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Novel load-breakdown methodology for a university office building

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ABSTRACT

Various methodologies can be adopted to evaluate different sub-loads in an office building. These approaches may be based on either non-intrusive or intrusive load monitoring techniques, or a combination of both. This paper presents a novel methodology for evaluating sub-load profiles starting from the total electric load of buildings, following a breakdown methodology. Starting with the total electric load of the building under investigation, this methodology estimates the sub-loads within the total building load, using information regarding the operation of the heating, ventilation, and air-conditioning system (HVAC) and the building management. The proposed methodology has been applied to a reference case study, specifically a university building in the South of Italy. Data collected from a measurement campaign on the main components of the HVAC system have been used to validate the proposed approach, showing that the relative error between measured and estimated data is about 3%. As such, this methodology stands out as an effective process for providing a thorough and comprehensive understanding of buildings' electricity consumption and for helping in identifying anomalies, faults, and inefficiencies.

1. Introduction

Energy efficiency in buildings aims to guaranteeing primary energy savings, reducing greenhouse gas emissions and operating costs. The final goal is to achieve a zero-emission and fully decarbonised building sector by 2050. However, final energy demand from the building sector in 2023 accounts for approximately 28.4 % of the total global demand [1]. Most buildings have poor energy performance, and different interventions (energy conversion systems, envelope, energy demand management) could be considered for energy savings. Particular attention should be paid to public buildings, for which various management strategies can be introduced to mitigate their energy demand and improve their energy efficiency. In this context, the introduction of a Building Energy Management System (BEMS) can yield energy savings ranging from 10 % to 50 % [2].

Ensuring optimal energy performance is a central concern for facility managers and stakeholders involved in building energy management. A robust strategy to support users in monitoring performance over time involves estimating expected energy consumption—typically derived from historical operational data and/or simulation tools—and comparing it with actual use (i.e., energy benchmarking). However, while benchmarking provides a high-level comparison between actual and expected energy performance, it does not offer detailed insights into how specific systems or components contribute to overall consumption.

To move from performance assessment to actionable strategies, it becomes essential to have a clear understanding of the main energy sub-loads. This allows the identification of loads that can be better managed or shifted in response to time-dependent tariffs (e.g., electricity, natural gas) or better matched with the local generation of renewable-based energy systems.

Therefore, investigating methodologies in the scientific literature that support detailed energy breakdown is a crucial step toward the implementation of targeted and cost-effective energy management (e.g., anomaly detection [3], application of demand side management strategies [4]).

A load breakdown methodology could help in finding the main energy sub-loads of a building, starting from information available from different sources. These data can be collected either through sensors installed by end-users or via smart meters provided by energy distributors—such as electricity meters (for active and reactive power) or volumetric gas flow meters. User-installed sensors typically provide real-time data, whereas data from utility smart meters is usually available with a time delay, which can range from minutes to hours or even

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Nomenclature

A	Area [m^2]
BAS	Building Automation System
BEMS	Building Energy Management System
COP	Coefficient Of Performance [-]
DSO	Distribution System Operator
E	Energy [kWh]
$\dot{E}$	Power [kW]
EER	Energy Efficiency Ratio [-]
EHP	Electric-driven Heat Pump
HEMS	Home Energy Management System
HVAC	Heating, Ventilation and Air Conditioning
IT	Information Technology
KPI	Key Performance Indicator
ILM	Intrusive Load Monitoring
NILM	Non-Intrusive Load Monitoring
SMB	Small and Medium Businesses
V	Volume [m^3]

Greek symbols

α	Power grid emission factor [kg $CO_{2,eq}$/kWh_{El}]
η	Efficiency [-]

Boolean variables

a_i	Boolean HVAC operation 15-minute time-step (i = 1, …, 35040)
b_i	Boolean occupancy 15-minute time-step (i = 1, …, 35040)
c_j	Boolean HVAC operation 1 day time-step (j = 1, …, 365)
d_j	Boolean occupancy 1 day time-step (j = 1, …, 365)
e_h	Boolean HVAC operation for a specific day 15-minute time-step (h = 1, …, 96)
f_h	Boolean occupancy for a specific day 15-minute time-step (h = 1, …, 96)

Subscripts and superscripts

AUX	Auxiliaries
BL	Base Load
BUI	Building
El	Electric
h	15 min time step for a specific day (h = 1, …, 96)
HVAC	Heating, Ventilation and Air Conditioning
I	15-minute time step (i = 1, …, 35040)
j	1 day time step (j = 1, …, 365)
k	Type day of the week (k = 1,…5, 6; 1: Monday, …, 5: Friday, 6: Closing day)
no-HVAC	Heating, Ventilation and Air Conditioning not operating
OCC	Occupancy
p	Primary
PG	Power Grid

months, depending on the data management practices of the distributor. In both cases, finding a methodology that supports the breakdown of whole building energy consumption data is of significant importance. This is the case of data related to electricity consumption at the whole building level, which is available aggregately and depends on different sub-loads (e.g., artificial lighting, HVAC systems, office equipment) that could be influenced by external drivers such as weather conditions and building occupancy patterns. Different breakdown techniques can be used to disaggregate the total electrical load into a set of sub-loads. The type and number of these sub-loads largely depend on the building type (e.g., residential, office, commercial) and the characteristics of the heating, ventilation, and air conditioning (HVAC) systems in place.

Following the selection of appropriate breakdown techniques, the consequent step involves processing the raw data to identify load-specific events, typically corresponding to the activation or deactivation of electrical devices. This event detection process allows for the characterization of transient, steady-state, and cycling behaviours, supporting accurate feature extraction for each sub-load. The quality of this analysis can be enhanced by incorporating contextual information, such as HVAC system schedules (heating, cooling, intermediate periods), occupancy patterns (e.g., weekends, holidays, off-hours), and climatic conditions (e.g., outdoor temperature, humidity, solar radiation), which all influence load behaviour.

1.1. Background and literature review

Starting from the need for accurate load characterization and disaggregation, this section provides a literature review of data-driven approaches for electricity consumption breakdown, considering residential and non-residential buildings to evaluate the best options that have been or could be considered, in particular, for office buildings.

Even if the focus of the paper is the evaluation of data disaggregation methodology applied to office buildings, the literature review includes the residential, commercial and industrial sectors, where this technique is well-developed. The aim is to evaluate the advantages and limitations of using methods, typically applied in the scientific literature to residential and other sectors, to office buildings.

First, load breakdown may be implemented by means of machine learning methods [5] and deep learning approaches involving complex neural networks [6].

As regards the disaggregation of building energy demand data, Non-Intrusive Load Monitoring (NILM) techniques have played a crucial role in data disaggregation so far [7]. They represent a software-based approach with data acquired in real-time at defined sampling rates using a single smart electricity meter installed by end users.

The performance of NILM approaches could be enhanced through the adoption of Home Energy Management Systems (HEMS) able to monitor and schedule the operation of smart home appliances, as well as smart energy conversion systems supplying heating and cooling energy [8].

Software for data management should be able to detect an event due to a state change, for example, of an appliance, that leads to a modification of the power (active, reactive) required. For each appliance, a load signature (turn-on transient response, total operation cycle) helps defining its operating cycle (two-state, multi-state, continuously variable) [9] and hence identifying its load from the total one, especially in case of high-frequency sampling rate [10]. Current and voltage waveforms could also be considered due to their dependence on a specific appliance or load [11].

An alternative path based on Intrusive Load Monitoring (ILM) approach involves the installation of smart plugs integrating electricity meters next to each equipment or appliance. These smart plugs can transmit data in real-time via Wi-Fi or Ethernet networks, to a cloud server or to a datalogger recording the information, which could be then managed by software applications (mobile apps or computer-based tools) that show both the current power usage and historical data on energy required (consumption on an hourly, weekly, and monthly basis). However, the need for numerous devices makes hardware-based ILM techniques complex and, at times, cost-inefficient, even though they offer very high accuracy [12,13].

As regards non-residential buildings, researchers have explored NILM, ILM, and hybrid methodologies to identify the most effective solutions for load disaggregation.

In non-residential settings, NILM techniques can be challenging to implement due to the wide variety of loads that depend on occupancy patterns and the specific activities performed within the building. In such cases, a preprocessing method based on the analysis of historical electricity consumption data, e.g. from electricity distributors, can assist in identifying the main energy loads. A simplified approach may involve time-series decomposition methods applied to historical data. In [14], a time-series decomposition-based method is proposed and applied to an office building in Ottawa, Canada, to disaggregate major energy loads. The proposed methodology identifies three primary sub-loads: lighting and plug loads (sub-load I), electricity used by energy conversion systems for cooling (sub-load II) and heating (sub-load III). The method is validated using submeters installed by the end user. Lighting and plug loads are effectively identified during transitional seasons where neither cooling nor heating is required. Based on the Normalized Root Mean Square Error metric, the results show error values of 13 % for sub-load I, 5 % for sub-load II, and 7 % for sub-load III.

A NILM methodology has been applied to an office building in [14] using data acquired from smart meters and a Building Automation System (BAS), which provides the operational status information for HVAC systems, supplemented by heating meter data [15]. In this case, BAS helps capture operating patterns of HVAC systems and auxiliary components such as the fans, pumps, and valves, enabling a more accurate estimation of electricity consumption for space heating and cooling. Submeters are installed to validate the disaggregation algorithm. The model achieves 6–8 % accuracy for air handling units electricity demand and up to 26 % error for lighting and plug loads in the worst-case scenario.

Gowrienanthan et al. [6] address the challenges of applying NILM in industrial and commercial buildings with three-phase power supplies. They propose a deep learning-based method for energy disaggregation, trained on four datasets including both three-phase and one-phase appliances, as well as non-appliance loads (e.g., laptops, light bulbs, chargers, and routers). While preliminary results are promising, a full-scale application of this method has not yet been demonstrated.

Norford and Leeb [16], as early as 1996, investigated the feasibility of extending residential NILM techniques to commercial buildings. The focus was primarily on HVAC systems, where the BAS enabled data acquisition on start-up and shutdown events of electric heat pumps and auxiliaries. The NILM methodology's performance was evaluated using a watt transducer connected to a three-phase power supply serving HVAC equipment in two campus buildings, combining steady-state analysis and transient pattern recognition, and showing difficulties in quantifying start-up energy demand for devices with variable-speed drives.

Henriet et al. [17] also acknowledge the challenges of applying NILM to commercial buildings and present a comprehensive framework for power load disaggregation. Their work includes the analysis of existing public datasets and the development of a tool to generate evaluation datasets for NILM research.

Toledo-Orozco et al. [18] propose a methodology for power load disaggregation in an industrial setting using NILM and machine learning techniques, based on data provided by the electricity distributor with a 15-minute time step. The methodology is implemented in Python, and its calibration and validation are carried out using data from smart meters already installed in three different industries (ceramic, plastics, and food processing). The primary goal of the study is to investigate the flexibility in power demand that large consumers could offer to the Distribution System Operator (DSO). The results obtained show that the disaggregation of consumption realised by implementing NILM approaches allows intelligent energy management also in the industrial sector, with improved energy consumption habits due to the changes in load profiles.

A NILM-based analysis is also conducted on commercial buildings to disaggregate electric loads [19]. The goal of the project is to develop a commercial NILM product. The authors emphasize the challenges of applying NILM technique in commercial buildings. To test the methodology, different devices are monitored using dedicated power meters that record data at 1-second intervals. While the algorithms are improved and tested, the model cannot be successfully validated.

Kumar and Gopinath [20] develop the DeepEdge-NILM device, which was tested in a commercial building to disaggregate loads from similar devices and air conditioners. The authors develop a deep learning framework based on a neural network that can identify distinct load signatures, significantly improving disaggregation results. They highlight the importance of the training phase, which typically lasts two to three weeks, to capture the different load combinations. In the best scenario, the model achieves an average accuracy of 81.5 %, with individual air conditioner detection accuracy ranging from 54 % to 96 %. However, they also highlight limitations when applying their approach to other types of loads, such as lighting systems.

Abhinav et al. [21] propose a methodology using unsupervised algorithms for energy disaggregation in Small and Medium Businesses (SMBs). Their approach is developed using a database containing electric consumption data from over 1000 SMBs, recorded at 15-minute intervals. The methodology focuses on disaggregating energy into three main load types: base, HVAC, and operational. Special attention is paid to evaluating HVAC demand, incorporating behavioural analysis of HVAC usage.

Batra et al. [22] explore methodologies for applying NILM techniques to both residential and commercial buildings. They analyse IT (Information Technology) office buildings where HVAC and IT loads are dominant. Data from an educational campus in India is used to validate the proposed tools and methods, showing that commercial buildings experience higher variability in electricity demand than residential buildings, thus exacerbating the transient behaviour of heating and cooling systems.

Ling et al. [23] introduce a NILM methodology based on a random forest to disaggregate total electricity use into four main load categories: HVAC systems, artificial lighting, plug-in devices, and elevators. This method is applied to an office building located in a region characterised by hot summers and cold winters.

Yang et al. [24] propose a simulation-data-driven approach to energy disaggregation for industrial and commercial buildings. Their method is based on load breakdown using voltage-dependent load functions, enabling detailed load separation without relying exclusively on high-frequency measurement data. In addition, a multi-channel neural network-based load disaggregation model is developed, reaching a high level of accuracy.

1.2. Research gaps and aim of the paper

Based on the literature review, the NILM approach does not consistently yield satisfactory results for disaggregating electrical loads in office buildings due to the complexity, variety, and simultaneity of electrical loads. Disaggregating similar electrical loads (e.g., multiple air conditioners, IT equipment) remains a major technical challenge, even with advanced methods like deep learning and neural networks. Model accuracy varies greatly depending on the load type and operating conditions, indicating issues with model generalization. Overall, the reliability of the proposed solutions in real-world scenarios is hindered by the lack of validation of proposed models due to insufficient data or technical constraints. Many methodologies require high-resolution data (e.g., 1-second intervals) or the installation of sub-metering devices, contradicting the "non-intrusive" nature of NILM. This makes large-scale deployment excessively costly and complex, especially for office buildings. Also, NILM techniques have been underdeveloped for three-phase systems, which are typical in industrial and commercial buildings. In the end, the analysed methods are often tailored to specific buildings or load types, with poor transferability to other scenarios, and a standardized and adaptable framework is still missing.

An enhancement of the techniques proposed by the scientific literature for application in non-residential buildings involves the installation of a limited number of power meters capable of measuring total electricity consumption and HVAC-related energy use in real-time with a high sampling rate. Additionally, the integration of a BAS, commonly employed for HVAC control, can significantly improve the granularity and accuracy of electric load disaggregation. This hybrid approach, combining NILM and ILM techniques with BAS integration for HVAC monitoring, offers a promising balance between the cost of the monitoring infrastructure and its effectiveness in load breakdown. It represents a practical solution for identifying energy-saving opportunities in complex building systems.

In this context, the present paper applies a novel methodology to an office building to evaluate the main electricity sub-loads with a 15-minute time step. The approach is based on a time-series decomposition method used to disaggregate total electricity load into four contributions: base load, occupancy-driven electric loads, HVAC auxiliaries, and Electric-driven Heat Pump (EHP) demand. The method is further enhanced by incorporating basic information on HVAC system operation at daily, weekly and seasonal scales. This approach is considered analogous to NILM methodologies that rely on real-time data, while benefiting from BAS-provided schedules and operational patterns related to HVAC systems. Notably, even in the absence of a BAS, the methodology remains applicable by collecting operational data directly from facility managers or HVAC operators. The results obtained can also assist in identifying anomalies in energy consumption related to specific sub-loads, thereby supporting improved energy diagnostics. Furthermore, with sub-load data available, the use of dynamic simulation software capable of modelling both the building and its HVAC systems can be considered to evaluate its potential impact of targeted interventions (e.g., artificial lighting optimization, building envelope improvements, HVAC upgrades, and energy management strategies). The methodology requires total building electricity consumption data over one year (with a 15-minute or hourly resolution), alongside auxiliary information such as HVAC operational schedules, nominal data of energy conversion systems, characteristics of HVAC auxiliaries, and building occupancy patterns. It is designed for the analysis of electricity consumption and excludes fuel-based systems. While not universally applicable, this methodology is well-suited for typical office buildings with centralized, electricity-based HVAC systems. In cases where the hydronic distribution system includes pumps with inverters, auxiliary loads can be grouped with HVAC consumption, simplifying the disaggregation into three main sub-loads.

This methodology addresses several issues that have been identified in the scientific literature, such as:

- In tertiary buildings, load disaggregation using NILM can lead to unsatisfactory results.
- Existing methodologies often require multiple smart meters collecting data for at least one year to achieve adequate validation.
- Upgrading BAS systems to enable detailed load disaggregation typically involves significant increases in investment cost and operational costs.

To validate the proposed methodology, a three-phase digital multimeter compliant with Class 1 accuracy for active energy (according to IEC/EN 62053–21) was installed to monitor EHP electricity data (voltage, active power, active energy, etc.) at 15-minute intervals. Using data collected from December 2024 (installation month) through March 2025, the methodology demonstrated an average overestimation of EHP electricity input of about 3 %, confirming its reliability.

The remainder of the paper is organized as follows: Section 2 provides an overview of the load disaggregation methodology employed in this study. Section 3 describes the case study under analysis, and Section 3.4 details and discusses the results. Eventually, Section 4 offers a comprehensive overview of the findings and outlines potential future developments in this area of research.

2. Load breakdown methodology

In this section, the methodology developed for load disaggregation is introduced.

2.1. Data collection

This paper proposes a disaggregation methodology to evaluate the electricity demand of an office building, specifically for lighting, office equipment, and HVAC systems. It requires the availability of data from a DSO or a power meter for at least one year, along with information obtained from an energy audit, such as HVAC systems (nominal data, auxiliaries, hydronic circuit details, variable refrigerant flow, and scheduled operation), building features, and scheduled occupancy (daily, weekly, and yearly occupancy profiles). This methodology can be applied to office buildings equipped with an air-to-water EHP, where the hydronic system is operated by circulating pumps with fixed electric power consumption.

The total electricity demand of the building ($E^{BUI}_{El,i}$) for each 15-minute time-step over one year (i = 1, …, 35040) is influenced by various components. In the case of an office building, these can be categorized into four main groups:

- EHP electric load ($E^{EHP}_{El,i}$).
- HVAC auxiliaries (circulating pumps, fans) for ventilation, and space heating and cooling circuits, $E^{AUX}_{El,i}$.
- Additional loads, excluding HVAC ones, which are present when access to the building is allowed. These loads could be considered dependent on the building's occupancy. Occupancy-related demand includes miscellaneous loads (laptops, printers, elevator, …), and lighting loads (artificial lighting), $E^{OCC}_{El,i}$.
- Base load ($E^{BL}_{El,i}$), which includes transformer losses (MV/LV), standby equipment, beverage dispensers, electric boilers for sanitary hot water, emergency lighting, IT racks, electronic devices, and other continuous loads.

Therefore, the total electric demand can be expressed as indicated in Eq. (1):

$$E^{BUI}_{El,i} = E^{EHP}_{El,i} + E^{AUX}_{El,i} + E^{OCC}_{El,i} + E^{BL}_{El,i} \tag{1}$$

$E^{EHP}_{El,i}$ and $E^{AUX}_{El,i}$ are related to the building's space heating and cooling demand and can be aggregated into the HVAC load ($E^{HVAC}_{El,i}$). On the other hand, $E^{OCC}_{El,i}$ and $E^{BL}_{El,i}$ are independent of HVAC operation and can be referred to as non-HVAC loads ($E^{no-HVAC}_{El,i}$).

The methodology used to estimate the contribution of each of the four components to the total electric load is detailed using a simplified scheme, as detailed in the following sections. Even if specific building characteristics, such as building envelope composition (opaque and transparent), heated area and volume, or the availability of an energy performance certificate, are not required for applying this breakdown methodology, such information can be valuable for interpreting results, particularly when comparing with benchmark data or findings in the technical and scientific literature.

2.2. First step: Evaluation of base load

The first step (I) in the methodology involves estimating the base load for each timestep, denoted as $E^{BL}_{El,i}$, as detailed in Fig. 1.

This step requires the following data for each 15-minute interval: total building electric load ($\overrightarrow{E^{BUI}_{El(i)}}$); the scheduled HVAC operation ($\overrightarrow{a_{(i)}}$);

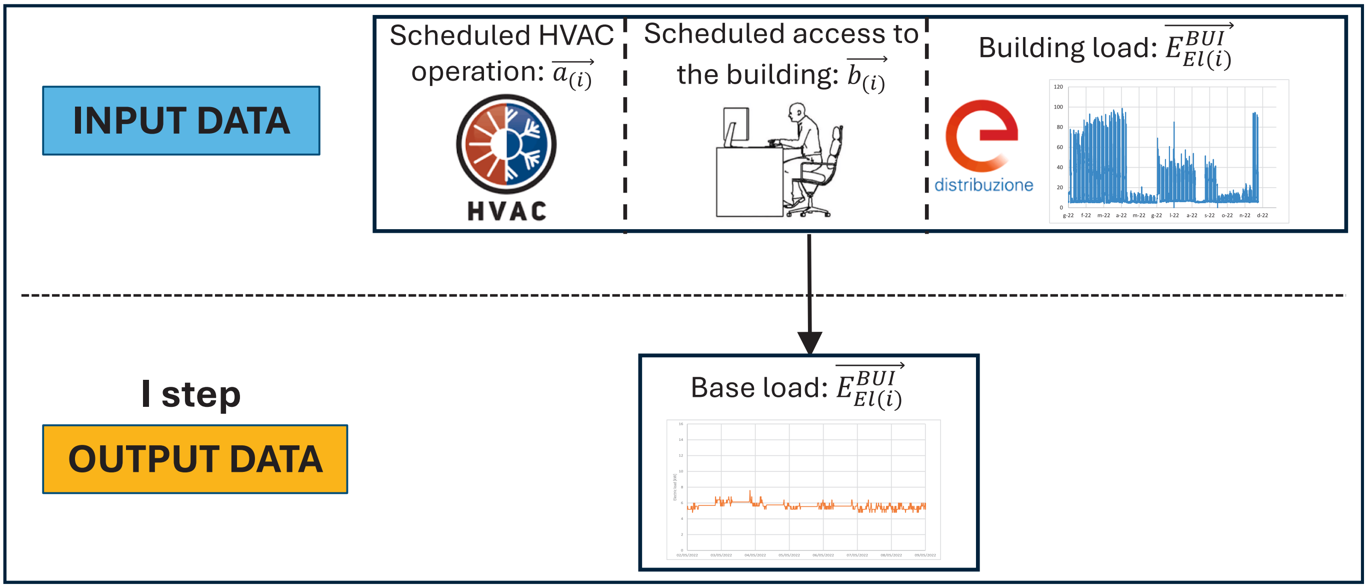

Fig. 1. First step of the methodology used for load breakdown.

the scheduled access to the building ($\overrightarrow{b_{(i)}}$). Specifically, the arrays $\overrightarrow{a_{(i)}}$ and $\overrightarrow{b_{(i)}}$ contain Boolean variables indicating the HVAC system status (0 = OFF and 1 = ON) and the potential occupancy (0 = NO access, 1 = YES access), respectively.

The base load $\overrightarrow{E_{El(i)}^{BL}}$ is evaluated in two sub steps (I.1, I.2):

- I.1: in the case of HVAC OFF and no occupancy ($a_i + b_i = 0$), the total electricity demand equals the base load, as indicated in Eq. (2). This typically correspond to nighttime and early morning on weekdays, as well as weekends and public holidays.

$$E_{El,i}^{BL} = E_{El,i}^{BUI} \tag{2}$$

- I.2: for time steps where either the HVAC system or the building is occupied ($a_i + b_i > 0$), the base load cannot be directly measured. Instead, it is approximated using the average load during time steps of the same day when both HVAC and occupancy are absent. Let j = 1, …, 365 be the day index of the year, and h = 1, …, 96 be the index of the 15-minute intervals per day. Considering the daily Boolean indictors $e_h = \{0,1\}$ for HVAC status (0 = OFF, 1 = ON) and $f_h = \{0,1\}$ for occupancy status (0 = NO, 1 = YES), the average base load for day j is calculated as indicated in Eq. (3). Then, for time steps when $a_i + b_i > 0$, the base load is assumed equal to the daily average, according to Eq. (4).

$$\overline{E}_{El,j}^{BL} = \frac{\sum_{h=1}^{96}\left[E_{El,h}^{BUI} \bullet (1-e_h)\cdot(1-f_h)\right]}{\sum_{h=1}^{96}[(1-e_h)\cdot(1-f_h)]} \tag{3}$$

$$E_{El,i}^{BL} = \overline{E}_{El,j}^{BL} \tag{4}$$

By combining the outputs from Eq. (2) and Eq. (4), the base load for all time steps throughout the year can be determined as indicated in Eq. (5). A recap of the algorithm used for implementing this step is reported in Table 1.

$$\overrightarrow{E_{El(i)}^{BL}} = \left(E_{El,1}^{BL}, E_{El,2}^{BL}, \cdots, E_{El,35040}^{BL}\right) \tag{5}$$

The flow chart related to the algorithm used to evaluate base load is reported in the appendix section (Fig. A1).

2.3. Second step: Evaluation of occupancy load

The second step (II) involves evaluating the occupancy-related electric load for each interval ($E_{El,i}^{OCC}$), as detailed in Fig. 2.

It can be divided into two sub-steps (II.1, II.2):

Table 1
Step I: average base load evaluation.

Definitions
- Let i be the 15-minute time step index within one year (1 to 35040).
- Let j be the day index within one year (1 to 365).

Inputs
- $\overrightarrow{E_{El}^{BUI}}$: total building electric load at each 15-minute interval (vector of size 35040).
- $\overrightarrow{a}$: HVAC status at each 15-minute interval (0 = OFF, 1 = ON; vector of size 35040).
- $\overrightarrow{b}$: occupancy access at each at each 15-minute interval (0 = NO, 1 = YES; vector of size 35040).

Output
- $\overrightarrow{E_{El}^{BL}}$: estimated base load at each 15-minute interval (vector of size 35040).

Algorithm Steps

Initialize $\overrightarrow{E_{El}^{BL}}$.

Else, set $E_{El,i}^{BL} = \overline{E}_{El,j}^{BL}$.

For each day j, compute daily average base load for inactive periods $\overline{E}_{El,j}^{BL}$(HVAC OFF and no occupancy).

For each time step i, compute the sum $a_i + b_i$.

If the sum is equal to zero, set $E_{El,i}^{BL} = E_{El,i}^{BUI}$.

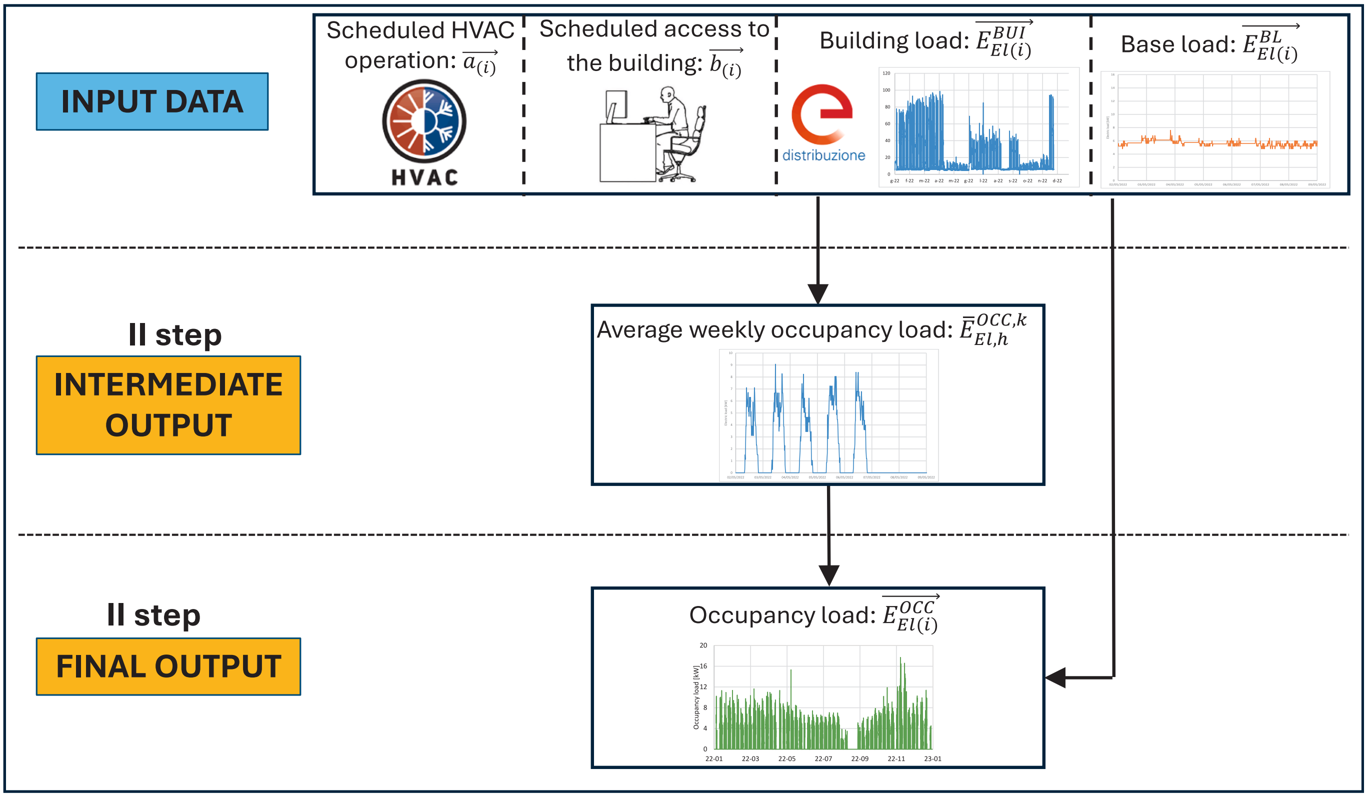

Fig. 2. Second step of the methodology used for load breakdown.

- II.1: in the first sub-step, the preliminary annual occupancy load vector ($\overrightarrow{E^{OCC*}_{El(i)}}$) is estimated. For evaluation, it requires the following input data, based on a 15-minute time step: total building electric load ($\overrightarrow{E^{BUI}_{El(i)}}$); base load ($\overrightarrow{E^{BL}_{El(i)}}$), as determined in the previous step of the methodology; scheduled HVAC operation ($\overrightarrow{a_{(i)}}$). In addition, for each day (j = 1, …, 365), the following variables are required:
  - Scheduled HVAC operation indicator ($\overrightarrow{c_{(j)}}$): a Boolean variable equal to 0 if the HVAC system is off during the day, and 1 if it is on.
  - Scheduled occupancy indicator ($\overrightarrow{d_{(j)}}$): a Boolean variable equal to 0 for non-occupancy days (e.g., weekends, holidays, closing days), and 1 for occupied days.
  - Day-type variable (k_j): indicates the weekday of occupancy. For weekdays with occupancy, $k = 1, \cdots, 5$ (1 = Monday, …, 5 = Friday). For building closure days, $k = 6$.

On days without occupancy ($d_j = 0$; $k_j = 6$), the occupancy load is assumed to be zero, as per Eq. (6).

$$E^{OCC}_{El,i} = 0 \tag{6}$$

On weekdays with occupancy ($d_j = 1$) but without HVAC activation ($c_j = 0$), typically during intermediate seasons, the occupancy-related is computed using Eq. (7):

$$E^{OCC}_{El,i} = E^{BUI}_{El,i} - E^{BL}_{El,i} \tag{7}$$

The resulting occupancy load from these days is used to create five representative type days, one for each weekday (Monday to Friday). These type days are used to estimate occupancy loads when HVAC is ON ($c_j = 1$) and occupancy is present ($d_j = 1$). For each type day ($k = 1, \cdots, 5$) the average 15-minute occupancy load is calculated using Eq. (8):

$$\overrightarrow{\overline{E}}_{El(h)}\ OCC, k = (\overline{E}^{OCC,k}_{El,1}, \cdots, \overline{E}^{OCC,k}_{El,96}) \tag{8}$$

For example, the type day for Monday ($k = 1$) is evaluated as follows:

- first time step of the day ($h = 1$, Eq. (9)):

$$\overline{E}^{OCC,1}_{El,1} = \frac{\sum_{g=1}^{N} E^{OCC,1}_{El,1,g}}{N} \tag{9}$$

- last time step ($h = 96$, Eq. (10)):

$$\overline{E}^{OCC,1}_{El,96} = \frac{\sum_{g=1}^{N} E^{OCC,1}_{El,96,g}}{N} \tag{10}$$

where N is the number of Mondays considered in the dataset and g is the index for each instance of the weekday ($g = 1, \cdots, N$). A similar approach is followed for the other four type days. Thus, during weekdays with both occupancy and HVAC operation ($d_j = 1$, $c_j = 1$), the occupancy load is estimated based on the corresponding type day average ($\overrightarrow{\overline{E}}_{El(h)}\ OCC, 1$, …, $\overrightarrow{\overline{E}}_{El(h)}\ OCC, 5$). By combining the results from Eq. (6) for non-occupancy days ($d_j = 0$), Eq. (7) for occupancy days without HVAC ($d_j = 1$, $c_j = 0$) and Eq. (8) for days with occupancy and HVAC on ($c_j = 1$, $d_j = 1$, $k = 1, \cdots, 5$), the preliminary occupancy load for the entire year can be evaluated using Eq. (11). A recap of the algorithm used for implementing this step is reported in Table 2.

$$\overrightarrow{E^{OCC*}_{El,i}} = (E^{OCC*}_{El,1}, \cdots, E^{OCC*}_{El,35040}) \tag{11}$$

- II.2: in the second sub step, this profile, identified using "*", must be further refined with a specific focus on days when the HVAC system is scheduled ON ($c_j = 1$), but not active during time steps ($a_i = 0$) in which occupancy is present ($b_i = 1$). In such cases, certain values

Table 2
Step II.1: preliminary occupancy load evaluation.

Definitions
- Let i be the 15-minute time step index within one year (1 to 35040).
- Let h be the 15-minute time step index within a single day (1 to 96).
- Let j be the day index within one year (1 to 365).

Inputs
- $\overrightarrow{E_{El}^{BUI}}$: total building electric load at each 15-minute interval (vector of size 35040).
- $\overrightarrow{E_{El}^{BL}}$: base load at each 15-minute interval (vector of size 35040).
- $\overrightarrow{a}$: HVAC status at each 15-minute interval (0 = OFF, 1 = ON; vector of size 35040).
- For each day j:
  - c_j: scheduled HVAC day indicator (0 = OFF, 1 = ON).
  - d_j: scheduled occupancy indicator (0 = NO, 1 = YES).
  - k_j: day type (1 = Monday, …, 5 = Friday, 6 = Closure/non-occupancy day).

Output
- $\overrightarrow{E_{El(i)}^{OCC*}}$: preliminary estimated occupancy load at each 15-minute interval (vector of size 35040).

Algorithm Steps

Initialize $\overrightarrow{E_{El(i)}^{OCC*}}$.
For each day j, check the value of k_j.
  If k_j equals 0, for all h time steps of j, set $E_{El,i}^{OCC} = 0$.
For each day j, check the value of d_j.
  If d_j equals 0, for all h time steps of j, set $E_{El,i}^{OCC} = 0$.
  Else, if d_j equals 1:
    If c_j equals 0 (occupancy day without HVAC), for all h time steps of j, compute $E_{El,i}^{OCC} = E_{El,i}^{BUI} - E_{El,i}^{BL}$.
For each day j with d_j equal to 1 and c_j equal to 0, compute the average occupancy load across all matching days for each 15-minute time step h as $\overline{E}_{El,h}^{OCC,k} = \frac{1}{N}\sum_{g=1}^{N} E_{El,h,g}^{OCC,k}$. g is the index of the individual day matching weekday k and N is the total number of such days.
For each day j with d_j equal to 1 and c_j equal to 1, identify the corresponding weekday k_j. Then, for each 15-minute time step h, assign the occupancy load from the matching average type-day ($E_{El,i}^{OCC} = \overline{E}_{El,h}^{OCC,k}$).
The result is the fully constructed annual vector of occupancy-related electric load $\overrightarrow{E_{El(i)}^{OCC*}}$.

included in Eq. (10) ($\overrightarrow{E_{El(i)}^{OCC*}}$) should be modified using Eq. (7). For these time steps, the occupancy load $E_{El,i}^{OCC}$ is recalculated as the difference between the building electric load $E_{El,i}^{BUI}$ (a known value) and the base load $E_{El,i}^{BL}$, which was evaluated in the first step of the methodology. This correction is essential, as occupancy loads estimated from type-day profiles may underestimate or overestimate the occupancy load. The adjusted occupancy load across the full year is represented by Eq. (12):

$$\overrightarrow{E_{El(i)}^{OCC}} = \left(E_{El,1}^{OCC}, \cdots, E_{El,35040}^{OCC}\right) \tag{12}$$

Finally, the electricity demand associated with the HVAC system ($E_{El,i}^{HVAC}$) for each time step can be calculated using Eq. (13). The algorithm developed for implementing this step is shown in Table 3.

$$E_{El,i}^{HVAC} = E_{El,i}^{BUI} - E_{El,i}^{BL} - E_{El,i}^{OCC} \tag{13}$$

A further decomposition of the HVAC load may be performed ($E_{El,i}^{HVAC} = E_{El,i}^{EHP} + E_{El,i}^{AUX}$). This breakdown enables two additional refinement steps within the overall methodology.

In appendix section the flow charts describing the evaluation of preliminary occupancy load (Step II.1, Fig. A2) and occupancy load (Step II.2, Fig. A3) are included.

2.4. Third and fourth steps: HVAC auxiliary load and EHP load evaluation

The third step enables the evaluation of electricity required by HVAC auxiliary components ($E_{El,i}^{AUX}$), while the final step leads to the estimation

Table 3
Step II.2: refined occupancy load and HVAC load evaluation.

Definitions
- Let i be the 15-minute time step index within one year (1 to 35040).

Inputs
- $\overrightarrow{E_{El}^{BUI}}$: total building electric load at each 15-minute interval (vector of size 35040).
- $\overrightarrow{E_{El}^{BL}}$: base load at each 15-minute interval (vector of size 35040).
- $\overrightarrow{E_{El(i)}^{OCC*}}$: preliminary occupancy load at each 15-minute interval (vector of size 35040)
- $\overrightarrow{a}$: HVAC status at each 15-minute interval (0 = OFF, 1 = ON; vector of size 35040).
- $\overrightarrow{b}$: occupancy access at each at each 15-minute interval (0 = NO, 1 = YES; vector of size 35040).

Outputs
- $\overrightarrow{E_{El(i)}^{OCC}}$: refined occupancy load at each 15-minute interval (vector of size 35040).
- $\overrightarrow{E_{El(i)}^{HVAC}}$: HVAC load at each 15-minute interval (vector of size 35040).

Algorithm Steps

For each time step i,
  Set $E_{El,i}^{OCC} = E_{El,i}^{OCC*}$.
  If a_i equals 0 and b_i equals 1, $E_{El,i}^{OCC} = E_{El,i}^{BUI} - E_{El,i}^{BL}$.
  Compute the HVAC electricity load as $E_{El,i}^{HVAC} = E_{El,i}^{BUI} - E_{El,i}^{BL} - E_{El,i}^{OCC}$.

of the electric load of the EHP ($E^{EHP}_{El,i}$), as detailed in Fig. 3.

To perform these evaluations, the nominal electricity for HVAC auxiliaries ($E^{AUX}_{El,nom}$) at each time step is required. In many hydronic systems interacting with EHPs, circulating pumps typically operate at fixed load during the HVAC system's operation. The evaluation of both $E^{AUX}_{El,i}$ and $E^{EHP}_{El,i}$ requires the following input data for each 15-minute time step of the year: total building electric load ($\overrightarrow{E^{BUI}_{El(i)}}$); the base load ($\overrightarrow{E^{BL}_{El(i)}}$); the occupancy-related load ($\overrightarrow{E^{OCC}_{El(i)}}$); the scheduled HVAC operation ($\overrightarrow{a_{(i)}}$). Additionally, for each day j, the daily HVAC schedule ($\overrightarrow{c_{(j)}}$) is required. On days when the HVAC system is off ($c_j = 0$), both $E^{AUX}_{El,i}$ and $E^{EHP}_{El,i}$ are equal to zero. When the HVAC system is scheduled to operate on a given day ($c_j = 1$), three possible conditions can be identified:

- during the initial activation of the HVAC system, a misalignment between the actual measured electric load (e.g., from DSO data) and the scheduled HVAC activation may occur. This typically happens at the first time step where the HVAC is turned on, with $a_i = 1$ and $a_{i-1} = 0$, $E^{HVAC}_{El,i} < E^{HVAC}_{El,i+1}$ and $E^{AUX}_{El,i+1} = E^{AUX}_{El,nom}$. In this case $E^{HVAC}_{El,i}$ is lower than $E^{HVAC}_{El,i+1}$, implying that the electricity required by auxiliaries is less than the nominal value ($E^{AUX}_{El,i} < E^{AUX}_{El,i+1}$). To adjust for this, a reduction factor is introduced, and the auxiliary load during HVAC start-up ($E^{AUX-ON}_{El,i}$) is estimated using Eq. (14).

$$E^{AUX-ON}_{El,i} = E^{AUX}_{El,i+1} \bullet \frac{E^{HVAC}_{El,i}}{E^{HVAC}_{El,i+1}} \tag{14}$$

- During regular operation, $E^{AUX}_{El,i} = E^{AUX}_{El,nom}$.
- At time steps characterized by the shutdown or the deactivation of HVAC system, $E^{AUX}_{El,i}$ is typically lower than $E^{AUX}_{El,nom}$. However, scheduled HVAC operation or BAS data usually provide reliable information on system operating hours. In this case, for the time step immediately following HVAC shutdown, the auxiliary electricity consumption is estimated using Eq. (15), where x represents the number of consecutive time steps in which the HVAC system is operating prior to shut down.

$$E^{AUX-OFF}_{El,i+x} = E^{AUX}_{El,nom} - E^{AUX-ON}_{El,i} \tag{15}$$

The recap on the algorithm developed for implementing steps III and IV is reported in Table 4.

Finally, the flow chart describing the evaluation of HVAC auxiliaries (Step III) and EHP load (Step IV) is included in the appendix section (Fig. A4).

The last two steps of the methodology could be modified considering the possibility that there is no data on the scheduled operation of the HVAC system. By subtracting the loads estimated in step I (base load) and step II (occupancy load) from the total building demand, the load due to the HVAC system could be estimated. Finally, on the basis of data available from auxiliaries, the electricity required by EHP could be evaluated.

3. Case study

The proposed methodology is here applied to a case study reporting main data related to building, location and energy conversion systems used to satisfy energy demand. Further sections are related to the evaluation of the main results and the methodology validation.

3.1. Building

The historical building considered in this case study belongs to University of Sannio (Fig. 4) and hosts offices and university classrooms. It is in southern Italy (Benevento), which is characterised by 1′316 heating degree days according to the methodology applied by Italian Legislation, considering 20 °C as the reference temperature [25]. Thereby, this city falls within climate zone "C" according to Italian climatic zones. The building has a rectangular shape and is composed of three floors having a heated/cooled area equal to 1'261.82 m^2 and a heated/cooled gross volume equal to 6'093.46 m^3, while the ratio between external area and volume is equal to 0.46 m^{-1}. The transparent and opaque building envelope features are reported in Table 5, [26,27].

According to Italian legislation [28], in the climatic zone of Benevento, the heating period is between November 15th and March 31st, and space heating can be guaranteed for a maximum of 10 hours per day. Starting from October 2022, to reduce final energy demand due to space heating, a Ministerial Decree [29] imposed the reduction of the period in

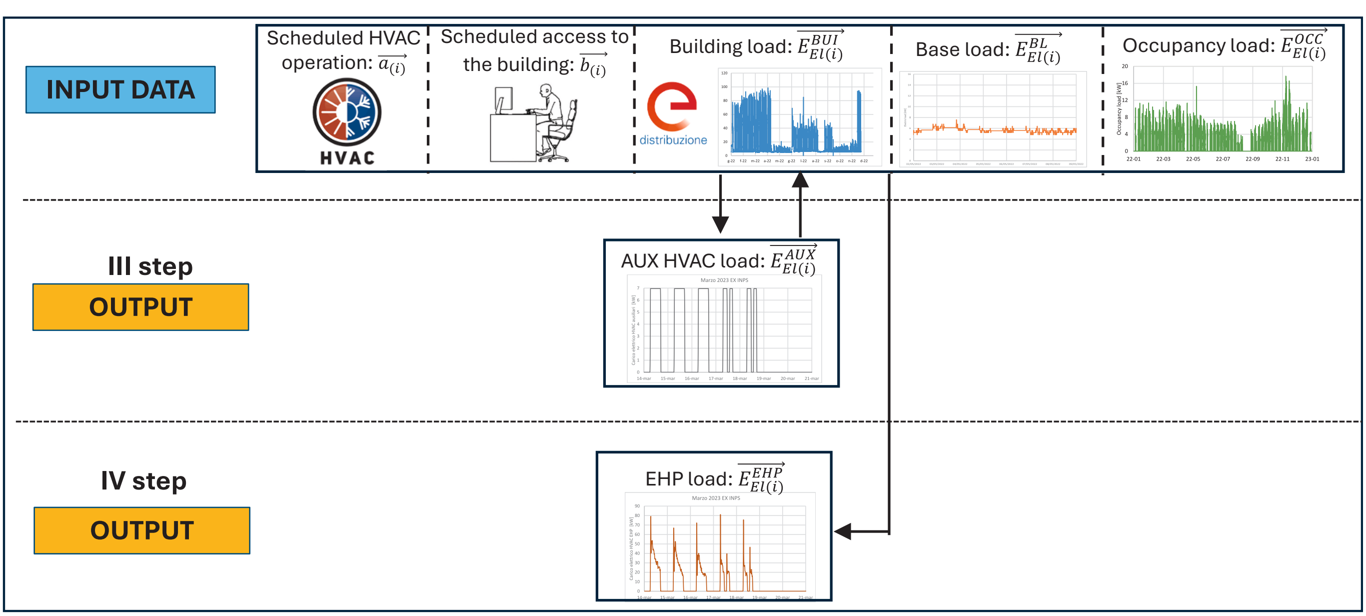

Fig. 3. Third and fourth steps of the methodology used for load breakdown.

Table 4
Steps III and IV: evaluation of HVAC auxiliary load and EHP load.

Definitions
- Let i be the 15-minute time step index within one year (1 to 35040).

Inputs
- $\overrightarrow{E^{HVAC}_{El,i}}$: HVAC electricity load at each 15-minute time interval (vector of size 35040).
- $\overrightarrow{a}$: HVAC status at each 15-minute interval (0 = OFF, 1 = ON; vector of size 35040).
- $E^{AUX}_{El,nom}$: nominal electricity demand of HVAC auxiliaries.

Outputs
- $\overrightarrow{E^{AUX}_{El}}$: HVAC auxiliary components' electric load at each 15-minute interval (vector of size 35040).
- $\overrightarrow{E^{EHP}_{El}}$: EHP load at each 15-minute interval (vector of size 35040).

Algorithm Steps
For each time step i,
  Else, if a_i equals 0,
    Set $E^{AUX}_{El,i} = 0$.
    Set $E^{EHP}_{El,i} = 0$.
    Set $x = 0$.
    If a_i equals 1,
      Increment the counter x by one.
      If a_{i-1} equals 0 and $E^{HVAC}_{El,i}$ is lower than $E^{HVAC}_{El,i+1}$, the HVAC is ramping up. Hence, compute $E^{AUX-ON}_{El,i} = E^{AUX}_{El,nom} \bullet \frac{E^{HVAC}_{El,i}}{E^{HVAC}_{El,i+1}}$ and set $E^{AUX}_{El,i} = E^{AUX-ON}_{El,i}$.
      If a_{i-1} equals 1, set $E^{AUX}_{El,i} = E^{AUX}_{El,nom}$.
      If a_{i-1} equals 1, the HVAC is shutting down. Hence, compute $E^{AUX-OFF}_{El,i} = E^{AUX}_{El,nom} - E^{AUX-ON}_{El,i-x}$ and set $E^{AUX}_{El,i} = E^{AUX-OFF}_{El,i}$.
    Compute $E^{EHP}_{El,i} = E^{HVAC}_{El,i} - E^{AUX}_{El,i}$.

Fig. 4. Building: frontal view.

Table 5
Building envelope features.

Building component	Transmittance, U [W/m^{2}K]	Thickness, s [m]	Solar heat gain coefficient, g-value [–]
External walls	0.74	0.64	–
Roof	1.36	0.35	–
Ground floor	2.71	0.46	–
Ceiling	2.60	0.26	–
Windows	5.86	–	0.48

which space heating systems could be activated (from November 22nd to March 23rd for Benevento) and maximum daily heating hours (between 9 and 10 hours for Benevento). Instead, the cooling period commonly starts on June 15th and ends on September 15th, and space cooling systems have no limitation either in the activation period or maximum daily operating hours.

3.2. Energy conversion system

Space heating and cooling demands of the building are satisfied by using an air-to-water EHP with R410A as refrigerant, located on the rooftop of the building. Table 6 shows nominal data of EHP with an EER (Energy Efficiency Ratio) equal to 2.14 and a COP (Coefficient Of Performance) equal to 3.10 [30]. Further elements included in the HVAC system are a thermal/cooling energy storage of 750 L and three circulating pumps (P1, P2, P3) serving three sections of the distribution circuit, as reported in Fig. 5. The circulating pumps work in an on–off mode, and they have no inverters. When the HVAC system is in operation, the electric load due to auxiliaries (circulating pumps) remains

Table 6
EHP nominal data according to UNI EN 14511–3:2018, [30].

Parameters	Cooling (Water: 7 °C / 12 °C, outdoor air: 35 °C)	Heating (Water: 45 °C/ 40 °C, outdoor air: 7 °C)
Cooling/Thermal [kW]	230.7	293.5
Electric power [kW]	107.9	94.6
Nominal EER/COP	2.14	3.10

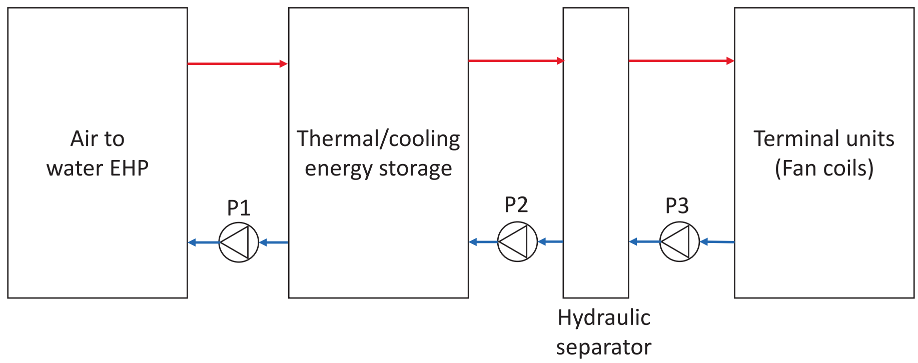

Fig. 5. Simplified scheme of HVAC system.

constant at 6.96 kW.

3.3. Methodology application: Input data and constraints

Data available from DSO [31], for 1 year with a timestep of 15 min has been acquired to apply the breakdown methodology to the considered case study.

The following boundary conditions have been considered to apply the proposed disaggregation electricity load methodology to evaluate the four main loads of the university building:

- the average base load during occupancy hours has been evaluated for each day based on the average electric load during no occupancy hours (from 00:00 AM to 7:45 AM and from 8:00 PM to 11:59 PM) in agreement with step I of the methodology.
- Occupancy load occurs only during weekdays, between 7:45 AM and 8:00 PM. People are only allowed to access the building during these hours. Holidays and scheduled closing periods are also considered.
- Artificial lighting is managed by occupancy sensors (on/off mode) and daylight dimming. This means that there are no lighting loads during non-occupancy hours.
- The load due to auxiliaries (circulating pumps) has been considered constant ($\dot{E}_{El}^{AUX} = 6.96 kW$) during the operation of EHP. Three circulating pumps, not having inverters, work at nominal loads during the scheduled operation of the HVAC system. The power required by pumps has been evaluated using AC current clamp meters [32] installed for 2 weeks, both in the summer and winter periods, and the data available from the measurement agrees with manufacturer data.
- The scheduled operation of EHP is acquired (heating period, cooling period, daily operating hours) from the BAS system.

The proposed methodology allows the evaluation of four contributions of electric loads every 15 min.

3.4. Main results

In the first part of this section, a detailed analysis of the average weekly load due to occupancy is reported. In the second part, data on four sub-loads on a yearly and a monthly basis are analysed. Furthermore, KPIs are introduced and compared to those available in the scientific literature.

3.4.1. Average occupancy load evaluation

The electric load representative of a week, evaluated considering average values for each time step, is reported in Fig. 7 and assessed using step II of the proposed methodology. In particular, it has been considered only weekdays during the intermediate period in which the HVAC system is not in operation. During this period, the total load consists only of the base load and the load associated with occupancy. Excluding base load, according to the methodology proposed for step I, a different electric load could be evaluated for each day of the intermediate period. For each day of the week and with a time step of 15 minutes, the average load has been evaluated. In Fig. 6, as an example, 11 Thursday have been considered to evaluate the average trend (dotted line) of occupancy load representative of this day. A similar approach has been used for the other days of the week, considering for each day at least 10 days included in the intermediate period. This is a simplified approach that does not account for the dependence of a part of the load (the artificial lighting component) on weather conditions.

The average electric load due to occupancy, evaluated excluding base load, varies depending on the day of the week, and it is evaluated considering the days when the HVAC system is off. This load is zero during nighttime and on weekends, as shown in Fig. 7. The maximum daily electricity demand (60.5 kWh) and peak load (7.04 kW) occur on Tuesday, while Friday has the lowest peak load (4.46 kW) and daily electricity demand (34.9 kWh). Every day, approximately between 1:00 PM and 2:00 PM, there is a reduction in the occupancy load due to the lunch break. Based on these results, it has been estimated that during the period when the HVAC system is operational, the occupancy load follows the trend reported in Fig. 7.

Focusing on the period in which there is no HVAC demand, daily electricity demand on a weekly basis due to occupancy is reported for a subset of data related to 2022. More detailed statistical data for the days considered to estimate the daily average load due to occupancy are reported in Table 7, which presents statistical data on a daily basis for this load. Further data could also be derived from Fig. 8.

The mean value represents the average electricity demand due to occupancy for each day, and it shows good agreement with the median. The relative standard deviation is in the range of 12–16 %, and this data can be considered acceptable due to the low weight of occupancy load on total building demand during the HVAC period, which is lower than 5 %. Occupancy load depends on actual occupancy, affecting plug loads and energy demand due to artificial lighting, which is also influenced by the time of year and weather conditions.

3.4.2. Data on different sub-loads

Applying the proposed methodology, the main building sub-loads are reported in Fig. 9. Fig. 9a shows the total building load and the trend load (black dotted line), evaluated by considering the average load on a weekly basis. The trend load helps identify intermediate periods characterized by no HVAC system operation and building closing periods. The base load slightly varies throughout the year, usually ranging between 5 and 8 kW, Fig. 9c. Anomalies resulting in loads exceeding 10 kW are primarily caused by failures in the artificial lighting management system, where lights remain turned on during night hours. During the first two weeks of November, the EHP could not be generally activated due to Italian legislation restrictions; however, in a few rooms, electric heaters were used, leading to an electricity load due to occupancy higher than expected. The occupancy load is higher during the

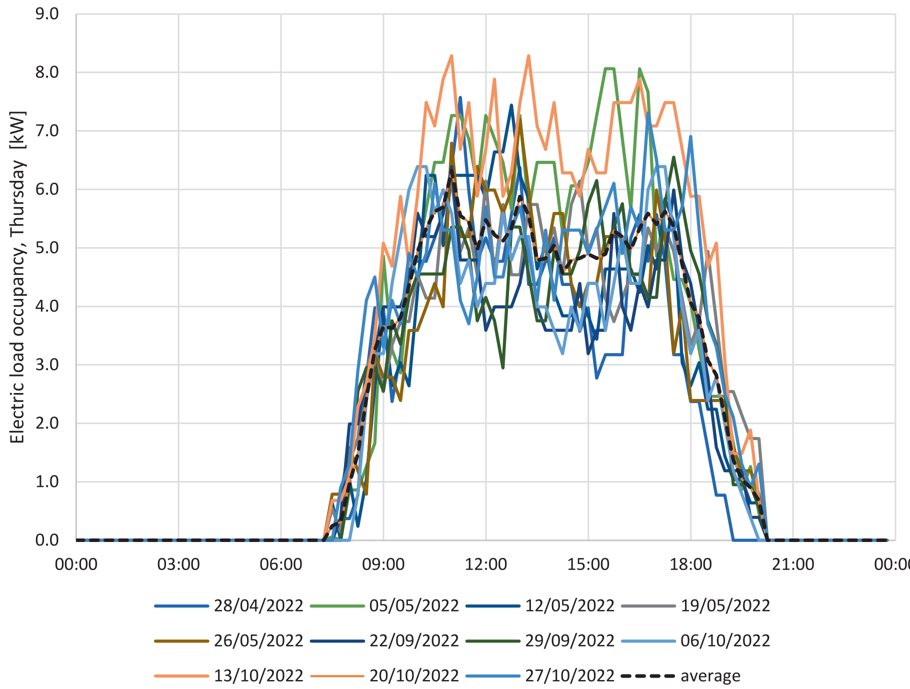

Fig. 6. Occupancy-related load evaluated for Thursdays included in in the intermediate period.

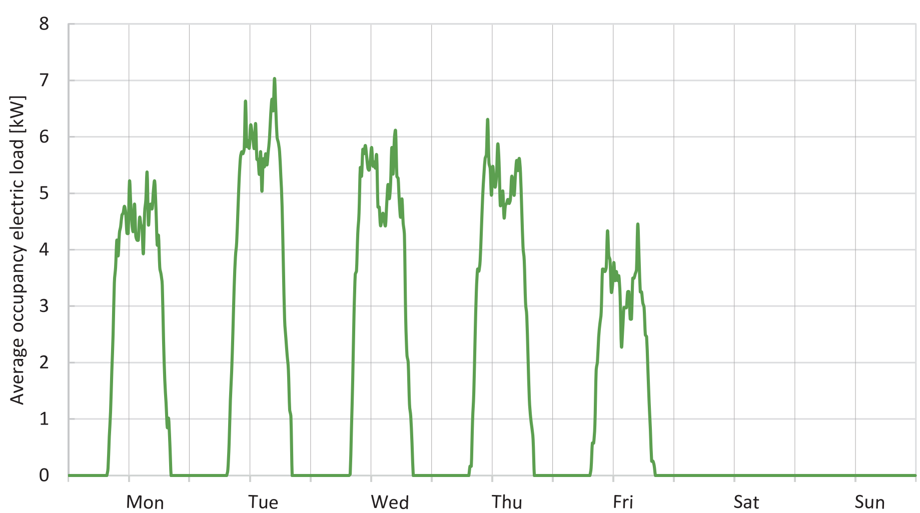

Fig. 7. Weekly average electric load due to occupancy only, year 2022.

Table 7
Statistical data on a daily basis for electricity in the no-HVAC period due to occupancy in 2022.

	Mean value [kWh]	Root mean square deviation [kWh]	Relative standard deviation [%]	Median [kWh]	Interquartile Range [kWh]
Monday	46.64	7.24	15.53	47.01	9.75
Tuesday	60.49	7.94	13.13	60.90	5.47
Wednesday	54.61	8.10	14.84	55.29	10.44
Thursday	52.85	7.51	14.21	49.88	5.01
Friday	34.86	4.44	12.73	35.84	3.91

heating period, while there is no load during building closure (weekends, holidays), Fig. 9e. Fig. 9b illustrates the HVAC auxiliaries load, which is null when the HVAC is not in operation. Fig. 9d and Fig. 9f highlight electricity input to EHP for space heating and cooling, respectively.

The estimated yearly electricity consumption for EHP in 2022 is 34.9 MWh, while auxiliaries require 9.3 MWh. The electricity due to occupancy and base loads is 12 MWh and 54.9 MWh, respectively. The electricity demand due to occupancy accounts for 10.8 % of the total load, the base load reaches 49.4 %, while the HVAC system accounts for 39.8 %. During the summer, the month with the highest electricity consumption is July, with 10.3 MWh; in winter, March is the month requiring more electricity (14.2 MWh). Low occupancy in summer, combined with the closing period due to the summer holiday, results in lower monthly consumption compared to the winter period.

In Table 8 it is reported on a monthly basis the electricity shares due to HVAC (E_{El}^{EHP}, E_{El}^{AUX}) and no-HVAC demand (E_{El}^{OCC}, E_{El}^{BL}) in 2022. Load breakdown is performed using actual data.

3.4.3. Key performance indicators

The data available from the previous section could be used to

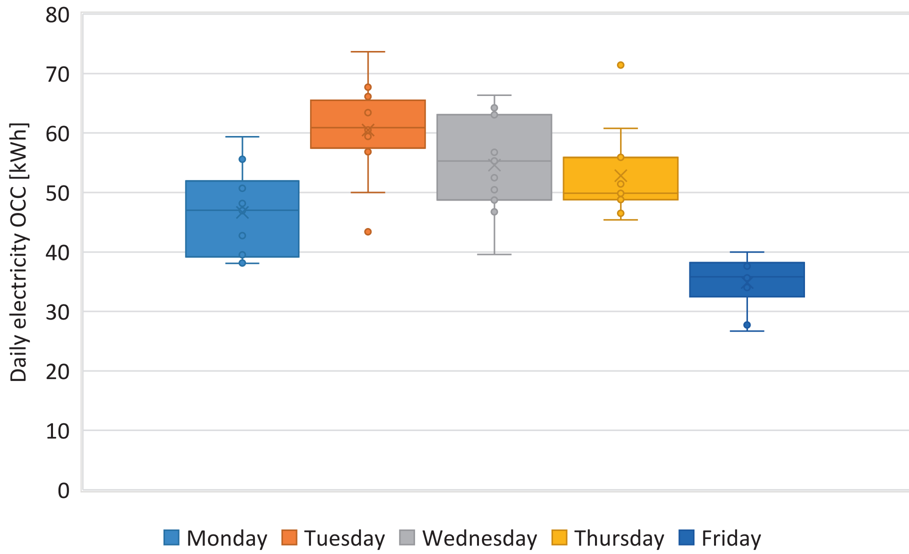

Fig. 8. Daily electricity demand data in no-HVAC period due to occupancy in 2022.

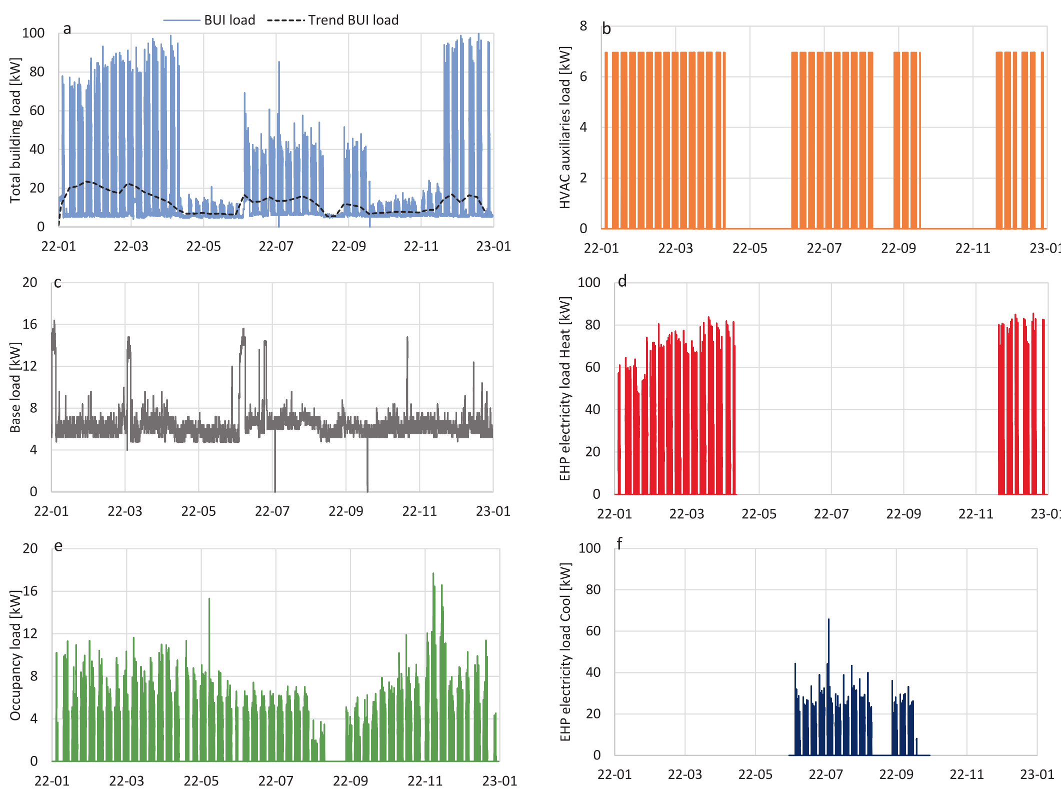

Fig. 9. Load disaggregation: a) building; b) HVAC auxiliaries; c) base; e) EHP electricity input heating; f) occupancy; e) EHP electricity input cooling.

evaluate KPIs (Key Performance Indicators) related to primary energy demand and environmental impact in terms of equivalent CO_2 emissions.

Considering the Italian electricity mix in 2022, the CO_2 emission factor and power grid efficiency could be considered to calculate KPIs with respect to heated area and volume. According to the methodology proposed by Marrasso et al. in [33], and data available from Italian transmission system operator TERNA [34] and Italian Institute for Environmental Protection and Research (ISPRA) [35], average equivalent CO_2 emission factor (α) for Italian electricity mix including renewables and transmission and distribution losses is equal to 0.339 $kgCO_{2,eq}$ per kWh of electricity delivered to end-user. Power grid efficiency, evaluated including renewables and transmission and distribution losses (η_{El}^{PG}) for 2022, is equal to 0.725. In this parameter, primary energy is related only to fossil fuels, and primary energy from renewables is considered null.

The following energy-based KPIs could be introduced for comparison purposes considering the primary energy due to fossil fuel required by the whole building with reference to heated area A (Eq. (16)) and heated volume V (Eq. (17)):

$$KPI_{Ep}^{BUI,A} = \frac{E_{El}^{BUI}}{\eta_{El}^{PG} \cdot A} \tag{16}$$

Table 8
Electricity consumption on annual and monthly basis for 2022.

Month	E_{El}^{OCC} [kWh]	E_{El}^{BL} [kWh]	E_{El}^{EHP} [kWh]	E_{El}^{AUX} [kWh]	E_{El}^{BUI} [kWh]
January	999	5'038	6'827	1'270	14'134
February	1'066	3'968	6'620	1'462	13'115
March	1'298	5'062	6'378	1'432	14'169
April	967	4'213	1'037	298	6'514
May	1'100	4'007	0	0	5'107
June	881	5'743	2'140	1'021	9'786
July	968	4'884	3'291	1'205	10'348
August	471	4'490	1'731	706	7'398
September	776	4'189	1'070	595	6'630
October	1'129	4'422	0	0	5'552
November	1'544	4'421	1'669	421	8'055
December	825	4'454	4'094	872	10'245
year	**12'024**	**54'892**	**34'856**	**9'282**	**111'054**

$$KPI_{Ep}^{BUI,V} = \frac{E_{El}^{BUI}}{\eta_{El}^{PG} \cdot V} \tag{17}$$

The evaluation of these KPIs may be extended to each sub-load or a combination of them (HVAC, no-HVAC).

While for environmental purposes following KPIs (Eq. (18), Eq. (19)) could be considered for building electricity demand:

$$KPI_{CO_2}^{BUI,A} = \frac{E_{El}^{BUI} \cdot \alpha}{A} \tag{18}$$

$$KPI_{CO_2}^{BUI,V} = \frac{E_{El}^{BUI} \cdot \alpha}{V} \tag{19}$$

These performance indicators could be evaluated for each sub-load or a combination of them. Table 9 and Table 10 report KPIs related to energy and environmental data. The term "LOAD" is generic and refers to different sub-loads or the entire building load, as reported in the five columns.

These data can be compared to the benchmark KPIs made available for Italy by the Italian National Agency for New Technologies, Energy, and Sustainable Economic Development (ENEA) for office buildings [36]. Benchmark $KPI_{Ep}^{BUI,A}$ data available from ENEA for an office building having the same climatic zone of Benevento is in the range 178 ÷ 286 kWh/m^{2}year. The KPI value of the office building under investigation is equal to 121.39 kWh/m^{2}year, which is lower than the benchmark range. With respect to benchmark data for HVAC system, ENEA gives a range for $KPI_{Ep}^{HVAC,A}$ between 97 kWh/m^{2}year and 167 kWh/m^{2}year while for the analysed case the value is 48.25 kWh/m^{2}year.

Environment-based KPI indicators could be interesting to evaluate the trend in reaching the decarbonization goals required by 2030 and 2050 ($KPI_{CO_2}^{BUI,A} = 0$). The results highlight that more efforts should be considered to reduce the carbon footprint of the building through, e.g.:

- Intervention on the Italian power grid, supporting renewables.
- Installation of a PV (Photovoltaic) system on the building rooftop covering part of the electricity demand.

Table 9
Energy-based KPIs for the whole building and different sub-loads.

	Occupancy	Base load	EHP input	HVAC auxiliaries	Total electricity building
$KPI_{E_p}^{LOAD,A}$ [kWh/m^{2}year]	13.14	60.00	38.10	10.15	121.39
$KPI_{E_p}^{LOAD,V}$ [kWh/m^{3}year]	2.72	12.43	7.89	2.10	25.14

Table 10
Environmental-based KPIs for the whole building and different sub-loads.

	Occupancy	Base load	EHP input	HVAC auxiliaries	Total electricity building
$KPI_{CO_2}^{LOAD,A}$ [kg CO$_2$/m^{2}year]	3.23	14.75	9.36	2.49	29.84
$KPI_{CO_2}^{LOAD,V}$ [kg CO$_2$/m^{3}year]	0.67	3.05	1.94	0.52	6.18

- Reducing building transmittance (transparent envelope, opaque envelope).

3.5. *Load breakdown methodology validation*

For a limited period, AC current clamp meters [33] having an accuracy of 3 % ±5 digits were installed on the circulation pumps, showing good agreement with manufacturer data. In addition, a three-phase digital multimeter [37] was installed on EHP in December 2024, and the measurements were used to validate the breakdown methodology. Its accuracy for active energy is equal to ± 0.5 % ±0.5 digits.

The estimated data overestimates the actual electrical consumption of the EHP by about 3.3 %, as shown in Fig. 10, for a specific week in December. On a daily basis, the breakdown approach overestimates the electricity required by EHP by a range of 1.63 % to 5.13 %.

Furthermore, a comparison between the occupancy load evaluated by means of the proposed breakdown methodology and that estimated using the measured data from a digital multimeter installed on EHP has been performed. In the latter case, occupancy load has been estimated using Eq. (20):

$$E_{El,i}^{OCC} = E_{El,i}^{BUI} - E_{El,i}^{EHP} - E_{El,i}^{AUX} - E_{El,i}^{BL} \tag{20}$$

where:

- Total building load ($E_{El,i}^{BUI}$) is available from the local distributor.
- Base load ($E_{El,i}^{BL}$) and auxiliary HVAC electric ($E_{El,i}^{AUX}$) loads are evaluated in the same way of the proposed methodology, considering Step I and Step III, respectively.
- EHP electricity ($E_{El,i}^{EHP}$) data is measured with a digital multimeter.

The accuracy of occupancy load estimation is, of course, higher in the second case, having 2 measured data ($E_{El,i}^{BUI}$, $E_{El,i}^{EHP}$) as input.

In Fig. 11, a comparison between the occupancy load evaluated using the two methodologies is reported. Starting from 4:00 PM, the hour in which the HVAC system is off for those days, both curves are superimposed. On a weekly basis, the breakdown method underestimates, with respect to a methodology that uses input data from a multimeter, the electricity demand due to occupancy by 5.16 %. On a daily basis, the difference between the two methods results in a variation of ±20 %. This result was predictable because the occupancy load can vary not only with occupancy but also with weather conditions (lighting).

4. Conclusion

Various techniques can be evaluated to monitor energy consumption, with the goal of identifying both opportunities for energy savings and anomalies that result in unexpectedly high loads. The level of analysis can vary in accuracy depending on the frequency of data acquisition and the degree of load disaggregation. Approaches such as NILM, ILM, or a combination of both can support the identification of the main energy loads associated with a given end-user. By distinguishing between different energy loads—based on the building's

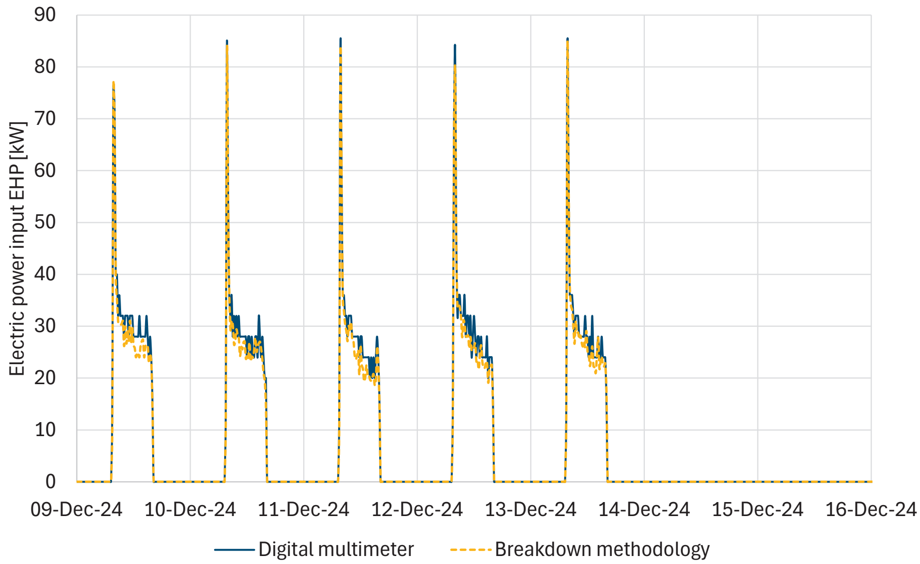

Fig. 10. Comparison between measured (digital multimeter) and estimated (breakdown methodology) data due to EHP electricity input.

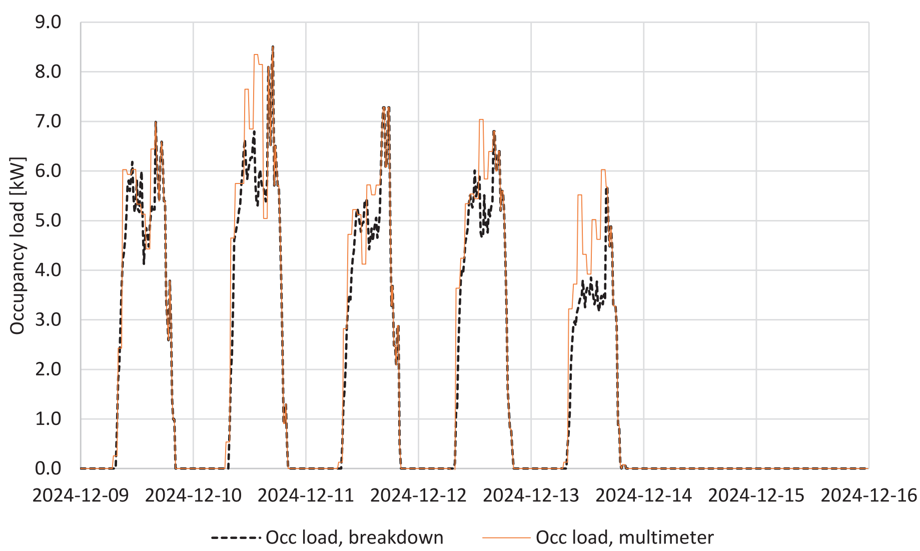

Fig. 11. Occupancy load evaluated considering the proposed breakdown methodology without and with data available from a digital multimeter.

functional use—it becomes possible to detect abnormal consumption patterns or estimate the potential impact of targeted interventions on specific loads.

The information needed to apply the proposed approach for load breakdown could be easily acquired, leading to useful results.

The proposed breakdown methodology was applied to a specific case study, and four distinct categories of electrical loads were identified: base load, occupancy-related load, HVAC auxiliaries, and the electricity input to an electric-driven heat pump. Particular focus was placed on accurately estimating the EHP electricity input, which was validated using high-resolution data collected via a three-phase digital multimeter. The validation process confirmed the robustness of the approach, with a relative error of about 3 %, thus demonstrating the process reliability in estimating sub-loads even in the absence of dedicated smart meters.

Furthermore, a comparison between the occupancy load evaluated by means of the proposed breakdown methodology and that estimated using measured data from a digital multimeter on EHP has been performed. Having data measurement from total building demand and EHP input, the estimation of occupancy load is more accurate. The proposed breakdown method underestimates the electricity demand due to occupancy by about 5 % on a weekly basis.

The load disaggregation also enabled the rapid detection of anomalies, such as those caused by the wrong management of the artificial lighting system during night hours.

Moreover, the analysis revealed that the base load accounted for 49.4 % of total electricity consumption—a significant share that needs further investigation to understand its composition and related optimisation opportunities.

Overall, the proposed methodology offers a practical and scalable approach for identifying key energy sub-loads in non-residential buildings. It provides energy managers with actionable insights and reference performance patterns, allowing for more targeted and cost-effective interventions to reduce consumption and improve operational efficiency.

Energy-based and environmental-based benchmark data on office buildings available in the scientific literature could be helpful in identifying the most critical loads on which attention should be focused.

In future works, through dynamic simulation software, the building and related HVAC systems could be simulated, evaluating the impact of interventions (e.g., building envelope, energy conversion systems, energy management system) even if more information is required (e.g., indoor/outdoor air temperature, inlet/outlet EHP water temperature, solar radiation) for an accurate analysis, even if they are typically available if BAS is installed.

This simulation analysis could be very useful to evaluate in which way an intervention on building transmittance (opaque and transparent envelope), on main components of the HVAC system (e.g., energy conversion system, hydraulic circuit, pumps) and its management based on outdoor air temperature (e.g., scheduled operation, EHP outlet water temperature) could affect primary energy demand, greenhouse gas emissions and operating costs.

CRediT authorship contribution statement

Elisa Marrasso: Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Carlo Roselli:** Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Giovanna Pallotta:** Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Alfonso Capozzoli:** Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Giacomo Buscemi:** Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Marco Savino Piscitelli:** Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization.

Declaration of competing interest

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

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Appendix

In this section, the flow charts considered to evaluate four sub-loads are reported.

Fig. A1 shows input and output data considered to apply the I step of the methodology to estimate the base load.

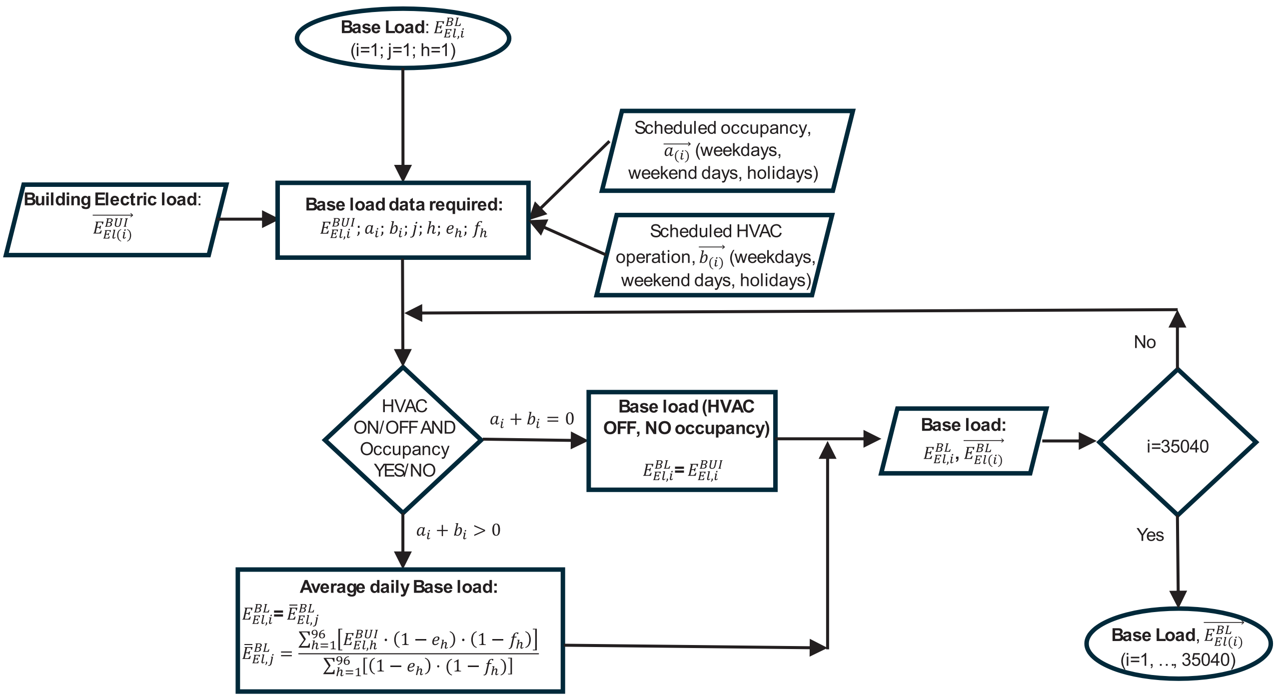

Fig. A1. Flow chart considered to evaluate base load (I step).

The preliminary occupancy load (II.1 sub-step) is calculated following the procedure reported in Fig. A2. The final occupancy load (II.2 sub-step) is then estimated using the flow chart shown in Fig. A3.

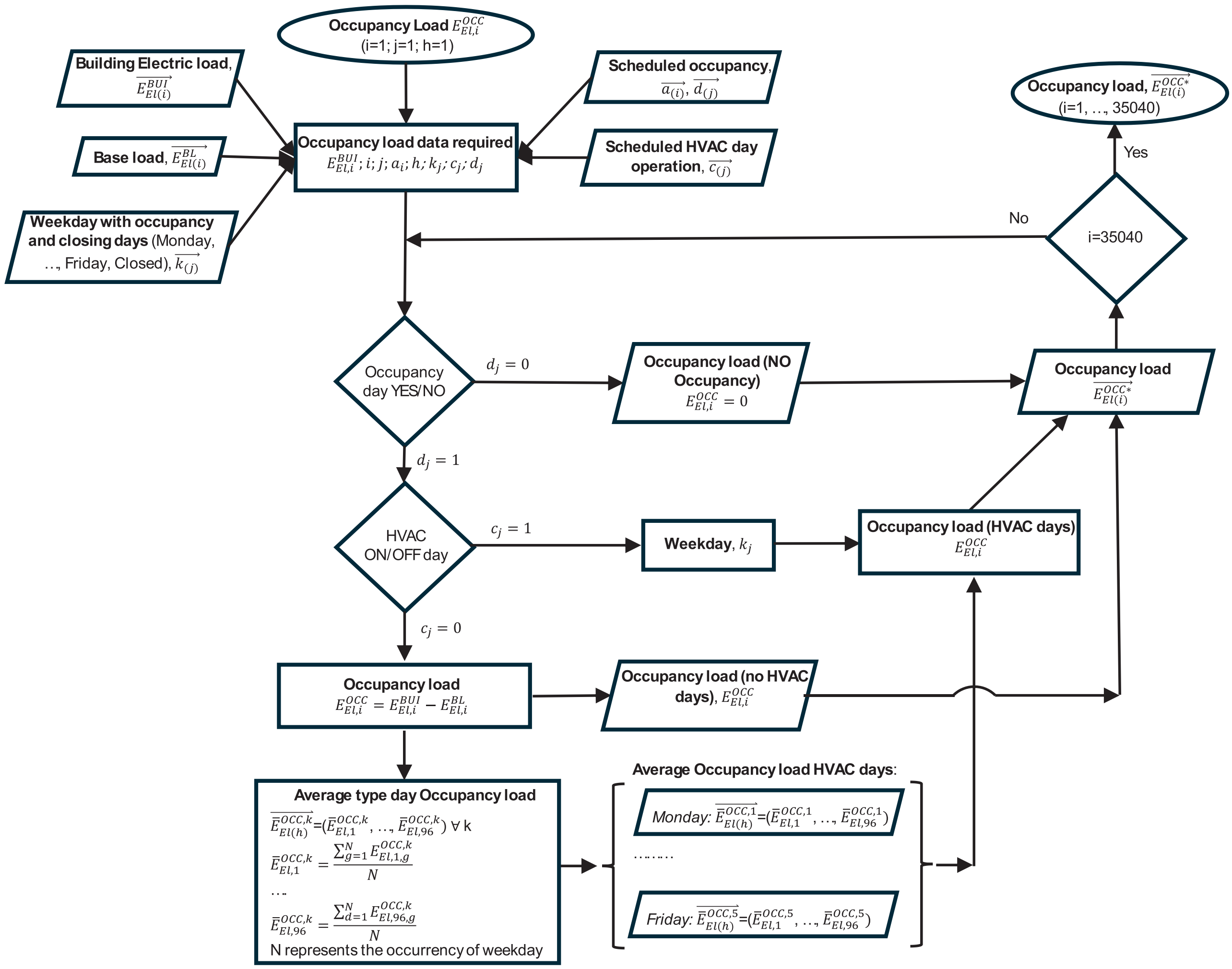

Fig. A2. Flow chart considered to evaluate occupancy load, first sub-step (II.1).

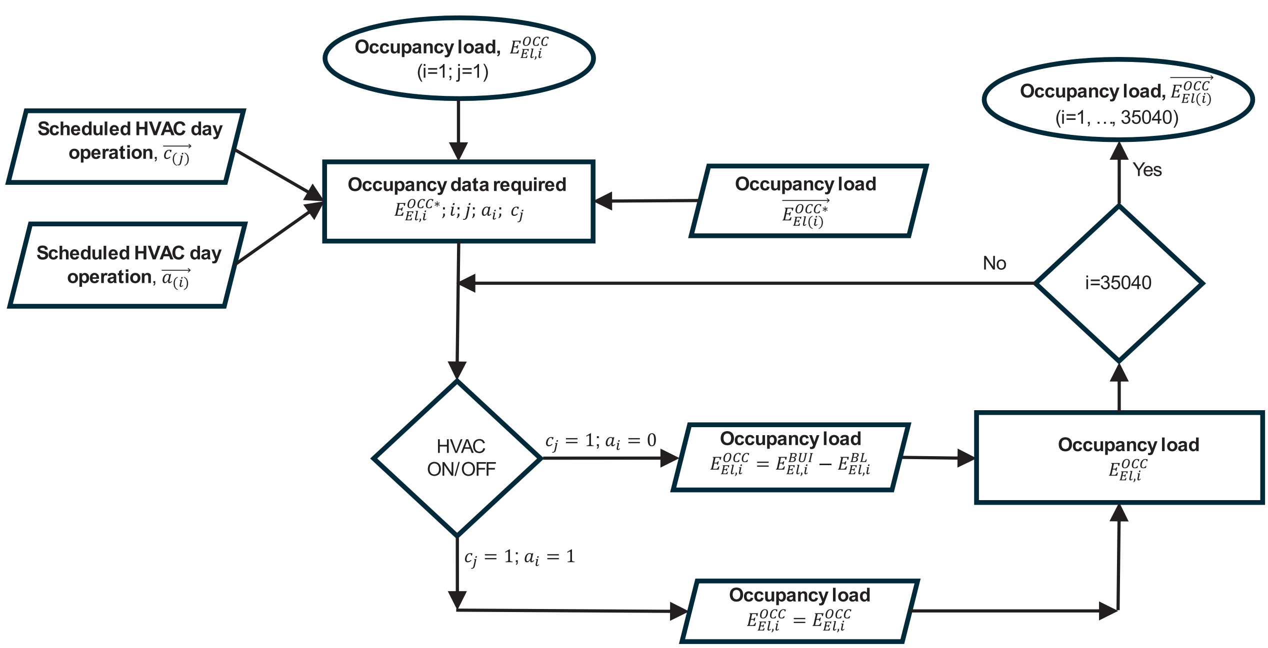

Fig. A3. Flow chart considered to evaluate final occupancy load, second sub-step (II.2).

Finally, HVAC auxiliaries (III step) and EHP (IV step) loads are evaluated considering the methodology proposed in Fig. A4.

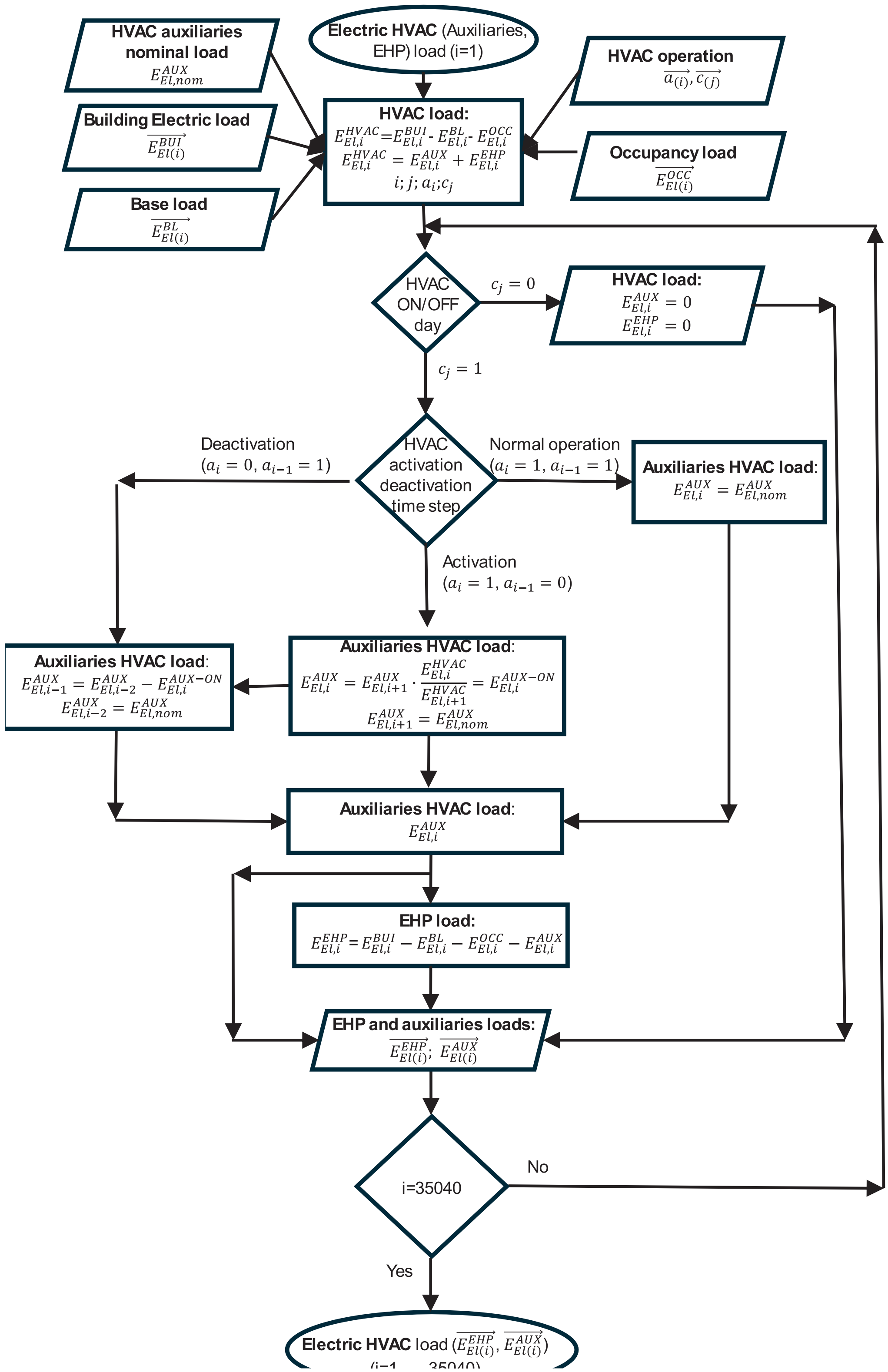

Fig. A4. Flow chart considered to evaluate auxiliaries and HVAC load (III, IV).

Data availability

Data will be made available on request.

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