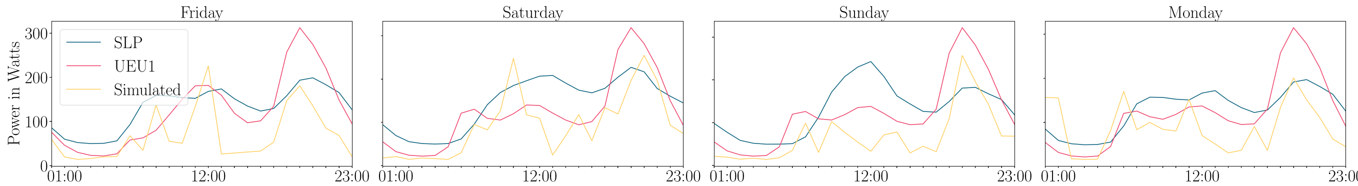
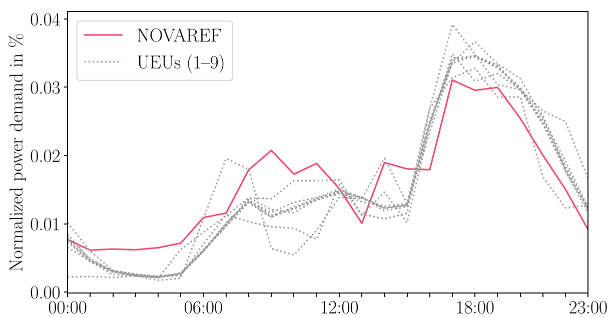



**Fig. 10.** Hourly power demand comparison: Electricity Standard Load Profile (Fünfgeld & Tiedermann, 2000) (blue line), Typical Load Profile UEU 1 (red line) and a selected particular simulated UEU 1 (yellow line) for a household with a demand of 1.015 MWh/year. The typical UEU 1 was multiplied by a defined constructed area and total energy demand to get the electricity load profile. Detailed profiles are plotted for Friday, Saturday, Sunday, and Monday in March. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)




| UEU | Correlation (-) |
|---|---|
| UEU 1 | 0.909 |
| UEU 2 | 0.909 |
| UEU 3 | 0.907 |
| UEU 4 | 0.908 |
| UEU 5 | 0.911 |
| UEU 7 | 0.838 |
| UEU 8 | 0.908 |
| UEU 9 | 0.834 |

**Fig. 11.** Validation of simulated data against the NOVAREF project for the city of Oldenburg achieving a correlation between 0.8 and 0.9 for the different UEUs. One single day is depicted. On the right is shown the Correlation matrix of simulated electricity load profiles of typical UEUs against measured data from NOVAREF project for the city of Oldenburg for one year.

Furthermore, the results obtained were validated against measured data from a prior study, the NOVAREF project (Lange & Zobel, 2017), conducted in the city of Oldenburg across multiple apartments. Fig. 11 illustrates the behavior of simulated data for one selected day, where the correlation between UEU 1 to UEU 5 and the normalized load profile from the NOVAREF project was notably high, achieving a value of 0.9. For the remaining UEUs, the correlation ranged between 0.8 and 0.85. Fig. 11 also presents the correlation values between the NOVAREF simulation and each one of the UEUs, underscoring the robustness of the simulated data in replicating observed energy consumption patterns. The high errors highlighted in Table 7 related to the electrical consumption indicate that the maximum and minimum curves for the normalized UEU-electricity profiles need higher refinement. Nevertheless, the mean curve has a high statistical confidence when compared to SLPs and other models as shown in Figs. 10 and 11.

### *4.4. Example of a district energy analysis*

In order to illustrate the practical applications of the methodology described in this study, a random district within the city of Oldenburg was chosen to analyze its energy demand and extract its heat and electricity load profiles respectively. The chosen district is made up of eight different UEUs, one of class 9, one of class 2 and the others of class 3 as shown in Fig. 12. The figure also shows the building stock classified into the specific heat demand of each building as to have an idea of how the energy demand is distributed. From the methodology above each UEU is multiplied by its total constructed area and total energy demand to get the heat and electricity load profile, the same results can be obtained by adding up all the individual building's load profiles but the computational cost is higher. This does not mean much in a small area like the one chosen, but when scaled to larger areas, the computational cost can be significant. The heat and electricity energy demands need to be analyzed separately to understand better their current status and have better control over possible transformation plans.

The heat energy demand is calculated for every single building under the three different refurbishment scenarios, Fig. 12 only shows the standard refurbishment state but the profiles show the variation in demand for all three cases. By analyzing the total demand for each one of the refurbishment scenarios in the study area, we get three different values for the total yearly heat demand of 19.93, 9.90 and 6.26 GWh/a respectively. This results in a 101% difference between the standard and the no refurbishment scenarios, and a 37% difference between the standard and the advanced refurbishment scenario. An absolute difference of 13.6 GWh/a with standard deviation of 7.07 GWh/a. A validation of the same area made with the tool HOTMAPS of the European Union, which is a free tool to give an estimate of the heat demand of different regions within the European Union, results in a total yearly heat demand of 10.76 GWh/a. This means a difference of 85% with the no refurbishment scenario, 8% with the standard scenario and 42% with the advanced refurbishment scenario, for a overall mean difference of 45%. The results and errors presented here seem to be consistent with other methodologies already published (Hotmaps, 2019; Pezzutto, Croce, et al., 2019; Pezzutto, Zambotti, et al., 2019). The variable that influences the most the total validation and performance of the model is the refurbishment state of the building stock even if the hourly variations of the profiles have a standard variation over 100%. The results for the electricity demand cannot be compared with real data because it was not possible to obtain measurements for the region due to data protection laws. However, the validation and statistical correlation was of the previous section are still valid. The total simulated electricity demand of this district is 2.3 GWh/a for calculated 623 households in the district. Nevertheless, to verify the behavior of the simulated electricity load profile, it was compared with the load profile that would be representative of 623 households for the dataset from Lange and Zobel (2017). The standard deviation is thus calculated to be 126.6 MWh/a with an overall mean difference of 39.6%. This result indicates that the simulated electricity demand per household is approximately 3795 kWh/a. A comparison of this value with the suggested yearly electricity consumption in Germany for homes with one to three or more people, which averages 3383 kWh/a (Statistische Ämter des Bundes und der Länder, 2023a), reveals a deviation of 412 kWh/a.

The methodology presented in this paper is able to differentiate between different refurbishment states for the building stock giving a best-worst case scenario for energy planers, particularly important in the context of the municipality heating plan in Germany.

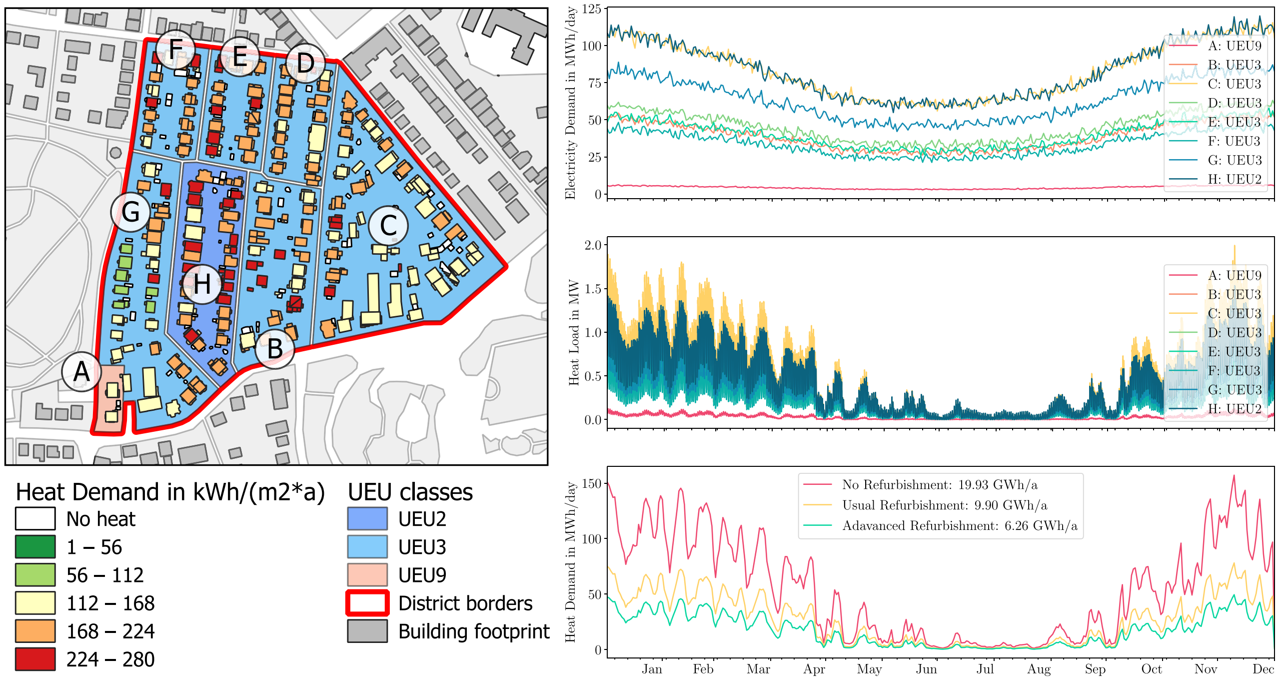



**Fig. 12.** Example of a randomly chosen district in the city of Oldenburg, displaying UEU-types 2, 3, and 9. Heat demand per building is depicted in kWh/(m$^2$· a). Heat and electricity load profiles for each UEU are presented under TRY$_{2015}$ conditions, along with the total heat demand according to the three refurbishment scenarios.

## 5. Discussion and practical application

The practical value of this methodology is highlighted by the need for many German municipalities to create heating plans for their communities. Given the constraints of limited personnel and the absence of standardized procedures at the municipal level, the methodology presented in this paper offers a way to streamline and automate the initial phase of developing these heating plans. This phase involves assessing the current condition of buildings and their energy demands, making the methodology a valuable tool for expediting this process. This method demonstrates how leveraging data and analytical methods in conjunction with standardized engineering processes can create a model that collects and processes open data for large settlement areas to provide coherent energy demand results with high-temporal resolution. The methodology extends previous models by Blanco et al. (2024), enabling district-level focus while maintaining building-level accuracy.

For the account of total heat demand the most critical parameter seems to be the refurbishment state of the building stock as it gives the highest uncertainty, in contrast the parameter of the building age although it results originates from a 100 × 100 m grid and disaggregated to a building level through an ML model developed in previous studies, it re-gains the original statistical confidence of the census data at the UEU-level as the buildings are aggregated back into a district. This means that although the building age is an important parameter, its uncertainty and significance are lower with respect to the refurbishment state. This results in an important advantage of the model presented in this study as it provides different refurbishment scenarios at the district level for the users or urban planers to choose or combine at will. Simulation results of an electrical load profile for a household, compared with both electrical SLP and NOVAREF, show similarity with typical UEU load profiles, meeting the flexibility needs of current and future residential conglomerations. Urban projects may consider lower minimum loads due to efficient appliances, but peaks can vary based on heating options such as heat pumps or thermal district connections, and e-mobility requirements.

The geolocation of UEUs linked with their total electrical and heat demand aids in selecting suitable technologies and energy sources for local geographical characteristics. For instance, a residential project might exploit geothermal energy based on underground rock or water reservoir characteristics. Proximity to a thermal district pipe supplied by a heat waste provider or a CHP system may influence heating technology choice, resulting in lower peak loads. These variables impact the optimal renewable energy systems and highlight the need for flexible, easily implemented load profiles based on project parameters and geolocated resources.

This method's significant advantage over previous models is its ability to provide different demand scenarios with high-temporal resolution according to the refurbishment state of buildings, typically an expensive dataset for engineering offices to acquire on-site. By presenting best- and worst-case scenarios, engineering offices can explore different refurbishment scenarios by adjusting the results with their own factors. It is important also to highlight the limitations of the model: although the underlying data has a building level accuracy it is aggregated at the UEU and District levels, so the presented profiles should only be used at the corresponding spatial resolution. The model is limited to the geographical region of Germany as the profiles are highly related to the energy demand of the German building stock, although building models, weather and TABULA data are available for other European countries, validation with other geographical regions has not been made. Last but not least, the model does not include any economical decisions on the type of technology that a region should use to reduce their carbon emissions. It is meant to provide a high temporal resolution energy demand analysis of the current building stock upon which technical decisions and other technical processes can be based. The goal is to determine the heat demand of regions in order to plan where new supply technologies (e.g., heat pumps, heat networks) should be implemented. The methodology was put into practice in different pilot projects with different engineering offices throughout Germany, yielding detailed, documented decision processes for their heating plans. Nevertheless, Additional refinement of the methodology is required, by including more specific non-residential building analysis, different heat demand norms and regulations, and expansion to other European databases.

## 6. Conclusion

This paper presents a new methodology to generate typical heat and electricity load profiles for various urban spaces classified in previous studies. These profiles are hourly-specific and based on the hourly $TRY_{2015}$ data from the German weather service. The presented methodology can be applied to different weather conditions and refurbishment scenarios of the building stock.

The significant contribution of GHG emissions from the building sector, combined with prior research on heat demand calculations and Germany's regulatory framework targeting emissions reduction, strongly motivated this paper. Due to limited detailed building data, lack of qualified personnel, resources, and complex data protection laws, municipalities need new tools to analyze their energy needs in the building sector. The methodology and results presented in this study aim to help municipalities and city planners with these issues and also aims to be a helpful tool for the initial phases of municipal heating plans in Germany.

The methodology described in this paper details a model that automatically collects geographical data for any area within Germany, the model then processes the data in order to: first, generate a building stock database with specific information about each building; second, collect regional weather data; third, calculate specific load profiles for each building type to create hourly profiles; fourth, classify the building stock into the TABULA building typology, thereby calculating the total energy demand of each building under various refurbishment scenarios; and finally, combine the specific load profiles with the energy demand of buildings within a specific region. The model and its validations are limited to the geographical region, weather conditions and current building stock of Germany. Normalizing the UEU load profiles provides a faster and more efficient way to calculate the energy load profile for large building settlements. This methodology was applied to the city of Oldenburg, showcasing a comprehensive energy analysis for a randomly selected district at the UEU level.

The authors recognize that neither municipalities nor city planners will use complex models in their decision-making processes. Therefore, the future outlook of this study is to develop user-friendly software and QGIS plugins to facilitate the integration of our findings for city and energy planners. At the same time the integration with other tools for simulation and designing of district heating and cooling networks results to be a promising solution to increase the share of renewable energy within the heating and cooling sector.

### CRediT authorship contribution statement

**Luis Blanco:** Writing – review & editing, Writing – original draft, Visualization, Validation, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Alejandro Zabala:** Writing – review & editing, Writing – original draft, Investigation, Formal analysis, Conceptualization. **Björn Schiricke:** Writing – review & editing, Supervision. **Bernhard Hoffschmidt:** Resources, Funding acquisition.

### Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Luis Armando Blanco Bohorquez reports a relationship with German Aerospace Center DLR that includes: employment. Luis Armando Blanco Bohorquez has patent KLASSIFIZIERUNG VON URBANEN ENERGIEEINHEITEN UND ENERGETISCHEN QUARTIEREN MIT TECHNIKEN DER KÜNSTLICHEN INTELLIGENZ pending to German Aerospace Center DLR. This article is part of the doctoral studies of the main author. The doctoral studies are conducted in the RWTH Aachen University in Germany.

### Data availability

Data will be made available on request.

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