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A high resolution urban energy atlas for spatiotemporal energy-demand assessment of 1.69 million buildings

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The building sector is central to achieving climate neutrality because of its major contribution to final energy consumption and greenhouse gas emissions. However, regional energy planning remains constrained by the lack of high-resolution spatial and temporal datasets capable of simultaneously representing residential, tertiary and industrial buildings. This study develops a high-resolution interactive Wallonia Energy Atlas that combines cadastral information, regional energy statistics, building archetypes and standardized temporal load profiles. The proposed methodology combines detailed cadastral information for approximately 1.69 million buildings with regional energy statistics and building archetypes to estimate annual energy indicators using a hybrid top-down/bottom-up approach. These annual estimates are subsequently reconstructed into 8,760-hour profiles using standardized BDEW load profiles for five energy indicators: Heat Consumption (HC), Heat Demand (HD), Electricity Consumption (EC), Cooling Electricity Demand (CED) and Heating Electricity Consumption (HEC). The resulting energy data were spatially aggregated at four administrative levels (regional, provincial, arrondissement and municipal), covering 5 provinces, 20 arrondissements and 262 municipalities, and implemented within an interactive web application developed using Python, Dash and Plotly. The reconstructed hourly profiles show substantial differences in energy magnitude and temporal distribution among building categories. At the aggregate building level, average hourly heat consumption ranges from 3.33 kWh for semi-detached houses to 18.53 kWh for apartment buildings; these absolute values reflect differences in building size and dwelling aggregation and are therefore complemented by area-normalized energy intensities. In the tertiary sector, transportation facilities record the highest electricity demand (40.07 kWh), whereas culture and sport buildings present the largest average heat consumption (18.26 kWh). Industrial facilities display considerably greater modelled energy requirements, with chemical industries reaching average hourly heat and electricity consumptions of 7,275.5 kWh and 2,843.0 kWh, respectively. Validation against seven monitored residential, tertiary and industrial cases showed a mean CV(RMSE) of approximately 27%, although the monitored cases primarily provide empirical evaluation of HC and EC. Load-duration analysis shows distinct reconstructed temporal patterns across sectors, with stronger seasonal variation in residential profiles, schedule-related patterns in tertiary profiles, and relatively persistent loads in industrial profiles; these temporal characteristics are partly inherited from the assigned BDEW archetypes. The Wallonia Energy Atlas therefore provides a regional-scale integration of cadastral data, annual energy estimates, standardized temporal profiles, multi-scale GIS aggregation and interactive visualization, supporting preliminary energy-system planning and regional decarbonisation assessment.

Keywords Building energy modelling, Urban energy atlas, Building stock, Hourly energy profiles, Load duration curve, GIS

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The transition towards climate-neutral societies has become one of the defining scientific and technological challenges of the twenty-first century. Achieving the objectives of the Paris Agreement, the European Green Deal and the global commitment to net-zero greenhouse gas emissions by 2050 requires profound transformations in energy production, distribution and consumption systems[1,2]. Among all end-use sectors, buildings occupy a strategic position because they simultaneously represent one of the largest consumers of energy, one of the principal contributors to greenhouse gas (GHG) emissions and one of the sectors offering the greatest opportunities for cost-effective emission reductions[3,4]. According to the International Energy Agency (IEA)[2], buildings accounted for approximately 30% of global final energy consumption and 26% of global energy-related CO_2 emissions in 2022. When emissions associated with the production of construction materials, including cement, steel and aluminium are incorporated, the overall contribution of the building sector exceeds one-third of global energy-related carbon emissions[2]. Similarly, the Sixth Assessment Report of the Intergovernmental Panel on Climate Change (IPCC) estimates that buildings were responsible for nearly 21% of global greenhouse gas emissions in 2019, highlighting the sector as one of the largest contributors to anthropogenic climate change[1]. These findings clearly demonstrate that improving building energy performance is indispensable for achieving climate neutrality and limiting global warming to 1.5°C[1].

The urgency of this transition is further intensified by rapid urbanisation. The United Nations projects that almost 70% of the world's population will reside in urban areas by 2050, resulting in unprecedented growth of the built environment and continuously increasing demands for heating, cooling and electricity[3]. Urban areas are therefore becoming the principal centres of energy consumption while simultaneously representing the greatest opportunities for implementing low-carbon technologies, renewable energy systems and sustainable urban planning[5,6]. However, effective decarbonisation strategies require much more than annual energy statistics. They demand detailed knowledge of where, when and how buildings consume energy throughout the year. Traditionally, regional energy assessments have relied on annual or monthly energy balances that are unable to represent the strong temporal variability induced by outdoor climate, occupancy schedules, equipment operation and user behaviour[7]. Such aggregated indicators are insufficient for analysing electricity peak demand, district heating performance, renewable energy integration or demand-side flexibility. In contrast, hourly energy profiles provide the temporal information required to connect building demand with energy-system operation. They enable the identification of peak and base loads, assessment of seasonal and intraday demand patterns, and evaluation of potential interactions between building demand and district heating, heat pumps, photovoltaic generation, thermal and electrical storage, and demand-side flexibility[8–10]. This global challenge is particularly relevant in Wallonia, where energy demand remains strongly influenced by buildings and energy-intensive industry. According to the 2019 Walloon Regional Energy Balance, total final energy consumption reached approximately 128.8 TWh, with industry accounting for about 34% of final consumption when non-energy uses are included, while the domestic and related sectors represent a substantial share of regional demand[11]. The regional building stock comprises approximately 1.69 million buildings distributed across residential, tertiary and industrial activities, with space heating remaining a major component of building energy use. Wallonia has also adopted ambitious climate objectives, including a 55% reduction in greenhouse-gas emissions by 2030 and a 95% reduction by 2050 relative to the reference year, with carbon neutrality targeted by 2050 at the latest[11]. These characteristics make Wallonia a particularly relevant case for developing spatially and temporally explicit energy-demand information capable of supporting building renovation, district-heating planning, electrification and regional decarbonisation.

Recent advances in digital technologies, high-performance computing, Geographic Information Systems (GIS), artificial intelligence and cloud-based computing have considerably expanded the capacity to analyse urban energy systems at unprecedented spatial and temporal resolutions[12–14]. Rather than investigating individual buildings, contemporary research increasingly focuses on entire building stocks, integrating cadastral databases, building archetypes, spatial information and dynamic energy simulations. These developments have given rise to a new generation of digital energy platforms capable of supporting evidence-based urban planning, regional decarbonisation strategies and climate-neutral city development. Nevertheless, the effectiveness of these approaches remains fundamentally dependent on the availability of high-resolution spatiotemporal datasets describing the heterogeneous behaviour of different building categories across multiple spatial scales.

Urban Building Energy Modelling (UBEM) has rapidly emerged as one of the most important research fields in urban energy science during the last decade[15–18]. Unlike conventional building energy simulation, which evaluates individual buildings independently, UBEM combines information on building geometry, construction characteristics, occupancy behaviour, climatic conditions and urban morphology to simulate the energy performance of thousands or even millions of buildings simultaneously. By coupling physics-based simulation with spatial analysis, UBEM has become an essential tool for evaluating urban retrofit strategies, district heating systems, renewable energy integration and long-term decarbonisation pathways[15,16]. Foundational developments in large-scale building-energy analysis have also been advanced through the IEA EBC Annex 70 and Annex 71 activities, which emphasized empirical building-energy analysis, stock-level modelling and improved understanding of the variability of energy use across building populations[17,18].

Existing UBEM methodologies can generally be classified into two complementary approaches: top-down and bottom-up models[15,19]. Top-down approaches estimate urban energy demand using aggregated relationships between historical energy consumption and socioeconomic indicators such as population, gross domestic product or climatic variables. Their principal advantage lies in relatively modest data requirements

and computational efficiency. However, because these models rely on aggregated observations, they cannot explicitly represent building-specific characteristics, renovation measures or technology substitution scenarios, thereby limiting their usefulness for detailed urban planning and infrastructure design[15,19]. Conversely, bottom-up approaches simulate the energy behaviour of individual buildings before spatially aggregating the results to neighbourhood, municipal or regional levels. These methods explicitly incorporate building geometry, thermal envelope characteristics, occupancy schedules, HVAC systems and weather conditions, thereby providing substantially greater physical realism and predictive capability[16,19–21]. As a consequence, bottom-up UBEM has become the preferred methodology for evaluating building stock decarbonisation, electrification pathways and future climate scenarios.

Parallel advances in Geographic Information Systems have considerably strengthened urban energy modelling by enabling the integration of cadastral databases, three-dimensional city models, remote sensing products and energy performance indicators within a common spatial framework[22–24]. GIS-based Urban Energy Atlases are increasingly recognised as powerful decision-support tools because they combine quantitative energy analysis with intuitive spatial visualisation. These platforms facilitate the identification of energy hotspots, evaluation of renovation priorities, optimisation of district heating expansion and assessment of renewable energy potential across entire territories[23–25]. Despite the remarkable progress achieved in Urban Building Energy Modelling (UBEM) over the last decade, several scientific and technological limitations continue to restrict its application to regional energy planning and climate-neutral urban development. Although numerous studies have successfully combined building energy simulation with Geographic Information Systems (GIS), most investigations remain limited either by their spatial coverage, temporal resolution, building typologies or accessibility of the generated datasets[15,25]. Consequently, decision-makers still lack comprehensive digital platforms capable of representing the dynamic energy behaviour of entire building stocks with sufficient spatial and temporal detail. A first limitation concerns the building categories considered. The vast majority of existing UBEM studies focus almost exclusively on residential buildings, reflecting both the availability of residential databases and the dominant contribution of households to urban heating demand[15,19,26]. Comparatively fewer investigations have addressed tertiary buildings, while industrial facilities remain largely neglected despite their substantial contribution to regional energy consumption and greenhouse gas emissions[27–29]. This sectoral fragmentation prevents consistent comparison of energy behaviour across the complete urban building stock and limits the ability of planners to develop integrated regional decarbonisation strategies.

A second limitation relates to temporal resolution. Many existing urban energy assessments continue to rely on annual or monthly energy indicators derived from statistical inventories or aggregated consumption databases[23,24,30]. Although these datasets are appropriate for estimating annual energy balances, they cannot accurately represent hourly fluctuations associated with weather conditions, occupancy schedules, industrial processes or electricity demand peaks. Yet, the rapid deployment of renewable energy systems, heat pumps, battery storage and smart grids requires detailed 8,760-hour energy profiles capable of supporting infrastructure sizing, flexibility assessment and demand-response analysis[8–10,31]. A third challenge concerns the availability of interactive Urban Energy Atlases. Recent GIS-based studies have demonstrated the usefulness of spatial energy mapping for identifying renovation priorities, district heating opportunities and renewable energy potential[20–23]. Nevertheless, most available atlases remain static visualisation tools that provide annual indicators without allowing users to dynamically explore hourly energy demand or compare multiple energy vectors across different administrative scales[24,25]. Furthermore, only a limited number of publicly accessible platforms integrate interactive maps with dynamic energy profiles, statistical summaries and multi-scale spatial analysis within a unified web environment[32–34]. Another important limitation lies in the scale of existing simulations. Most published UBEM applications[8] investigate neighbourhoods, university campuses or individual cities involving several hundred to several tens of thousands of buildings[15,20,26]. Relatively few studies have extended dynamic hourly modelling to entire regional building stocks comprising more than one million buildings, largely because of computational complexity, data availability and storage requirements[33–35]. Consequently, comprehensive regional energy datasets suitable for supporting long-term infrastructure planning remain scarce. Finally, reproducibility and accessibility remain major concerns. Although urban energy modelling has benefited from significant advances in open-source software and cloud computing, many simulation results remain inaccessible to researchers, practitioners and public authorities because they are distributed as static maps or supplementary datasets rather than operational decision-support tools[32–35]. The absence of publicly available interactive platforms limits scientific transparency, reduces reproducibility and restricts the practical uptake of research outcomes by policy-makers and urban planners. These limitations collectively demonstrate the need for a new generation of urban energy platforms capable of simultaneously integrating multiple building sectors, high-resolution hourly simulations, GIS-based spatial aggregation and interactive web visualisation. Addressing these challenges constitutes the principal scientific motivation of the present study.

Existing urban energy atlases and building-stock platforms provide important precedents for the present work, but they differ substantially in scope, modelling depth, temporal resolution, sectoral coverage and accessibility. Initiatives such as the Swiss City Energy Atlas[36] and the Berlin Building Stock Model[37] demonstrate the value of integrating building-stock information with spatial energy analysis, while the European Building Stock Observatory (EU BSO)[38] provides a harmonised information infrastructure for monitoring building characteristics, energy performance and decarbonisation across European countries. The TABULA[39] and EPISCOPE[40] projects further established harmonised European building typologies and building-stock modelling approaches based on building age, size, construction characteristics and typical energy performance, providing an important methodological precedent for archetype-based stock assessment. These initiatives have substantially advanced the availability and spatial representation of building-energy information, but they do not provide the same combination of regional-scale building-level modelling, continuous hourly energy profiles and integrated interactive visualization developed in the present study.

The present study builds on this established typology-based modelling tradition while extending it to a regional-scale, multi-sector framework combining residential, tertiary and industrial buildings with continuous 8,760-hour profiles and interactive spatial visualization.

The contribution of the Wallonia Energy Atlas therefore does not lie in introducing a fundamentally new temporal load-profile algorithm; rather, it lies in integrating established building-stock modelling and temporal-disaggregation approaches into a unified regional framework covering approximately 1.69 million buildings. The framework simultaneously represents residential, tertiary and industrial activities, generates five hourly energy indicators (HC, HD, EC, CED and HEC) over 8,760 h, aggregates these indicators across multiple territorial scales, and makes the resulting information accessible through an interactive web-based atlas. This combination of spatial scale, sectoral breadth, temporal resolution and interactive accessibility provides a complementary contribution to existing urban energy atlases and building-stock modelling frameworks.

To address the limitations identified above, this study develops the first high-resolution interactive Wallonia Energy Atlas, a regional-scale digital platform designed to characterise the spatiotemporal dynamics of the entire Walloon building stock. The proposed framework combines bottom-up building energy modelling, Geographic Information Systems (GIS), hourly temporal reconstruction and interactive web technologies to provide a comprehensive representation of building energy demand across residential, tertiary and industrial sectors. The first contribution of this work is the development of a bottom-up modelling framework integrating detailed cadastral information for approximately 1.69 million buildings with annual archetype-based energy indicators to generate 8,760-hour profiles of Heat Consumption (HC), Heat Demand (HD), Electricity Consumption (EC), Cooling Electricity Demand (CED) and Heating Electricity Consumption (HEC). Unlike most previous studies, the proposed methodology simultaneously represents the three principal building sectors within a unified modelling environment.

The second contribution is the implementation of a multi-scale geospatial aggregation framework, allowing dynamic energy indicators to be analysed at four administrative levels, namely the Walloon Region, five provinces, twenty arrondissements and 262 municipalities. This hierarchical organisation enables direct comparison of energy behaviour across different spatial scales while preserving the consistency of the underlying building-level simulations. A third major contribution is the development of an interactive online Urban Energy Atlas based on Python, Dash and Plotly technologies. Unlike conventional static energy maps, the proposed platform allows users to dynamically visualise spatial energy distributions, explore annual hourly profiles and compare multiple energy indicators through an intuitive web interface. By providing open access to dynamic simulation results, the platform substantially improves transparency, reproducibility and knowledge transfer between researchers, public authorities and infrastructure planners. The scientific contribution of this work extends beyond the development of a digital platform. By combining building stock modelling, hourly energy simulation, load duration curve analysis and interactive geospatial visualisation within a unified framework, this study establishes a transferable methodology for supporting regional energy planning, district heating expansion, renewable energy integration and climate-neutral urban development. The framework is potentially transferable to other regions where sufficiently detailed building-stock inventories and sectoral energy statistics are available. Such transferability, however, requires regional adaptation of building classifications, energy-intensity coefficients, climatic inputs, administrative geographies and, where possible, locally calibrated temporal load profiles. The framework should therefore be considered a transferable modelling architecture rather than a plug-and-play model requiring no regional recalibration.

The remainder of this paper is organised as follows. "Method" section presents the study area, datasets and methodological framework, including the development of the interactive Wallonia Energy Atlas. "Results" section analyses the hourly energy behaviour of residential, tertiary and industrial buildings together with the corresponding load duration curves. "Discussion" section discusses the scientific implications of the findings in comparison with the recent international literature, while "Conclusion" section summarises the principal conclusions and outlines future research directions.

Method

Study area and methodological framework

This study develops a high-resolution spatiotemporal energy-modelling framework to estimate hourly heating, cooling, and electricity requirements across the entire building stock of Wallonia, Belgium. The proposed framework combines geospatial cadastral information, regional energy statistics, sector-specific energy intensities, and standardized temporal load profiles to generate building-level hourly energy series for approximately 1.69 million buildings. Unlike conventional territorial-energy assessments that primarily focus on annual indicators aggregated at sectoral or administrative levels, the present approach enables the reconstruction of hourly energy profiles at the individual-building scale using standardized temporal archetypes. The Walloon Region was selected as the case study because of its diversified building stock, strong territorial heterogeneity, and strategic role in the Belgian energy transition. Located in southern Belgium, Wallonia covers approximately 16,901 km^2 and encompasses a wide range of urban, peri-urban, industrial, commercial, and rural environments. The region comprises five provinces, twenty arrondissements, 262 municipalities, more than 3,000 neighbourhoods, and nearly 10,000 statistical sectors, providing an exceptional spatial framework for investigating energy-demand patterns across multiple territorial scales. In addition, the availability of detailed cadastral information and comprehensive regional energy statistics makes Wallonia particularly suitable for the development and validation of advanced territorial-energy modelling approaches.

The methodological framework integrates both top-down and bottom-up modelling principles. The top-down component relies on official regional energy statistics to derive representative energy-intensity indicators for different building categories and economic activities. The bottom-up component combines these category-specific intensity values with cadastral building information. For each building, the total floor area was estimated

by multiplying the building footprint area, calculated from the polygon geometry in QGIS, by the recorded number of floors. The resulting total floor area was then multiplied by the corresponding category-specific energy-intensity coefficient to obtain the annual building-level energy indicator. Five complementary energy variables were considered throughout the analysis: Heat Consumption (HC), Heat Demand (HD), Electricity Consumption (EC), Cooling Electricity Demand (CED), and Heating Electricity Consumption (HEC). Residential buildings were subdivided into detached houses, semi-detached houses, terraced houses, and apartments, while tertiary and industrial activities were further classified into detailed functional and economic subsectors. The annual energy estimates constitute the first stage of the modelling process. Subsequently, hourly energy profiles were generated by coupling annual building-level energy values with standardized temporal load profiles. This procedure enabled the transformation of annual energy quantities into continuous hourly time series covering an entire year (8,760 h), thereby allowing the investigation of daily, weekly, seasonal, and sector-specific energy-demand dynamics. The resulting database provides a comprehensive representation of the temporal behaviour of heating, cooling, and electricity consumption across the Walloon building stock. The complete sequence of data inputs, preprocessing, energy estimation, temporal disaggregation, validation, uncertainty assessment, spatial aggregation and atlas deployment is summarized in Fig. 1.

The computational workflow was implemented using an integrated geospatial and scientific-computing environment. Spatial analyses and data preprocessing were performed using QGIS, while numerical calculations, data management, and model implementation were carried out within the Python scientific ecosystem using Jupyter Notebook. GeoPandas was employed for geospatial processing and spatial aggregation, Pandas for large-scale tabular-data management, NumPy for numerical computations and matrix operations, and Plotly and Matplotlib for data visualization and interactive dashboard development. This computational framework enabled the efficient processing of millions of buildings, the generation of large hourly-energy datasets, and the production of high-resolution spatial and temporal energy indicators suitable for regional planning, decarbonization studies, and energy-transition assessments.

Building stock database and sectoral classification

The development of hourly energy profiles for the Walloon building stock required the construction of a detailed geospatial database describing the physical, functional, and territorial characteristics of individual buildings. The analysis was based on the official Walloon cadastral dataset, which provides one of the most comprehensive representations of the regional built environment currently available for scientific research. The original database contained more than 2.6 million cadastral records represented as georeferenced polygon features. Following extensive preprocessing procedures including geometry validation, duplicate removal, consistency checks, and the exclusion of non-relevant structures, approximately 1.69 million buildings were retained for the subsequent energy-modelling process. Each building record contains a wide range of attributes describing geometric properties, construction characteristics, land-use functions, and administrative information. Building geometry was represented through cadastral footprint polygons, while the number of storeys was obtained from the corresponding cadastral records. These variables were combined to estimate the total usable floor area of each building, which constitutes a key parameter in the calculation of annual and hourly energy indicators. Additional information related to construction period, renovation history, and construction quality was used to characterize the heterogeneity of the building stock and to support quality-control procedures throughout the modelling workflow.

A hierarchical sectoral-classification scheme was developed to capture the diversity of energy-use patterns across the Walloon territory. Buildings were first grouped into three major sectors: residential, tertiary, and industrial. Residential buildings were further subdivided into four housing typologies, namely detached houses, semi-detached houses, terraced houses, and apartments. Tertiary buildings were classified into nine functional categories: commercial activities, education, healthcare facilities, administration, banking and services, transportation infrastructures, culture and sports facilities, energy and water infrastructures, and other service activities. For the principal comparative analysis presented in "Hourly energy profiles of tertiary buildings" section, eight categories were retained: Education, Administration, Banks and Services, Commercial, Culture and Sport, Energy and Water, Transportation, and Other Services. Healthcare was retained in the underlying classification and energy-intensity dataset but was not included in the principal eight-category comparison because a sufficiently consistent hourly-profile dataset was not available for inclusion in the comparative analysis. Industrial buildings were allocated to seven economic branches comprising agro-food industries, chemistry, metallurgy, mineral industries, steel production, textile manufacturing, and other industrial activities. The classification process relied primarily on cadastral activity codes, land-use descriptors, and building-typology information contained within the cadastral database. This detailed disaggregation was considered essential because energy-consumption characteristics vary substantially among building types, economic sectors, and functional activities. By moving beyond conventional sector-level analyses, the proposed classification framework enables a more realistic representation of energy-demand heterogeneity and provides the foundation for the generation of sector-specific hourly load profiles.

The spatial location of each building was referenced using the Belgian Lambert 1972 coordinate system (EPSG:31370), ensuring compatibility with regional geospatial datasets and administrative boundaries. Unique statistical identifiers embedded within the cadastral records enabled the automatic assignment of each building to multiple territorial levels, including statistical sectors, neighbourhoods, municipalities, arrondissements, and provinces. This hierarchical spatial structure subsequently facilitated the aggregation and visualization of hourly energy indicators across different geographic scales. The resulting building-stock database constitutes the core input of the proposed spatiotemporal modelling framework. By combining geometric information, functional classification, construction characteristics, and territorial identifiers, the database provides a robust foundation for estimating annual energy indicators and generating hourly profiles of heat consumption, heat demand,

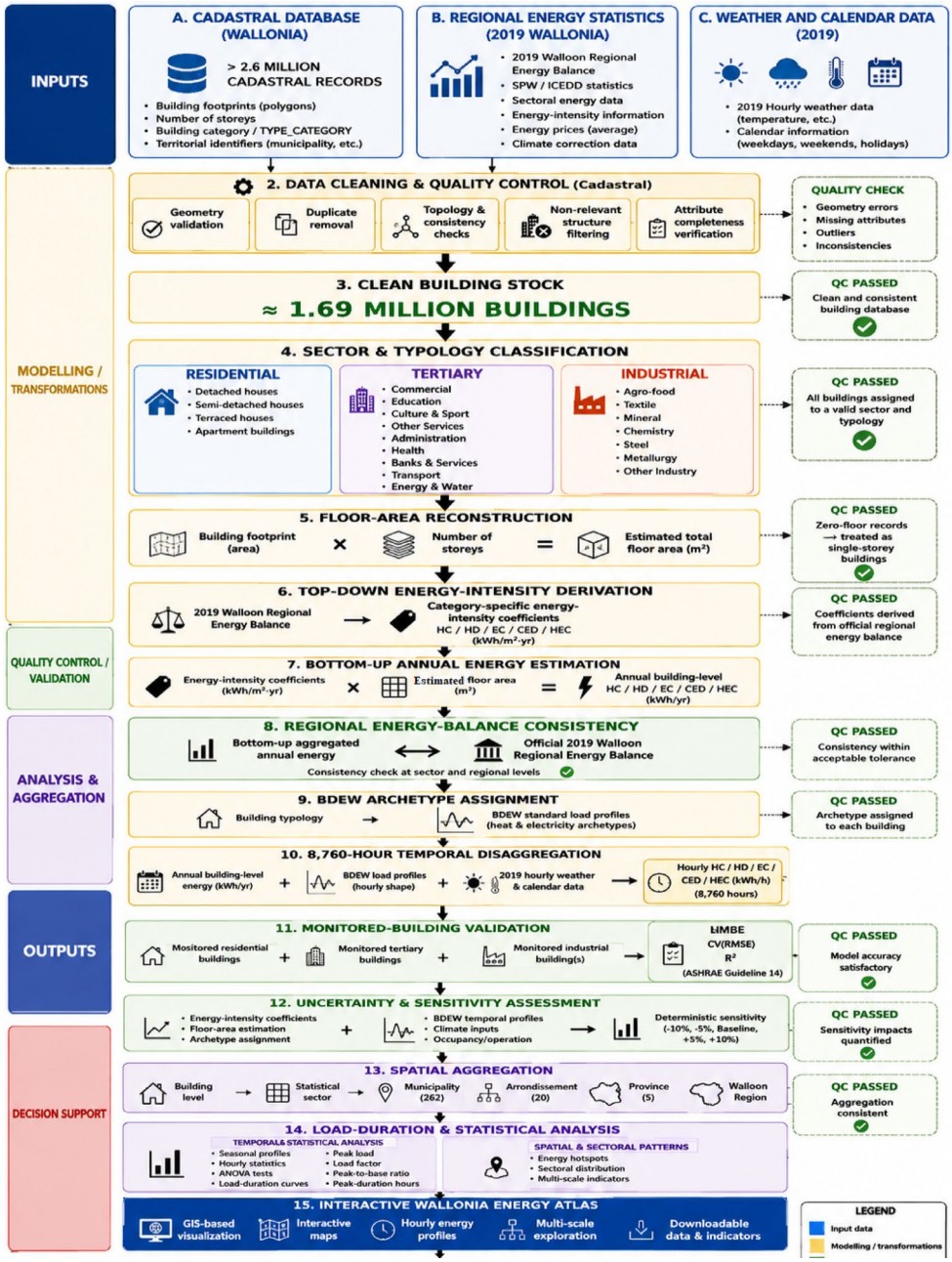


Fig. 1. Step-by-step methodological workflow for the generation, validation, analysis and deployment of hourly building-energy profiles across the Walloon building stock. The workflow distinguishes input datasets, modelling transformations, quality-control and validation procedures, and final analytical and decision-support outputs.

electricity consumption, cooling electricity demand, and heating electricity consumption across approximately 1.69 million buildings in Wallonia.

Annual building-level energy estimation

The generation of hourly energy profiles requires reliable estimates of annual building-level energy consumption. Consequently, a preliminary modelling stage was implemented to quantify annual Heat Consumption (HC), Heat Demand (HD), Electricity Consumption (EC), Cooling Electricity Demand (CED), and Heating Electricity Consumption (HEC) for each building included in the Walloon building stock database. In this study, HC and HD represent two distinct but related heat indicators. HC denotes the annual heat consumption allocated to the building, whereas HD represents the corresponding useful heat requirement or heat demand under the adopted modelling assumptions. The difference between HC and HD is therefore interpreted as a difference between consumption and useful demand estimates and is not explicitly attributed to distribution losses, system inefficiencies, or unmet demand, which are not separately modelled in the present framework. The proposed

approach combines detailed cadastral information with official regional energy statistics through a hybrid top-down and bottom-up modelling framework. The statistical foundation of the model was derived from the 2019 Walloon Regional Energy Balance published by the Service Public de Wallonie (SPW) in collaboration with the Institut de Conseil et d'Études en Développement Durable (ICEDD)[41]. This database provides harmonized information on final energy consumption, building-stock characteristics, sectoral energy use, dwelling typologies, climatic indicators, and end-use energy distributions across residential, tertiary, and industrial sectors. These datasets were used within the top-down component of the framework to derive representative energy-intensity coefficients for each building category considered in this study. The resulting coefficients quantify annual heat consumption (HC), heat demand (HD), electricity consumption (EC), cooling electricity demand (CED), and heating electricity consumption (HEC) per unit of estimated floor area. Here, EC represents total annual electricity consumption allocated to the building category; CED represents the annual electricity demand attributed to cooling; and HEC represents the annual electricity component attributed to electrically driven heating. HEC is reported separately from EC to identify the heating-related electricity component and should not be added to EC as an independent end-use because it is treated as a component of total electricity consumption. The complete set of coefficients obtained from this top-down procedure and subsequently used in the bottom-up building-level estimation is reported in Supplementary Table 1.

The coefficients are therefore study-derived regional intensity parameters rather than generic literature values. They were calculated from Walloon regional energy statistics and associated building-sector information and subsequently assigned to individual cadastral buildings according to their primary "TYPE_CATEGORY". This two-stage procedure links regional energy balances to the spatially explicit cadastral building stock while preserving consistency between the top-down regional totals and the bottom-up building-level estimates (Table 1).

Prior to energy estimation, the cadastral database underwent an extensive harmonization procedure to improve geometric consistency and energy representativeness. Building footprints, cadastral built areas, and the number of storeys were systematically analyzed to reconstruct realistic floor areas. Particular attention was devoted to multi-storey buildings, for which footprint area alone may significantly underestimate the actual usable floor space. The estimated total floor area was calculated by combining building footprint area with the number of storeys and was subsequently used as the principal explanatory variable in the energy-estimation process. Following the harmonization stage, sector-specific energy-intensity coefficients expressed in kWh m^{-2} were assigned to each building category. Distinct coefficients were defined for residential, tertiary, and industrial subsectors in order to account for differences in occupancy patterns, operational characteristics, technological equipment, and energy-use behaviour. The annual energy indicators were then estimated by multiplying the corresponding intensity coefficients by the estimated building floor area.

Annual Heat Consumption (HC) was estimated with Eq. (1):

$$HC_i = \frac{I_{HC} * A_{floor,i}}{10^6} \tag{1}$$

where HC_i is the annual heat consumption of the building (GWh yr^{-1}), I_{HC} is the heat-consumption intensity coefficient associated with the building category (kWh m^{-2} yr^{-1}), $A_{floor,i}$ is the estimated total floor area of building $i\,(m^2)$, and 10^{-6} is the conversion factor from kWh to GWh. HC was calculated using the category-specific heat-consumption intensity derived from the Walloon Regional Energy Balance and the corrected floor area. HD was estimated independently using the corresponding category-specific heat-demand intensity. Thus, HC and HD are parallel annual indicators derived from the same bottom-up allocation framework, rather than two successive stages of a detailed HVAC energy-loss model.

The total building floor area was estimated according to Eq. (2):

$$A_{floor,i=}\, A_{footprint,i} * N_{floors,i} \tag{2}$$

Where $A_{floor,i}$ is the estimated total floor area of building $i\,(m^2)$, $A_{footprint,i}$ is the cadastral building footprint area obtained from the polygon geometry (Shape_Area) in QGIS (m^2), and $N_{floors,i}$ is the number of floors recorded for building i.

The cadastral dataset did not contain missing floor-count values. A value of zero indicated a building with no additional recorded storey; for the purpose of floor-area estimation, such cases were assigned $N_{floors,} = 1$, corresponding to the ground floor. Thus, the estimated total floor area was calculated by multiplying the cadastral footprint area by the number of floors, with zero-floor records treated as single-storey buildings.

Following the top-down derivation of the category-specific intensity coefficients, each cadastral building was assigned the five corresponding intensity parameters according to its TYPE_CATEGORY. The annual energy indicator for each building was then obtained by multiplying the category-specific intensity by the corrected building floor area. This procedure constitutes the bottom-up spatial disaggregation step of the framework.

Heating Electricity Consumption (HEC) was estimated for residential and tertiary buildings but was not explicitly modelled for industrial buildings. This distinction does not imply that industrial process heating is exclusively supplied by non-electric energy sources. Rather, the available regional energy statistics did not provide sufficiently detailed and consistent subsector-specific information to separate electricity used for process heating from electricity associated with other industrial end uses. Because assigning an industrial HEC coefficient without such information would require additional assumptions that could not be independently validated, industrial HEC was excluded from the present building-level estimation framework. This limitation is particularly relevant in the context of increasing industrial electrification and should be addressed in future work using process-specific electricity shares and plant-level energy data.

Sector	Building category	HC	HD	EC	CED	HEC	Unit
Residential	Apartment	230.9	190.6	42.4	0.76	7.45	kWh m^{-2} yr^{-1}
Residential	Terraced	190.9	155.2	50.6	0.91	10.36	kWh m^{-2} yr^{-1}
Residential	Semi-detached	154.5	125.4	40.2	0.72	8.24	kWh m^{-2} yr^{-1}
Residential	Detached	193.6	157.5	30.4	0.55	6.24	kWh m^{-2} yr^{-1}
Tertiary	Commercial	116.2	98.0	106.2	8.28	3.84	kWh m^{-2} yr^{-1}
Tertiary	Education	91.1	76.6	23.1	0.72	5.65	kWh m^{-2} yr^{-1}
Tertiary	Culture & Sport	191.8	161.4	10.2	1.6	0.31	kWh m^{-2} yr^{-1}
Tertiary	Other Services	191.8	161.4	10.2	1.87	0.38	kWh m^{-2} yr^{-1}
Tertiary	Administration	111.4	93.3	137.4	5.91	10.35	kWh m^{-2} yr^{-1}
Tertiary	Health	67.9	57.5	198.6	5.36	2.67	kWh m^{-2} yr^{-1}
Tertiary	Banks & Services	59.3	49.7	291.5	4.1	10.94	kWh m^{-2} yr^{-1}
Tertiary	Transport	87.4	72.2	742.9	54.97	3.96	kWh m^{-2} yr^{-1}
Tertiary	Energy & Water	308.3	260.6	873.7	27.1	4.76	kWh m^{-2} yr^{-1}
Industrial	Agro-food	3800	3500	1128.8	68.8	Not modelled	kWh m^{-2} yr^{-1}
Industrial	Other Industry	160	150	17.9	0.25	Not modelled	kWh m^{-2} yr^{-1}
Industrial	Steel	5300	4800	3875.2	7.75	Not modelled	kWh m^{-2} yr^{-1}
Industrial	Textile	6600	6100	1200.3	37.2	Not modelled	kWh m^{-2} yr^{-1}

Table 1. Top-down-derived energy-intensity coefficients used for building-level energy estimation. The intensity coefficients were derived in this study using the top-down procedure described in "Annual building-level energy estimation" section, based on the 2019 Walloon Regional Energy Balance and associated SPW/ICEDD datasets. The resulting coefficients were subsequently assigned to individual cadastral buildings according to their TYPE_CATEGORY and used in the bottom-up spatial disaggregation. HC, heat consumption; HD, heat demand; EC, electricity consumption; CED, cooling electricity demand; HEC, heating electricity consumption. HEC was not assigned to industrial categories because the available regional statistics did not provide sufficiently detailed subsector-specific information to separate electricity used for process heating from other industrial electricity end uses; HEC is therefore reported as N/A for industrial categories. HC and HD are reported as separate modelled indicators of heat consumption and useful heat demand, respectively, and their difference should not be interpreted as explicitly quantified system losses or unmet demand. HEC represents the electricity component associated with electrically driven heating and is reported separately from total EC to identify its contribution without double counting.

Substituting $A_{floor,i}$ into the previous Eq. (3):

$$HC_i = \frac{I_{HC} * \left(A_{floor,i=} A_{footprint,i} * N_{floors,i}\right)}{10^6} \tag{3}$$

Similarly, the remaining annual energy indicators were estimated as:

$$HD_i = \frac{I_{HD} * A_{floor,i}}{10^6} \tag{4}$$

$$EC_i = \frac{I_{EC} * A_{floor,i}}{10^6} \tag{5}$$

$$CED_i = \frac{I_{CED} * A_{floor,i}}{10^6} \tag{6}$$

$$HEC_i = \frac{I_{HEC} * A_{floor,i}}{10^6} \tag{7}$$

For industrial categories, HEC is not assigned and is therefore treated as not available (N/A), as explained above. The estimation of industrial HEC is beyond the scope of the present modelling framework and will be investigated in future work using subsector-specific process characteristics and industrial electrification data.

Hourly profile generation

The annual energy indicators estimated in "Annual building-level energy estimation" section provide valuable information regarding the magnitude of building energy consumption; however, they do not capture the temporal variability of energy use throughout the year. To reconstruct hourly energy dynamics, annual building-level energy estimates were temporally disaggregated using the established German BDEW (Bundesverband der Energie- und Wasserwirtschaft) standard load-profile methodology. The use of BDEW profiles is not intended as a methodological innovation in itself; rather, these standardized profiles provide a computationally tractable and

reproducible approach for transforming annual energy indicators into hourly time series across a building stock of approximately 1.69 million buildings. This choice represents a deliberate simplification. BDEW profiles were developed for German building-stock and energy-system contexts and therefore may not fully reproduce Belgian-specific occupancy schedules, appliance-use patterns, operating practices, building regulations, tariff structures or cultural behaviours. In the present study, no country-specific behavioural recalibration of the standard BDEW profiles was performed. Instead, the profiles were mapped to Walloon building categories and combined with Walloon cadastral characteristics, regional energy-intensity coefficients and 2019 Walloon weather data. Consequently, the resulting hourly profiles should be interpreted as standardized, sector-representative temporal distributions constrained by Walloon annual energy estimates rather than as building-specific measured load curves. Accordingly, differences between categories sharing the same BDEW archetype should be interpreted primarily as differences in annual energy magnitude rather than independently derived temporal behaviour. The normalized hourly shape is imposed by the selected archetype, while category-specific energy intensities, floor areas and building counts determine the resulting absolute load levels.

The BDEW framework provides standardized temporal profiles representative of different building functions while accounting for seasonal variations, outdoor temperature conditions, day types, and occupancy-related behavioural patterns. Two independent sets of profiles were generated: heat profiles and electricity profiles. For heat-related applications, hourly normalized profiles were generated using the Heat-Building module available in the Demandlib Python package. The method requires hourly outdoor temperature observations, calendar information, public holidays, and building archetypes. Hourly temperature data for the year 2019 were used to represent climatic conditions across Wallonia. The temperature series consisted of 8,760 hourly observations covering the entire year.

The BDEW methodology distinguishes between residential and non-residential heat-demand archetypes. Residential buildings were represented using the EFH (single-family house) and MFH (multi-family house) profiles, whereas tertiary and industrial buildings were associated with the most appropriate commercial and industrial BDEW categories. For each archetype, a normalized hourly heat profile ($P_{heat}(t)$) was generated such that:

$$\sum_{t=1}^{8760} P_{heat}(t) = 1 \tag{8}$$

where ($P_{heat}(t)$) represents the fraction of annual heat demand allocated to hour (t).

For electricity consumption, standard BDEW electricity load profiles (SLP) were generated using the ElecSlp module from Demandlib. The original profiles are provided at 15-minute resolution and were subsequently aggregated to hourly values through arithmetic averaging. Residential buildings were assigned the household profile H0, whereas tertiary and industrial buildings were associated with the most representative BDEW electricity categories (G0-G6). The resulting hourly electricity profiles were normalized according to:

$$\sum_{t=1}^{8760} P_{elec}(t) = 1 \tag{9}$$

where ($P_{elec}(t)$) denotes the normalized electricity profile at hour (t). Table 2 summarizes the correspondence established between Walloon building categories and the selected BDEW archetypes.

This assumption should therefore be interpreted as a temporal-disaggregation strategy rather than as evidence that Belgian and German occupancy or operational behaviours are identical.

The archetype assignment was based on functional correspondence between Walloon cadastral categories and the definitions of the available BDEW profiles. It was not intended to imply equivalence between German and Belgian building stocks. The assignment therefore represents a pragmatic and reproducible approximation, whose behavioural validity should be further tested using Belgian measured load data.

For industrial categories, the selected BDEW profiles should be interpreted as standardized temporal proxies rather than plant-specific production schedules. In particular, mineral, chemical, steel and metallurgical categories share the GMF heat archetype and G5 electricity profile; consequently, the model does not independently resolve process-specific temporal behaviour among these subsectors. Differences in their modelled hourly load magnitudes arise primarily from their respective annual energy-intensity coefficients and reconstructed floor areas. Industrial electricity and heat demand can depend strongly on production shifts, process continuity, maintenance periods and technology-specific operating conditions, which are not explicitly represented in the present framework. Sector-specific measured industrial profiles would therefore be required to resolve these process-level temporal differences.

This simplification is particularly relevant for the interpretation of industrial peak loads and load-duration curves. In addition, for industrial buildings, the estimated energy intensity represents building-related energy consumption rather than process-specific industrial energy use. Accordingly, the area-based estimates should not be interpreted as comprehensive facility-level industrial energy consumption, since production-related energy demand depends on process technologies, production throughput, equipment, operating schedules, and capacity factors. The 8,760 hourly values generated in this framework represent a temporally ordered modelled series rather than 8,760 independent statistical observations. Consequently, hourly observations were not treated as independent replicates for inferential comparisons among building categories. Descriptive statistics are used to characterize intra-annual temporal variability, while differences among categories are interpreted using absolute values and relative effect sizes.

Building category	Heat profile	Heat profile meaning	Electricity profile	Electricity profile meaning
Detached	EFH	Single-family house	H0	Residential household
Semi-detached	EFH	Single-family house	H0	Residential household
Terraced	EFH	Single-family house	H0	Residential household
Apartment	MFH	Multi-family house	H0	Residential household
Commercial	GKO	Retail and commercial buildings	G0	General commercial load
Education	GBA	Educational buildings	G1	Educational and office load
Culture and sport	GMK	Sports and cultural facilities	G2	Public facilities load
Other services	GHD	Service-sector buildings	G3	Service-sector load
Administration	GBD	Administrative and office buildings	G1	Office load
Health	GBH	Hospitals and healthcare facilities	G2	Healthcare load
Banks and services	GKO	Commercial and service buildings	G1	Office and services load
Transport	GHA	Transport facilities	G6	Infrastructure load
Energy and water	GMF	Utility and infrastructure facilities	G6	Infrastructure load
Agro-food industry	GGA	Agricultural and agro-industrial facilities	G4	Industrial load
Textile industry	GHD	Textile manufacturing facilities	G4	Industrial load
Mineral industry	GMF	Mineral-processing industry	G5	Heavy industrial load
Chemical industry	GMF	Chemical-processing industry	G5	Heavy industrial load
Steel industry	GMF	Steel production facilities	G5	Heavy industrial load
Metallurgy	GMF	Metallurgical facilities	G5	Heavy industrial load
Other industry	GHD	Other industrial facilities	G3	Mixed industrial/service load

Table 2. Mapping between Walloon building categories and BDEW standard load profiles. EFH = Single-Family House (Einfamilienhaus); MFH = Multi-Family House (Mehrfamilienhaus). H0 represents the standard residential electricity profile. G0–G6 correspond to commercial, institutional, service-sector and industrial BDEW electricity profiles. GKO, GBA, GMK, GHD, GBD, GBH, GHA, GMF and GGA are BDEW heat-demand archetypes used to represent specific non-residential building functions.

Development of HC(t), HD(t), EC(t), CED(t) and HEC(t)

Hourly energy series were generated by combining the annual building-level energy indicators with the normalized BDEW temporal profiles described in "Hourly profile generation" section. This procedure allowed the reconstruction of continuous hourly energy demand for every building contained in the Walloon building stock database. For each building (i), the annual Heat Consumption ((HC_i)) estimated previously was distributed over the 8,760 h of the year using the corresponding normalized heat profile ($P_{heat}\,(t)$). The hourly heat-consumption series was therefore calculated as:

$$HC_{building}\,(t) = HC_{building,annual} * 10^6 * P_{heat}\,(t) \tag{10}$$

where:

$HC_{building}\,(t)$ the heat consumption of the building at (kWh h^{-1}; $HC_{building,annual}$ is the annual heat consumption of the building (GWh yr^{-1}); $P_{heat}\,(t)$ is the normalized BDEW heat profile at hour t. Because the heat profile is normalized, the following condition is satisfied: $\sum_{t=1}^{8760} P_{heat}\,(t) = 1$, which guarantees that the sum of all hourly values is equal to the annual heat consumption. For consistency of units, annual energy quantities are first expressed in GWh $year^{-1}$ at the building level and converted to kWh $year^{-1}$ before temporal disaggregation. Multiplication by the dimensionless normalized hourly profile yields the energy associated with each one-hour interval, expressed in kWh. Because each time step represents exactly one hour, the corresponding average hourly power is numerically equal to this hourly energy value and is expressed in kW. Thus, kWh refers to energy consumed during the one-hour interval, whereas kW refers to the corresponding average power over that interval; these quantities are not used interchangeably.

The hourly heat demand was derived using the same normalized heat profile:

$$HD_{building}\,(t) = HD_{building,annual} * 10^6 * P_{heat}\,(t) \tag{11}$$

where $HD_{building,annual}$ is the annual heat demand of the building (GWh yr^{-1}).

Accordingly, HC(t) and HD(t) preserve the distinction between their respective annual quantities while sharing the same normalized temporal heat profile; the temporal disaggregation therefore does not introduce an additional efficiency or loss model. Therefore, the temporal differentiation among building categories is constrained by the assigned BDEW archetype. Where multiple categories share the same normalized archetype, the model preserves differences in annual magnitude but does not infer independent category-specific hourly shapes.

Electricity consumption was distributed using the normalized BDEW electricity profile:

$$EC_{building}(t) = EC_{building,annual} * 10^6 * P_{elec}(t) \quad (12)$$

$P_{elec}(t)$ is the normalized BDEW electricity profile.

Cooling electricity demand (CED) was temporally disaggregated using the normalized BDEW electricity profile as a pragmatic approximation for the regional-scale modelling of approximately 1.69 million buildings. Although cooling systems are predominantly electrically driven, their actual operation is primarily governed by outdoor temperature, solar gains, internal gains, occupancy, and cooling control strategies rather than by the generic electricity-load profile alone. Therefore, the use of the standard electricity profile for CED should be interpreted as a temporal-disaggregation assumption rather than as a physically explicit representation of cooling operation. This assumption preserves the annual CED estimate but may generate cooling loads during periods of low or negligible cooling requirement and may not accurately reproduce the timing or magnitude of summer cooling peaks. A weather-dependent cooling profile based on outdoor temperature and cooling-degree conditions would provide a more physically representative temporal distribution and is therefore identified as an important direction for future refinement.

$$CED_{building}(t) = CED_{building,annual} * 10^6 * P_{elec}(t) \quad (13)$$

Where $CED_{building,annual}$ is the annual cooling electricity demand of the building (GWh year^{-1}).

Heating electricity consumption was assumed to follow the temporal behaviour of heating requirements and was therefore distributed using the heat profile:

$$HEC_{building}(t) = HEC_{building,annual} * 10^6 * P_{heat}(t) \quad (14)$$

Where $HEC_{building,annual}$ denotes the annual electricity consumption associated with electrically driven heating systems. EC represents total electricity consumption associated with the building, whereas HEC represents only the electricity attributed to electrically driven heating systems. HEC is therefore treated as a component of EC rather than as an additional electricity end-use to be added to EC. Accordingly, HEC is reported separately to identify the heating-related component of electricity use and is not added to EC when calculating total electricity consumption.

This procedure was applied only to residential and tertiary buildings for which HEC was estimated. Industrial buildings were excluded from this calculation because no industrial HEC coefficient was derived in the annual energy-estimation step. Consequently, the industrial hourly database contains HC, HD, EC and CED profiles, whereas HEC is not reported for industrial categories.

This assumption reflects the strong temporal coupling between electrically driven heating systems and space-heating requirements throughout the year. Instead of processing buildings individually, annual energy vectors were multiplied by normalized profile vectors through outer-product operations. This approach drastically reduced computational time while maintaining exact consistency between annual and hourly energy quantities.

To efficiently generate hourly energy series for approximately 1.69 million buildings, a vectorized matrix-based approach was implemented. For each building category, the hourly energy matrix was computed as:

$$E = P \otimes A \quad (15)$$

Where : P is the normalized hourly profile vector (8760 × 1); A is the annual energy vector for all buildings belonging to the considered category (1×n); ⊗ denotes the outer-product operation. The resulting matrix contains hourly energy values for all buildings simultaneously and preserves the annual energy totals exactly. The generated hourly database comprises HC, HD, EC, CED and, where modelled, HEC. HEC was not generated for industrial categories because no industrial HEC coefficient was available, for approximately 1.69 million buildings and 8,760 hourly time steps, resulting in one of the most detailed spatiotemporal building-energy datasets currently available at the regional scale. These hourly series constitute the foundation for the subsequent spatial analyses, temporal investigations, and interactive visualization tools developed in this study. At the full building-stock scale, 1.69 million buildings × 8,760 h corresponds to approximately 14.8 billion hourly values for a single indicator and approximately 74 billion values for the five modelled indicators. Consequently, the complete building-level hourly arrays were retained locally for computational processing rather than directly distributed through the interactive Atlas. After building-level simulation, the hourly results were spatially aggregated at municipal, arrondissement and provincial levels. These aggregated datasets, with a total storage footprint of less than 100 MB, were used for interactive visualization and retrieval in the Wallonia Energy Atlas. Spatial aggregation was therefore performed after the building-level hourly simulation and did not replace the underlying building-scale energy modelling.

Spatial aggregation and multi-scale analysis

Following the generation of hourly energy series for individual buildings, a spatial aggregation procedure was implemented to investigate energy-demand patterns across multiple territorial scales. Although the proposed modelling framework produces energy profiles at the building level, many planning, policy, and energy-transition decisions are made at broader administrative and territorial levels. Consequently, aggregating building-level information is essential for identifying spatial inequalities, sectoral concentrations, and priority intervention areas. The aggregation process was performed using the geo-referenced cadastral database and the hierarchical territorial structure of Wallonia. Each building was associated with its corresponding statistical sector, neighbourhood, municipality, arrondissement, and province through unique spatial identifiers contained within the cadastral records. This hierarchical organization enabled the systematic aggregation of energy

indicators from the building scale to larger territorial units while preserving spatial consistency throughout the analysis. The spatial aggregation also serves a computational dissemination purpose. Although hourly profiles are generated at building level, the complete building-level matrices are too large for efficient interactive dissemination. Municipal-, arrondissement- and provincial-level hourly datasets were therefore generated from the building-level results and used as the primary datasets for Atlas access.

For a given territorial unit (z), the aggregated hourly heat consumption was calculated as:

$$HC_Z(t) = \sum_{i=1}^{n_z} HC_i(t) \tag{16}$$

where: $HC_Z(t)$ is the aggregated hourly heating consumption of territorial unit z (kWh h^{-1}); $HC_i(t)$ is the hourly heating consumption of building i (kWh h^{-1}); n_z is the total number of buildings within territorial unit z.

In the same order,

$$\text{Heat Demand}: \ HD_Z(t) = \sum_{i=1}^{n_z} HD_i(t) \tag{17}$$

$$\text{Electricity Consumption}: \ EC_Z(t) = \sum_{i=1}^{n_z} EC_i(t) \tag{18}$$

$$\text{Cooling Electricity Demand} \ CED_Z(t) = \sum_{i=1}^{n_z} CED_i(t) \tag{19}$$

$$\text{Heating Electricity Consumption}: \ HEC_Z(t) = \sum_{i=1}^{n_z} HEC_i(t) \tag{20}$$

The Nomenclature of Symbols Used in the Spatial is presented in Table 3.

The aggregation procedure was implemented using vectorized numerical operations and geospatial grouping techniques within the Python scientific-computing environment. This approach enabled the efficient processing of millions of hourly profiles while maintaining computational scalability and reproducibility.The resulting database provides hourly energy indicators at multiple spatial levels, ranging from individual buildings to municipalities, arrondissements, provinces, and the entire Walloon Region. Such a multi-scale structure allows the investigation of temporal and spatial variations in heating, cooling, and electricity demand, while facilitating comparisons among residential, tertiary, and industrial sectors. In addition to territorial aggregation, the hourly profiles were also grouped according to building categories and economic activities. This sectoral aggregation enabled the identification of distinct temporal consumption patterns associated with different residential typologies, service activities, and industrial branches. Consequently, the framework supports both spatial and sectoral analyses of energy demand and provides valuable information for regional energy planning, infrastructure design, building-renovation strategies, demand-side management, and decarbonization policies. The aggregated datasets were subsequently used to produce high-resolution maps, temporal analyses, and interactive visualization tools, including the Wallonia Energy Dashboard and the Wallonia Interactive Energy Atlas developed within this study. These tools allow stakeholders to explore hourly energy dynamics across the Walloon territory and to identify energy-demand hotspots at multiple geographic scales.

Interactive energy atlas and visualization platform

To facilitate the exploration, interpretation, and dissemination of the large volume of data generated in this study, an interactive visualization framework was developed and integrated into the modelling workflow. The platform was designed to enable the dynamic investigation of hourly energy-consumption patterns across the entire Walloon building stock while maintaining direct access to both building-level and territorial-scale information.

The visualization system combines geospatial analytics, interactive dashboards, and web-based mapping technologies. The platform was implemented using Python, Dash, Plotly, GeoPandas, Pandas, and NumPy, allowing the seamless integration of geographic information, annual energy indicators, and hourly energy profiles within a single interactive environment. The resulting framework provides a user-friendly interface for exploring the temporal and spatial characteristics of Heat Consumption (HC), Heat Demand (HD), Electricity Consumption (EC), Cooling Electricity Demand (CED), and Heating Electricity Consumption (HEC). At the regional scale, a dynamic energy dashboard was developed to visualize the temporal evolution of the five hourly indicators for each building category. The dashboard automatically loads the pre-computed hourly

Symbol	Description	Unit
$HC_i(t)$	Hourly heat consumption of building i	kWh h^{-1}
$HD_i(t)$	Hourly heat demand of building i	kWh h^{-1}
$EC_i(t)$	Hourly electricity consumption of building i	kWh h^{-1}
$CED_i(t)$	Hourly cooling electricity demand of building i	kWh h^{-1}
$HEC_i(t)$	Hourly heating electricity consumption of building i	kWh h^{-1}
N_z	Number of buildings in territorial unit z	–
z	Territorial unit (sector, municipality, province, etc.)	–
t	Hour of the year (1–8760)	h

Table 3. Nomenclature of symbols used in the spatial aggregation equations.

energy profiles and allows users to select residential, tertiary, or industrial categories through an interactive menu. For each category, two complementary visualizations are simultaneously displayed: (i) the first 72 h of the year, enabling the analysis of short-term daily fluctuations, and (ii) the complete annual profile (8,760 h), allowing the investigation of seasonal variations and long-term demand patterns. Interactive functions such as zooming, panning, curve selection, and data export are provided to facilitate detailed exploration of the results. Beyond the dashboard, an Interactive Energy Atlas was developed to provide direct spatial access to the estimated energy indicators. The atlas integrates the georeferenced cadastral database comprising approximately 1.7 million buildings and enables real-time navigation across the Walloon territory. Users can explore the spatial information from the regional level to fine geographic scales, while public energy indicators are presented at aggregated territorial levels to respect data-governance and privacy constraints.

The platform incorporates multiple filtering capabilities, including municipality codes (CODE_INS), building categories (TYPE_CATEGORY), and sectoral classifications. These filters dynamically update the displayed buildings and associated energy indicators, thereby allowing users to investigate specific geographical areas or economic sectors. When a building is selected, the corresponding hourly profiles HC(t), HD(t), EC(t), CED(t), and HEC(t) are immediately displayed together with the associated annual indicators. The visualization framework was specifically designed to support energy-planning applications, demand-side management studies, building-renovation strategies, and territorial-energy analyses. By combining spatial information with hourly energy dynamics, the platform enables the identification of energy-demand hotspots, temporal peak-load periods, and sector-specific consumption patterns that cannot be observed using conventional annual statistics alone. From a computational perspective, the platform relies on pre-generated hourly matrices stored in optimized binary formats (NumPy arrays), enabling the rapid retrieval and visualization of millions of hourly time series. This architecture substantially reduces computational overhead and allows interactive exploration of large-scale datasets that would otherwise be difficult to manipulate in real time. Overall, the Interactive Energy Atlas and Dashboard transform the generated database into a decision-support tool capable of assisting researchers, urban planners, public authorities, utility companies, and industrial stakeholders in understanding the temporal and spatial dynamics of energy demand throughout the Walloon Region. Figure 1 shows the methodological framework for generating hourly building-energy profiles in Wallonia.

For the load-duration analysis, the peak load was defined as the annual maximum hourly load. For load-duration curve analysis, the hourly values are interpreted as average power over each one-hour interval and are therefore expressed in kW. The load-duration curves consequently represent the duration distribution of hourly average power, rather than cumulative hourly energy consumption in kWh. To avoid sensitivity to isolated near-zero observations, the base load was represented by the 5th percentile of the annual hourly load distribution. The load factor was calculated as the ratio between mean annual hourly load and peak load. The peak-to-base ratio was calculated as peak load divided by the 5th-percentile base load. Peak-duration hours were defined as the number of hours with loads equal to or exceeding 90% of the annual peak. The peak-to-average ratio was calculated as the annual peak load divided by the mean annual hourly load. Equivalent full-load hours were calculated as the annual energy divided by the annual peak load. The P95/P50 ratio was calculated as the 95th percentile hourly load divided by the median hourly load.

Calibration and validation

The hourly modelling framework was evaluated using a limited set of monitored buildings representing residential, tertiary and industrial functions. The available measurements were used to assess HC and EC where corresponding monitored data were available; HD, CED and HEC were not independently evaluated against measurements. Because direct monitored data were not available for the approximately 1.69 million buildings represented in the atlas, the validation dataset was not intended to constitute a statistically representative sample of the complete regional stock. Rather, it was designed to test whether the temporal-disaggregation framework could reproduce observed energy-use patterns across distinct building functions before being applied at regional scale. The monitored cases comprised residential, tertiary and industrial buildings. The residential dataset included semi-detached and detached dwellings. The monitored residential dwellings were two-storey buildings constructed during the 1960 s and classified as Class 1 (pre-1985). The semi-detached dwelling was monitored over 2018–2020, while monitored data were also available for a detached dwelling in 2018. The tertiary validation cases comprised a hospital, an office/administrative building, and a laboratory-library facility. The industrial validation case corresponded to a construction-related industrial facility. Building locations and other identifying information are not reported because of confidentiality restrictions. The monitoring dataset combined hourly and daily measurements depending on building and data availability; therefore, the temporal resolution used for validation is explicitly reported for each case in Supplementary Table S1 (Appendix section).To evaluate the agreement between monitored and simulated energy profiles, the calibration criteria recommended by ASHRAE Guideline 14 were adopted[42]. Calibration is particularly important when model outputs are subsequently used to support building-retrofit and energy-policy decisions[43]. Model performance was assessed using three widely recognized statistical indicators: the Normalized Mean Bias Error (NMBE), the Coefficient of Variation of the Root Mean Square Error [CV(RMSE)], and the Coefficient of Determination (R^2). These indicators are commonly employed in building-energy modelling studies to quantify systematic deviations, residual variability, and the ability of a model to reproduce observed temporal trends. Since the present study focuses on hourly energy profiles, the acceptance thresholds recommended by ASHRAE Guideline 14[42] for hourly calibration were considered. For hourly data, the ASHRAE Guideline 14 reference criteria of $|NMBE| \leq 10\%$ and $CV(RMSE) \leq 30\%$ were used. An R^2 value above 0.75 was additionally considered as a commonly adopted reference criterion for assessing the agreement between measured and simulated temporal variations. These criteria were used as reference benchmarks for interpreting model-measurement agreement;

meeting them does not imply universal predictive accuracy across the regional building stock. The NMBE was calculated as:

$$\mathrm{NMBE}\,(\%) = \frac{1}{\overline{m}} * \frac{\sum_{i=1}^{n}(m_i - s_i)}{n - p} * 100 \tag{21}$$

$$\mathrm{CV\,(RMSE)}\,(\%) = \frac{1}{\overline{m}} * \sqrt{\frac{\sum_{i=1}^{n}(m_i - s_i)^2}{n - p}} * 100 \tag{22}$$

$$R^2 = \left(\frac{n * \sum_{i=1}^{n} m_i * s_i - \sum_{i=1}^{n} m_i * \sum_{i=1}^{n} s_i}{\sqrt{(n * \sum_{i=1}^{n} m_i^2 - \left(\sum_{i=1}^{n} m_i\right)^2) * (n * \sum_{i=1}^{n} s_i^2 - \left(\sum_{i=1}^{n} s_i\right)^2)}} \right)^2 \tag{23}$$

.

The statistical indicators were computed using the equations presented above, where $\overline{m}$ denotes the mean value of the monitored energy data, m_i represents the measured hourly value at time step (i), s_i corresponds to the simulated value, (n) is the total number of observations, and (p) is the number of adjustable model parameters. Following previous calibration studies, the number of adjustable parameters was set equal to one.

The calibrated residential profiles showed good agreement with monitored data. For the semi-detached dwelling, the calibrated HC profile achieved an NMBE of −8.15%, a CV(RMSE) of 26.84% and an R^2 of 84.25%. The corresponding detached-dwelling HC profile, evaluated against daily monitored data, achieved an NMBE of −0.11%, a CV(RMSE) of 27.58% and an R^2 of 94.71%. For residential electricity consumption, the calibrated detached-building profile achieved an NMBE of 9.35%, a CV(RMSE) of 29.55% and an R^2 of 76.85%. For tertiary buildings, the calibrated hospital profile achieved an NMBE of −3.98%, a CV(RMSE) of 21.87% and an R^2 of 91.08%, while the office and laboratory-library cases achieved NMBE values of 6.40% and − 2.17%, CV(RMSE) values of 25.69% and 28.88%, and R^2 values of 90.36% and 86.14%, respectively. The industrial case achieved an NMBE of 2.75%, a CV(RMSE) of 28.96% and an R^2 of 96.77%. For cases evaluated using hourly monitored data, the calibrated profiles satisfied the hourly ASHRAE Guideline 14 reference criteria ($|\mathrm{NMBE}| \leq 10\%$ and $\mathrm{CV(RMSE)} \leq 30\%$). Cases for which only daily monitored data were available were evaluated using the same statistical indicators, but were not interpreted as formal hourly ASHRAE validation cases. These results indicate that the annual energy estimates and the associated hourly disaggregation methodology provide a reliable representation of temporal energy-demand dynamics. These results provide empirical support for the temporal modelling of HC and EC for the monitored building functions. HD, CED and HEC were not independently validated against monitored measurements and are therefore interpreted as modelled estimates based on the annual energy coefficients and temporal-disaggregation assumptions. The calibration and validation statistics are presented in Fig. 2.

Although the validation dataset comprised a limited number of monitored buildings, the selected case studies were intentionally chosen to represent the major functional sectors of the Walloon building stock, including residential, tertiary, and industrial activities. The objective of the present study is not to reproduce the behaviour of individual buildings through detailed physics-based simulations, but rather to generate statistically representative hourly energy profiles for a very large building stock using a territorial-energy modelling approach. Consequently, the reliability of the framework depends primarily on its ability to reproduce realistic temporal energy-demand patterns across different building functions rather than on the exact prediction of individual-building behaviour. The monitored-building validation does not provide statistical evidence that every individual building in the 1.69 million-building stock is predicted with the same accuracy. Instead, it provides an empirical test of the temporal-profile generation procedure across several major functional archetypes. Confidence in the regional application is therefore based on multiple complementary levels of evidence: (i) monitored-building comparisons across residential, tertiary and industrial functions; (ii) calibration against observed temporal patterns; and (iii) consistency of the annual building-level estimates with independent regional energy statistics. The building-level validation should consequently be interpreted as evidence of methodological plausibility and temporal-profile performance rather than as a statistical sample-based validation of the entire Walloon building stock. Several sources of uncertainty may nevertheless influence the estimated hourly energy profiles. First, the modelling framework relies on a single regional outdoor-temperature dataset representative of Wallonia, which may not fully capture local microclimatic variations. Second, the BDEW standard load profiles used for temporal disaggregation represent generalized occupancy and operational behaviours and may not account for all building-specific usage patterns. Additional uncertainty originates from the assignment of building archetypes to cadastral categories, as well as from assumptions regarding occupancy schedules, operational characteristics, and end-use energy distribution. Despite these limitations, the use of standardized and internationally recognized load-profile methodologies ensures consistency across the entire building stock and facilitates reproducible large-scale assessments. The robustness of the proposed framework is further strengthened by the diversity of the validation cases. The satisfactory performance obtained for residential, tertiary, and industrial buildings demonstrates that the methodology remains applicable across a wide range of energy-use intensities, occupancy regimes, and operational conditions. This multi-sector evaluation provides evidence that the modelling framework can reproduce representative temporal patterns for the monitored HC and EC cases. However, it does not constitute independent validation of HD, CED or HEC. However, because the number of monitored buildings remains limited relative to the approximately 1.69 million buildings modelled, the validation should not be interpreted as demonstrating building-level predictive accuracy across the entire Walloon stock. Rather,

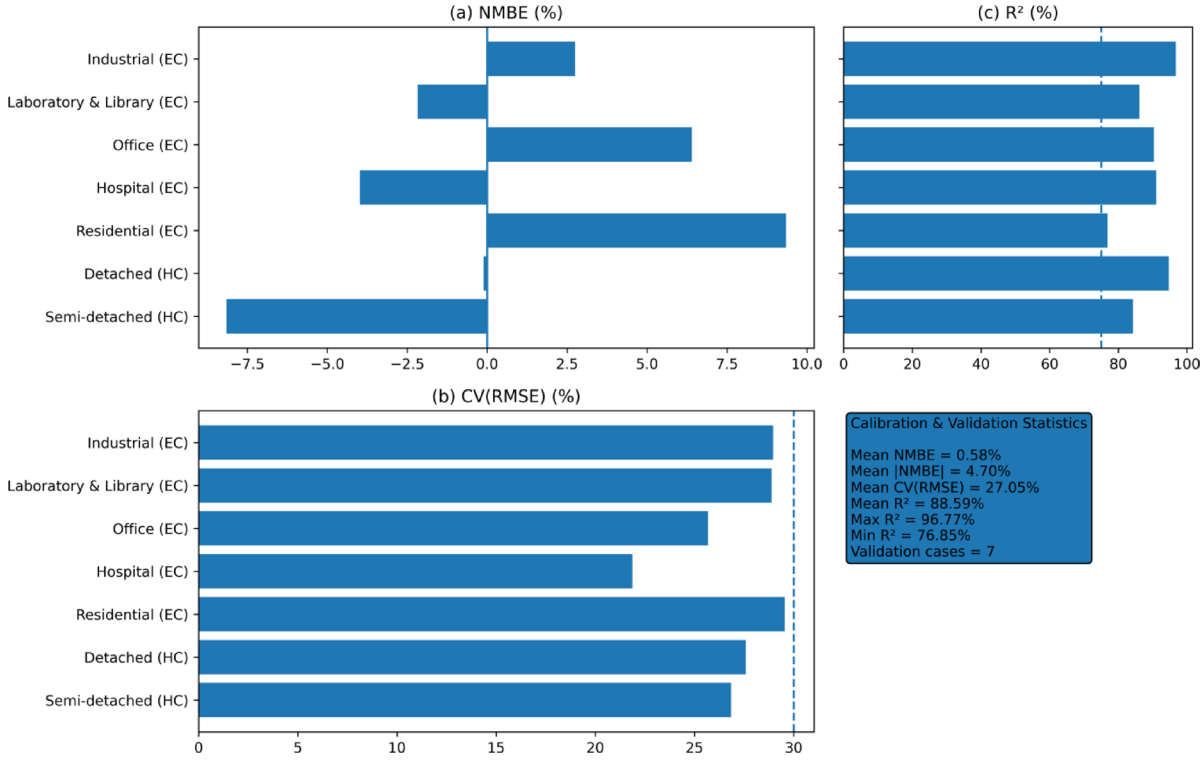


Fig. 2. Calibration and validation performance for the monitored residential, tertiary and industrial buildings. NMBE and CV(RMSE) are expressed as percentages, while R^2 is dimensionless.

it supports the use of the framework for regional-scale, statistically representative temporal energy modelling. The monitored data were obtained from smart-meter measurements. The available monitoring documentation does not provide manufacturer-specific meter accuracy specifications for the individual validation cases. We therefore do not assign an additional numerical measurement-accuracy value to the validation dataset. This limitation is explicitly acknowledged, while the use of ASHRAE-based statistical indicators provides a consistent assessment of discrepancies between measured and simulated profiles.

Uncertainty and sensitivity assessment

Several sources of uncertainty may affect the estimated annual and hourly energy indicators, including category-specific energy-intensity coefficients, reconstructed floor area, cadastral building classification and archetype assignment, climatic inputs, and the selection of standardized temporal profiles. Because these sources act differently on annual energy quantities and hourly temporal distributions, their effects were assessed using a structured deterministic sensitivity framework rather than a single probabilistic uncertainty distribution. For parameters for which an empirically constrained probability distribution was not available, probabilistic confidence intervals were not assigned in order to avoid introducing unsupported statistical assumptions. Instead, one-at-a-time sensitivity scenarios were used to quantify the direction and magnitude of changes that can be attributed to the principal uncertain inputs. The resulting ranges should therefore be interpreted as deterministic sensitivity envelopes rather than as 95% confidence intervals.

Uncertainty in energy-intensity coefficients and floor area directly affects annual energy quantities, whereas uncertainty in BDEW profiles primarily affects the temporal distribution of the annual energy total, including peak demand, load factor and load-duration characteristics. A formal probabilistic uncertainty-propagation analysis was not performed because empirically constrained probability distributions were not available for all major uncertain parameters. In particular, assigning arbitrary probability distributions to category-level energy intensities, cadastral classification errors and BDEW-profile deviations could generate apparently precise but poorly justified confidence intervals. Instead, a deterministic sensitivity assessment was used to identify the parameters with the greatest potential influence on the model outputs. Because annual building energy is calculated as the product of category-specific energy intensity and corrected floor area, a ± 10% perturbation of an energy-intensity coefficient results in an approximately ± 10% change in the corresponding annual energy estimate when all other parameters are held constant. A deterministic sensitivity analysis was therefore defined by perturbing the baseline energy-intensity coefficients by −10%, −5%, 0% (baseline), + 5% and + 10%, while keeping the corrected floor area and all other model parameters unchanged. The sensitivity was evaluated for HC, HD, EC, CED and HEC. Table S2 (Appendix) shows a sensitivity of annual energy indicators to variations in energy-intensity coefficients. *A*nnual energy is directly proportional to reconstructed floor area, the same ± 10% sensitivity range was applied to corrected floor area. Under the one-at-a-time assumption, this produces an

approximately ± 10% change in annual energy and in the magnitude of the corresponding hourly profile, while preserving its normalized temporal shape.

BDEW profiles are normalized to preserve the annual energy quantity, uncertainty associated with their temporal shape does not directly alter the annual regional energy balance. Its principal influence concerns the hourly distribution of demand, particularly peak magnitude, peak timing, load factor and load-duration characteristics. Consequently, BDEW-profile uncertainty is expected to be more important for infrastructure sizing and demand-response applications than for annual regional energy-balance estimates. Because the temporal representation of CED relies on the standard BDEW electricity profile rather than on an explicitly weather-dependent cooling profile, an additional source of uncertainty concerns the assumed temporal shape of cooling demand. This uncertainty is expected to have limited influence on annual CED totals because the profile is normalized, but it may affect the magnitude and timing of hourly cooling peaks. Therefore, the present CED profiles should be interpreted primarily as standardized temporal estimates rather than as physically resolved cooling-load profiles. The potential sensitivity to temporal-profile selection was considered conceptually because BDEW profiles determine the temporal distribution of the annual energy total. However, a fully quantitative alternative-profile comparison was not completed because a consistently justified alternative set of Walloon-specific temporal profiles was not available for all building categories. Consequently, no numerical uncertainty range is reported for BDEW-profile selection. The present analysis therefore treats BDEW-profile selection as a structural source of uncertainty affecting peak magnitude, peak timing, load factor and load-duration characteristics, while preserving annual energy totals through profile normalization. A weather-dependent sensitivity analysis based on outdoor-temperature or cooling-degree-hour criteria was not implemented in the present study because a sufficiently detailed, building-specific cooling-control and occupancy dataset was not available consistently across the 1.69 million-building stock. Such an analysis would require additional assumptions regarding cooling set-points, system availability, solar gains, internal gains, occupancy and equipment characteristics. Only a single regional climatic input was consistently available for the complete building stock, a statistically grounded weather-year uncertainty distribution could not be established. We therefore retain the baseline climatic dataset and explicitly identify weather-year and spatial climatic variability as an uncertainty source requiring further multi-year sensitivity analysis. Future work should therefore compare the present BDEW-based CED profiles with temperature-dependent cooling profiles using the same annual CED constraints. An alternative-assignment scenario was defined conceptually to assess the potential effect of reallocating buildings affected by ambiguous or potentially interchangeable categories to the most plausible alternative category.

Interactive Wallonia Energy Atlas

To facilitate the visualization, exploration and dissemination of the simulated energy data, an interactive Wallonia Energy Atlas was developed as a web-based application using the Python programming language. The platform was implemented with the Dash framework and Plotly, while GeoPandas and Pyogrio were used for spatial data processing and visualization. The application is deployed online through the Render cloud platform, allowing users to access the atlas directly from a standard web browser without requiring additional software installation. For interactive access, the Atlas uses spatially aggregated hourly datasets rather than the complete building-level hourly matrices. The disseminated datasets are available at municipal, arrondissement and provincial scales, while the underlying building-level arrays are retained separately for computational analysis. This architecture substantially reduces the data volume required for web-based retrieval while preserving the results of the underlying building-level simulation.The atlas provides a multi-scale representation of the Walloon building stock. Users can dynamically explore energy information at four administrative levels, namely the entire Walloon Region, the five provinces, the twenty arrondissements, and the 262 municipalities. For each spatial level, the platform displays interactive choropleth maps together with detailed statistical information describing the corresponding territorial entity. Five hourly energy indicators are available within the application, including Heat Consumption (HC), Heat Demand (HD), Electricity Consumption (EC), Cooling Electricity Demand (CED) and Heating Electricity Consumption (HEC). Users may select any indicator to visualize its spatial distribution across Wallonia. When a province, arrondissement or municipality is selected, the corresponding annual 8,760-hour energy profile is automatically displayed, enabling detailed investigation of temporal variations in building energy demand throughout the year. Beyond visualization, the platform is designed as a decision-support resource for researchers, public authorities and energy planners, while its effective operational integration depends on appropriate data updates, institutional workflows, user training and data-governance procedures. The combination of interactive maps, statistical summaries and hourly load profiles enables rapid identification of energy hotspots, comparison between administrative entities and assessment of sector-specific energy behaviour. Such functionalities provide valuable support for district heating planning, renewable energy integration, electricity network design and regional decarbonisation strategies. For operational use, the atlas should be regarded as a periodically maintained decision-support infrastructure rather than as a static dataset. Updating the atlas requires the periodic revision of the underlying cadastral building inventory, building classifications, regional energy statistics, climatic inputs and sector-specific energy-intensity coefficients. In practice, a full update would be appropriate following major revisions of the regional building-stock database or energy statistics, while more frequent updates could be applied to selected indicators when new administrative or energy datasets become available. The modular structure of the modelling framework allows these datasets to be updated without redesigning the complete atlas architecture. For integration into regional planning workflows, the atlas can complement existing GIS, energy-planning and infrastructure-assessment procedures by providing spatially aggregated energy indicators and hourly demand profiles that can be used as inputs for renovation prioritisation, district-heating assessment, electricity-network planning and renewable-energy integration. The atlas is therefore intended to complement, rather than replace, existing

administrative databases and planning tools. Further integration with institutional GIS environments, energy-management systems or standard geospatial data formats would facilitate routine use by regional authorities and energy utilities. Effective adoption by non-specialist users would nevertheless require basic capacity-building. Training should focus on interpreting energy indicators and units, understanding spatial aggregation levels, distinguishing annual energy quantities from hourly profiles, and recognising the assumptions and limitations of the underlying modelling framework. A short user guide, metadata documentation and practical examples would facilitate the use of the atlas by planners, local authorities and other non-specialist stakeholders without requiring expertise in urban energy modelling or programming. Data privacy and security are also important considerations because the underlying modelling framework uses cadastral information at building level. The public-facing atlas should therefore distinguish between the internal building-level modelling database and the information released through the interactive interface. For public dissemination, energy results are aggregated to administrative levels rather than exposing individual-building records or directly identifiable building attributes. This aggregation reduces the risk of linking energy estimates to individual properties. Any future extension towards building-level public access should be subject to appropriate data-governance, anonymisation or aggregation procedures and institutional privacy requirements.The complete interactive Wallonia Energy Atlas is publicly accessible at: Interactive Wallonia Energy Atlas[44].

Results

Hourly energy profiles of residential building typologies

Figure 3 presents the annual hourly energy profiles of the four principal residential building typologies in Wallonia, namely detached, semi-detached, terraced and apartment buildings. The profiles represent 8,760 temporally ordered modelled hourly values for each typology. The comparison therefore focuses on descriptive characteristics, temporal patterns and relative differences rather than inferential P-values. Because these hourly series are reconstructed from predefined BDEW temporal archetypes, the results describe standardized temporal demand patterns rather than independently observed building-specific behaviour. The reconstructed profiles show substantial differences in heating and electricity magnitude, associated with differences in building typology, floor area, energy intensity and assigned temporal archetypes.

Detached houses exhibit the largest heating requirements among the three individual dwelling typologies. Hourly heat consumption (HC) ranges from 0.065 to 16.091 kWh h^{-1} (Mean = 4.698, SD = 3.327), while heat demand (HD) varies between 0.053 and 13.090 kWh h^{-1} (Mean = 3.822, SD = 2.707). Electricity consumption (EC) ranges from 0.249 to 1.359 kWh h^{-1} (Mean = 0.738, SD = 0.290), whereas cooling electricity demand (CED) remains extremely small, varying between 0.005 and 0.025 kWh (Mean = 0.013, SD = 0.005). Heating electricity consumption (HEC) ranges from 0.002 to 0.519 kWh (Mean = 0.151, SD = 0.107). Detached houses exhibit the highest modelled heating load among the individual-dwelling typologies. The observed differences are therefore discussed in terms of absolute magnitude, normalized energy intensity and relative differences rather than statistical significance. Physically, the higher heating requirements of detached houses are explained by their large surface-to-volume ratio and the complete exposure of all external walls and roof to outdoor climatic conditions, which substantially increase conductive and convective heat losses during the heating season. The comparatively low cooling demand further confirms that the current climate of Wallonia remains heating-dominated.

Semi-detached houses present consistently lower thermal requirements than detached dwellings. Heat consumption varies from 0.046 to 11.414 kWh (Mean = 3.333, SD = 2.360), while heat demand ranges between 0.038 and 9.264 kWh (Mean = 2.705, SD = 1.916). Electricity consumption ranges from 0.292 to 1.598 kWh (Mean = 0.867, SD = 0.341), whereas cooling electricity demand remains limited (0.005–0.029 kWh, Mean = 0.016, SD = 0.006). Heating electricity consumption varies from 0.002 to 0.609 kWh (Mean = 0.178, SD = 0.126). Relative to detached houses, semi-detached dwellings show lower modelled heating loads, consistent with the reduced exposed envelope associated with shared walls. These results demonstrate the thermal benefit associated with a shared party wall, which reduces transmission heat losses by decreasing the external envelope area exposed to ambient conditions. Consequently, semi-detached buildings require approximately 29% less heating energy than detached houses while maintaining comparable electrical consumption patterns.

Terraced houses exhibit intermediate energy behaviour between detached and apartment buildings. Hourly heat consumption ranges from 0.050 to 12.268 kWh (Mean = 3.582, SD = 2.537), whereas heat demand varies between 0.040 and 9.974 kWh (Mean = 2.912, SD = 2.062). Electricity consumption ranges from 0.320 to 1.749 kWh (Mean = 0.949, SD = 0.373), while cooling electricity demand ranges between 0.006 and 0.031kWh (Mean = 0.017, SD = 0.007). Heating electricity consumption varies from 0.003 to 0.666 kWh (Mean = 0.194, SD = 0.138). Terraced houses exhibit intermediate thermal loads between detached and apartment buildings. Their modelled electricity consumption is slightly higher than that of semi-detached dwellings, although this difference should be interpreted as a difference in the imposed annual intensity and scaled profile rather than as direct evidence of behavioural differences. Despite their relatively compact geometry, terraced houses exhibit slightly higher electricity consumption than semi-detached dwellings, suggesting that occupant behaviour, appliance ownership and internal gains contribute more strongly to electrical demand than building compactness alone.

The category-specific intensity coefficients provide a normalized basis for comparing the modelled energy use per unit floor area.

Apartment buildings display markedly larger energy requirements than all other residential typologies. Hourly heat consumption ranges from 1.837 to 51.917 kWh (Mean = 18.533, SD = 11.401), while heat demand varies between 1.516 and 42.856 kWh (Mean = 15.299, SD = 9.411). Electricity consumption ranges from 1.148 to 6.270 kWh (Mean = 3.403, SD = 1.338), whereas cooling electricity demand ranges between 0.021 and 0.112 kWh (Mean = 0.061, SD = 0.024). Heating electricity consumption varies from 0.059 to 1.675 kWh (Mean = 0.598, SD = 0.368). Apartment buildings display substantially higher absolute loads than the other

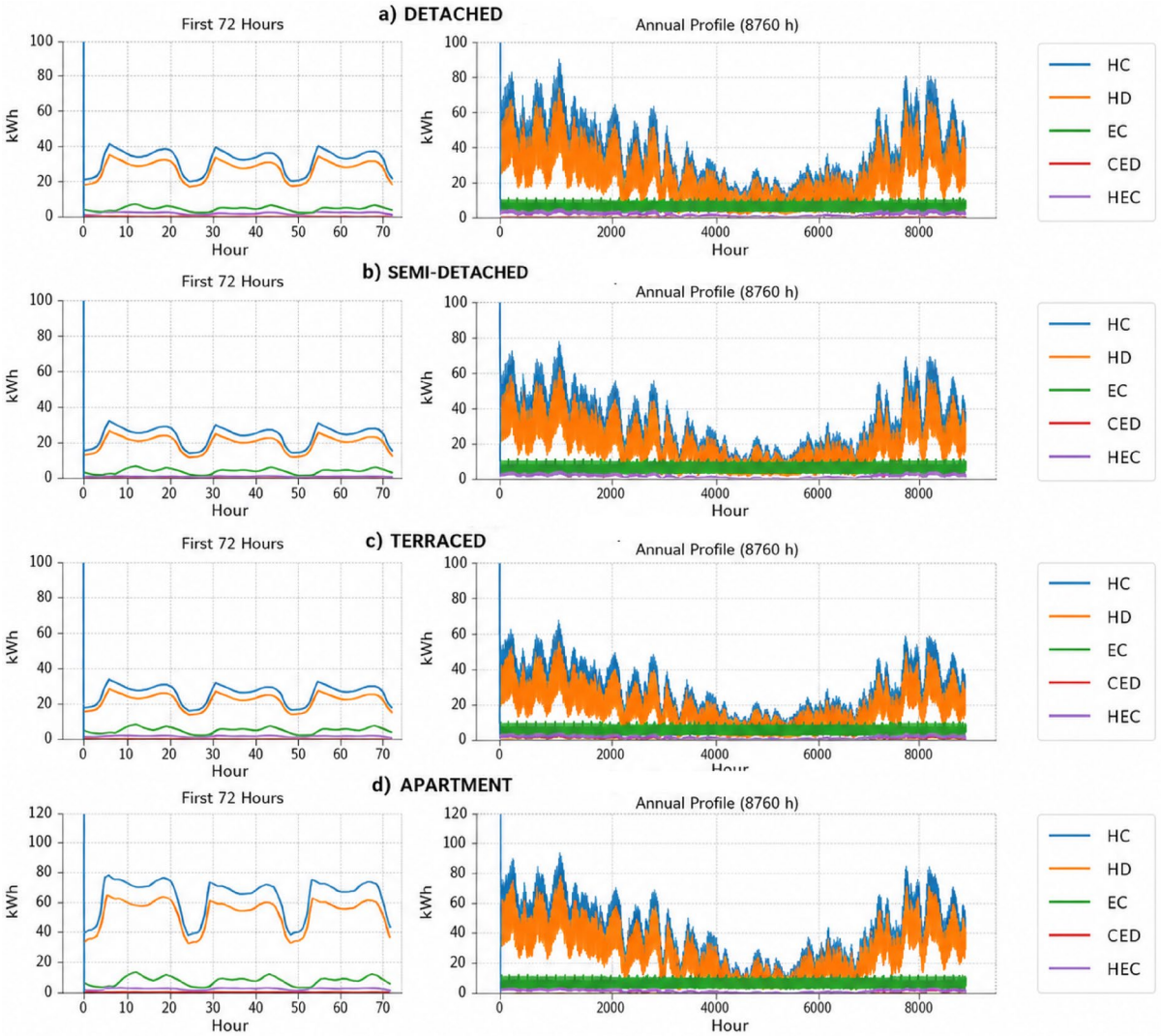


Fig. 3. Average hourly and seasonal energy profiles for residential building typologies in Wallonia. (**a**–**d**) Correspond to detached, semi-detached, terraced and apartment buildings, respectively. Profiles are shown for HC, HD, EC, CED and HEC over the 8,760-hour simulation period.

residential typologies. This difference primarily reflects the larger floor area and the aggregation of multiple dwelling units within individual apartment buildings rather than poorer thermal efficiency. The substantially larger energy values primarily result from the aggregation of numerous dwelling units within a single apartment building. Nevertheless, apartments generally exhibit superior thermal compactness and lower envelope losses per dwelling, implying that their higher total demand reflects building size and occupancy rather than poorer thermal efficiency. Apartment profiles represent entire multi-dwelling buildings, absolute per-building loads are not directly comparable with those of individual dwellings. Energy-efficiency comparisons should therefore rely primarily on normalized indicators such as energy intensity per unit floor area, reported in Table 1. On an area-normalized basis, the highest residential HC intensity is observed for apartments (230.9 kWhm^{-2} yr^{-1}), whereas semi-detached dwellings show the lowest value (154.5 kWh m^{-2} yr^{-1}). Thus, the higher aggregate hourly load of apartments primarily reflects their larger aggregated floor area and multi-dwelling occupancy, whereas the intensity values provide the more appropriate basis for comparing energy performance across residential typologies.

It is important to distinguish aggregate building energy demand from energy intensity when comparing residential typologies. The hourly values reported in this section represent the total demand of the simulated building and therefore depend strongly on its floor area and, in the case of apartment buildings, on the number of dwelling units aggregated within the building. They should consequently not be interpreted directly as indicators of energy efficiency. In the present modelling framework, energy performance is additionally characterized using the category-specific energy-intensity coefficients reported in Table 1, expressed in kWh m^{-2} yr^{-1}. These coefficients are applied consistently to buildings belonging to the same residential typology during the bottom-up disaggregation. For example, the model assigns HC intensities of 193.6, 154.5, 190.9 and 230.9 kWh m^{-2} yr^{-1} to detached, semi-detached, terraced and apartment buildings, respectively. Thus, the substantially higher

absolute energy demand observed for apartment buildings primarily reflects their larger aggregated floor area and multiple dwelling units, whereas the intensity coefficients provide the appropriate normalized basis for comparing energy use per unit of floor area across typologies.

Overall, the residential profiles show systematic differences in energy magnitude across typologies. These differences are interpreted primarily through building scale, normalized energy intensity, morphology and the temporal archetypes assigned to each category. Because the hourly profiles are generated from predefined temporal archetypes, the observed differences should not be interpreted as independent statistical evidence of typology-driven temporal variability. The remaining variability in the modelled profiles reflects temporal changes imposed by the climatic and BDEW profile structure, while additional real-world variability associated with construction age, renovation status, heating-system efficiency, occupancy and occupant behaviour is not explicitly resolved at the individual-building level.

Depending on the indicator, approximately 30.3–57.3% of the variance remains unexplained, potentially reflecting differences in construction age, renovation status, envelope characteristics, heating-system efficiency, occupancy density, occupant behaviour and appliance use that are not explicitly resolved at the individual-building level in the present regional modelling framework.

These findings highlight the importance of adopting building-type-specific renovation strategies and energy policies in order to maximize reductions in energy consumption and greenhouse gas emissions across the residential building stock of Wallonia. The descriptive statistics of the residential hourly energy profiles are reported in Table S3(Appendix).

Hourly energy profiles of tertiary buildings

Figure 4 presents the average hourly energy profiles of the eight principal tertiary building categories in Wallonia, including Education, Administration, Banks and Services, Commercial, Culture and Sport, Energy and Water, Transportation and Other Services. Although healthcare facilities are included in the broader tertiary classification described in "Building stock database and sectoral classification" section, they are not included in the principal eight-category comparison presented here. Healthcare remains part of the underlying building classification and energy-allocation framework but is excluded from Fig. 4; Table 4 to maintain consistency with the set of tertiary categories for which comparable hourly results are reported. The hourly profiles were obtained by averaging 8,760 hourly simulations for each building category. Compared with residential buildings ("Hourly energy profiles of residential building typologies" section), Tertiary categories exhibit substantially different reconstructed temporal profiles, reflecting differences in their assigned energy intensities and BDEW archetypes. The profiles are consistent with schedule-related patterns, but these patterns should not be interpreted as directly measured occupancy or operational behaviour. Educational buildings are characterized by relatively high thermal requirements combined with moderate electricity demand. Heat consumption (HC) ranges from 0.247 to 56.556 kWh (Mean = 15.737, SD = 13.733), while heat demand (HD) varies from 0.207 to 47.554 kWh (Mean = 13.232, SD = 11.547). Electricity consumption (EC) ranges between 0.639 and 16.749 kWh (Mean = 3.990, SD = 4.795), whereas cooling electricity demand (CED) remains relatively low (0.020–0.522 kWh, Mean = 0.124 kWh, SD = 0.149). Heating electricity consumption (HEC) varies between 0.015 and 3.508 kWh (Mean = 0.976 kWh, SD = 0.852). The pronounced weekday peaks and reductions during weekends and holidays are consistent with schedule-related patterns represented by the assigned BDEW archetype. While the significant reduction during weekends and holidays confirms the strong dependence of educational energy demand on building operation. The high seasonal amplitude further indicates that space heating remains the dominant end-use in educational facilities.

Administrative buildings exhibit comparable heating requirements but considerably higher electricity consumption than educational buildings. HC ranges from 1.010 to 64.469 kWh (Mean = 16.472, SD = 11.309), whereas HD varies between 0.846 and 53.994 kWh (Mean = 13.796, SD = 9.472). Electricity demand reaches 20.317 on average (SD = 24.416), ranging from 3.252 to 85.279 kWh, accompanied by CED values between 0.140 and 3.668 (Mean = 0.874, SD = 1.050). HEC ranges from 0.094 to 5.990 (Mean = 1.530, SD = 1.051). These profiles demonstrate the importance of office equipment, computing infrastructure, lighting systems and mechanical ventilation, which maintain significant electricity loads throughout working hours even when heating requirements decrease.

Banks and financial service buildings display one of the most distinctive electrical signatures among all tertiary categories. Heat consumption remains relatively limited, ranging from 0.365 to 15.478 kWh (Mean = 4.362 kWh, SD = 3.111), while heat demand varies between 0.306 and 12.973 kWh (Mean = 3.656, SD = 2.607). In contrast, electricity consumption reaches 21.442 kWh on average (SD = 25.768) and peaks at 89.999 kWh, substantially exceeding the corresponding heating loads. Cooling demand also increases markedly (0.048–1.266 kWh, Mean = 0.302, SD = 0.362), while HEC remains relatively moderate (0.067–2.856 kWh, Mean = 0.805, SD = 0.574). These observations reflect the intensive use of information technology, servers, automated banking equipment and continuous security systems, which generate significant internal heat gains and consequently increase cooling requirements.

Commercial buildings present a more balanced energy behaviour. HC varies between 0.546 and 23.147 kWh (Mean = 6.523 kWh, SD = 4.653), while HD ranges from 0.460 to 19.522 kWh (Mean = 5.501, SD = 3.924). Electricity consumption remains relatively stable throughout the year, varying between 2.175 and 12.423 kWh (Mean = 5.962 kWh, SD = 3.039). Cooling demand is comparatively larger than in residential buildings (0.170–0.969 kWh, Mean = 0.465 kWh, SD = 0.237), whereas HEC remains limited (0.018–0.765 kWh, Mean = 0.216, SD = 0.154). The annual profiles reveal pronounced seasonal variations driven by customer activity, opening hours and cooling needs associated with lighting and commercial refrigeration.

Culture and sport facilities exhibit the highest thermal requirements among all tertiary categories. HC ranges from 0.207 to 64.412 kWh (Mean = 18.263, SD = 13.372), while HD varies from 0.174 to 54.202

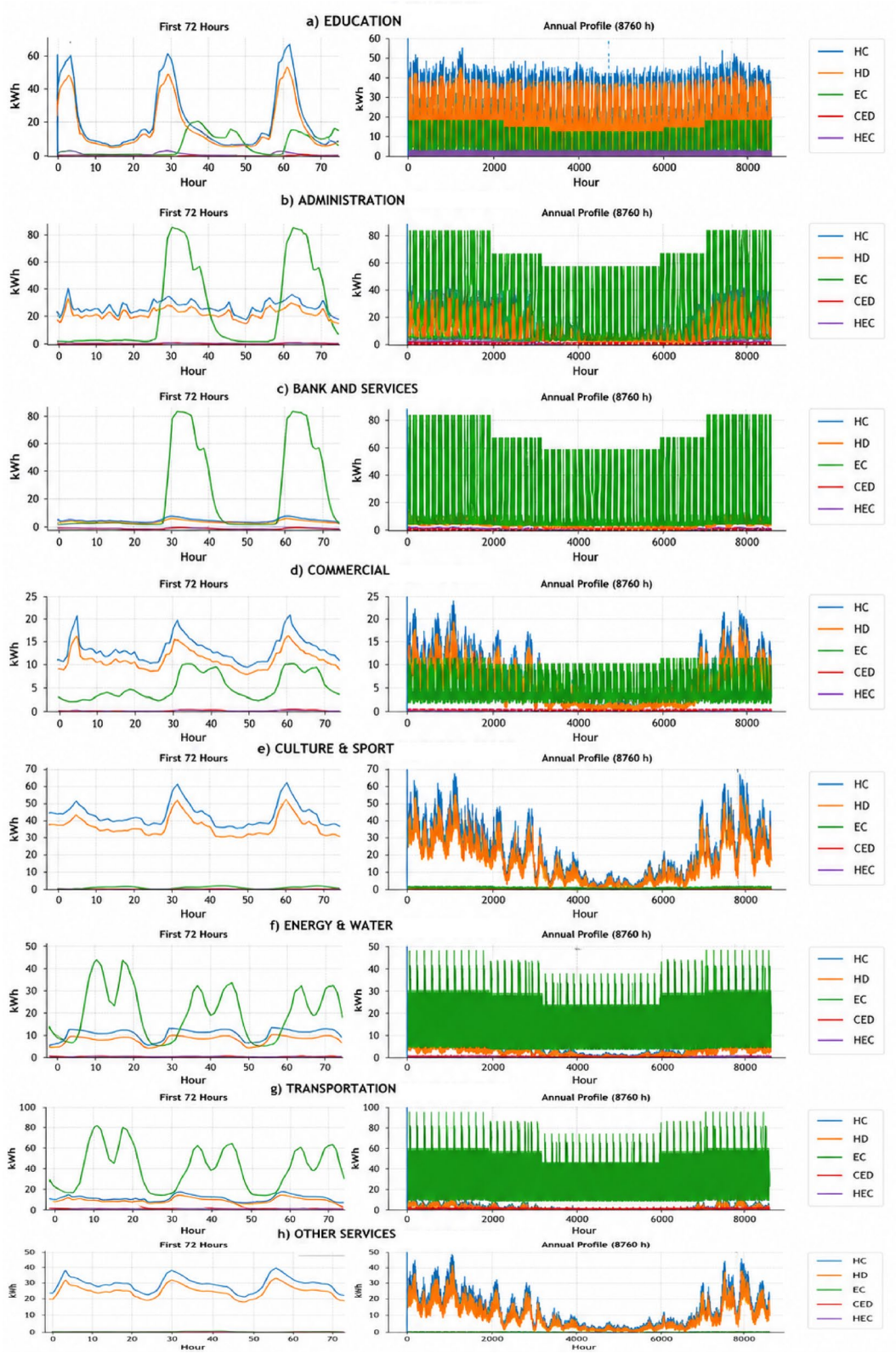


Fig. 4. Average hourly profiles (on left) and Seasonal evolution of hourly tertiary energy demand during the year(on right) of HC(t), HD(t), EC(t), CED(t), and HEC(t) for tertiary building categories ((**a**) Education, (**b**) Administration, (**c**) Banks and Services, (**d**) Commercial, (**e**) Culture and Sport, (**f**) Energy and Water, (**g**) Transportation and (**h**) Other Services). Total characteristics are given in Table S4 (Appendix).

Building category	Heating demand (HC)	Electricity demand (EC)	Peak HC	Peak EC	Main energy driver
Education	High	Moderate	56.560	16.751	Space heating
Administration	High	Very high	64.470	85.280	HVAC + office equipment
Banks & Services	Low	Very high	15.480	90.000	ICT and banking equipment
Commercial	Moderate	Moderate	23.150	12.421	Occupancy, lighting & retail activity
Culture & Sport	Very high	Low	64.410	2.131	Large conditioned volumes
Energy & Water	Moderate	Very high	21.460	53.510	Pumps and industrial equipment
Transportation	Low	Highest	23.490	104.330	Continuous infrastructure operation
Other Services	High	Very low	54.260	0.990	Space heating

Table 4. Comparative summary of the dominant energy characteristics of tertiary building categories. This table summarizes the dominant thermal and electrical characteristics of the eight tertiary building categories derived from the hourly profiles shown in Fig. 4. HC = Heat Consumption; EC = Electricity Consumption. Peak values correspond to the maximum hourly average demand observed over the 8,760-hour simulation period.

kWh (Mean = 15.368 kWh, SD = 11.253). Electricity consumption remains relatively modest (0.193–2.125, Mean = 0.971, SD = 0.542), accompanied by limited cooling requirements (0.030–0.333 kWh, Mean = 0.152 kWh, SD = 0.085) and very small heating electricity consumption (0.000–0.104 kWh, Mean = 0.030 kWh, SD = 0.022). The elevated heating demand mainly results from the large indoor volumes, high ventilation rates and intermittent occupancy characteristic of sports halls, theatres and cultural centres.

Energy and water facilities exhibit moderate heating requirements but consistently high electricity demand. HC ranges from 0.640 to 21.459 kWh (Mean = 7.252 kWh, SD = 4.566), whereas HD varies between 0.541 and 18.139 kWh (Mean = 6.130 kWh, SD = 3.860). Electricity consumption averages 20.552 kWh (SD = 11.202) with maximum values reaching 53.508 kWh, while CED ranges between 0.200 and 1.660 kWh (Mean = 0.637 kWh, SD = 0.347). HEC remains relatively small (0.010–0.331, Mean = 0.112, SD = 0.071). These electrical loads primarily originate from pumps, compressors, motors and continuously operating industrial equipment rather than from occupant-driven activities.

Transportation buildings represent the most electricity-intensive tertiary category. Although HC remains relatively modest (0.064–23.489 kWh, Mean = 4.714 kWh, SD = 4.242) and HD averages 3.894 (SD = 3.504), electricity consumption reaches the highest value among all sectors, varying between 12.601 and 104.330 kWh with an annual mean of 40.072 kWh (SD = 21.842). Cooling demand also reaches the highest levels (0.932–7.720, Mean = 2.965 kWh, SD = 1.616), whereas HEC remains comparatively limited (0.003–1.064 kWh, Mean = 0.214 kWh, SD = 0.192). These profiles are mainly explained by the continuous operation of railway stations, airports, tunnels, signalling equipment, escalators, lighting and mechanical ventilation systems, all of which require large amounts of electricity throughout the year.

Finally, buildings classified as Other Services display relatively high heating requirements with comparatively small electrical loads. HC ranges from 1.560 to 54.263 kWh (Mean = 13.743 kWh, SD = 10.201), while HD varies from 1.313 to 45.663 kWh (Mean = 11.564 kWh, SD = 8.584). Electricity consumption remains remarkably stable throughout the year (0.515–0.985 kWh, Mean = 0.731 kWh, SD = 0.138), accompanied by limited cooling demand (0.081–0.155 kWh, Mean = 0.115, SD = 0.022) and negligible heating electricity consumption (0.003–0.088 kWh, Mean = 0.022, SD = 0.016). This behaviour reflects the heterogeneous nature of this category, which includes service-oriented buildings with relatively low equipment density and limited cooling requirements.

Overall, Fig. 4 demonstrates that tertiary energy demand is primarily controlled by building function rather than building geometry. Heating remains the dominant energy end-use for educational, cultural and miscellaneous service buildings, whereas electricity consumption clearly dominates administration, banking, energy infrastructure and transportation facilities. The transportation sector exhibits the highest electrical demand, with an average EC of 40.072 kWh, almost six times greater than that of commercial buildings and nearly ten times greater than educational buildings. Conversely, culture and sport buildings record the highest heating requirements, emphasizing the importance of large conditioned volumes and intermittent occupancy. These results demonstrate the necessity of sector-specific energy efficiency strategies, as the operational characteristics governing energy demand differ substantially among tertiary building categories. Global statistics of tertiary building hourly energy profiles are shown into Table 4, whereas Table 5 gives confrontation of the dominant energy characteristics of tertiary building categories.

Hourly energy profiles of industrial buildings

Figure 5 presents the average hourly energy profiles of seven industrial sub-sectors in Wallonia, namely Agro-food, Chemistry, Mineral, Metallurgy, Steel, Textile and Other Industries. Compared with the residential and tertiary sectors, industrial buildings exhibit substantially larger thermal and electrical loads owing to continuous production processes, industrial equipment, process heating and mechanical systems. The annual profiles reveal that industrial energy demand is primarily controlled by manufacturing activities rather than occupancy schedules, leading to sustained loads throughout the year with comparatively smaller day-to-day fluctuations. The agro-food industry exhibits relatively high thermal requirements associated with industrial processing and refrigeration activities. Heat consumption (HC) ranges from 146.34 to 1956.91 kWh (Mean = 718.96 kWh, SD = 391.32 kWh), while heat demand (HD) varies from 134.79 to 1802.41 kWh (Mean = 662.20 kWh, SD = 360.43 kWh). Electricity consumption (EC) ranges between 96.43 and 423.24 kWh (Mean = 213.57 kWh,

Category	Indicator	Peak load (kW)	Base load P5 (kW)	Mean load (kW)	Load factor	Peak-to-base ratio	Peak-duration (h)
Detached	HC	16.09	0.62	4.70	0.292	25.93	7
Detached	EC	1.36	0.27	0.74	0.543	5.11	176
Detached	HEC	0.52	0.02	0.15	0.292	25.93	7
Semi-Detached	HC	11.41	0.44	3.33	0.292	25.93	7
Semi-Detached	EC	1.60	0.31	0.87	0.543	5.11	176
Semi-Detached	HEC	0.61	0.02	0.18	0.292	25.93	7
Terraced	HC	12.27	0.47	3.58	0.292	25.93	7
Terraced	EC	1.75	0.34	0.95	0.543	5.11	176
Terraced	HEC	0.67	0.03	0.19	0.292	25.93	7
Apartment	HC	51.92	4.14	18.53	0.357	12.54	28
Apartment	EC	6.27	1.23	3.40	0.543	5.11	176
Apartment	HEC	1.68	0.13	0.60	0.357	12.54	28
Commercial	HC	23.15	1.21	6.52	0.282	19.16	16
Commercial	EC	12.42	2.59	5.96	0.480	4.80	455
Commercial	HEC	0.76	0.04	0.22	0.282	19.16	16
Education	HC	56.56	1.83	15.74	0.278	30.96	23
Education	EC	16.75	0.67	3.99	0.238	24.98	384
Education	HEC	3.51	0.11	0.98	0.278	30.96	23
Culture sport	HC	64.41	2.39	18.26	0.284	26.96	16
Culture sport	EC	2.13	0.24	0.97	0.457	8.97	424
Culture sport	HEC	0.10	0.00	0.03	0.284	26.96	16
Other Services	HC	54.26	2.68	13.74	0.253	20.28	12
Other Services	EC	0.99	0.55	0.73	0.742	1.79	1880
Other Services	HEC	0.09	0.00	0.02	0.253	20.28	12
Administration	HC	64.47	2.84	16.47	0.256	22.71	6
Administration	EC	85.28	3.41	20.32	0.238	24.98	384
Administration	HEC	5.99	0.26	1.53	0.256	22.71	6
Health	EC	312.25	34.80	142.68	0.457	8.97	424
Banks Services	HC	15.48	0.81	4.36	0.282	19.16	16
Banks Services	EC	90.00	3.60	21.44	0.238	24.98	384
Banks Services	HEC	2.86	0.15	0.80	0.282	19.16	16
Transport	HC	23.49	0.38	4.71	0.201	61.13	12
Transport	EC	104.33	13.48	40.07	0.384	7.74	74
Transport	HEC	1.06	0.02	0.21	0.201	61.13	12
Energy water	HC	21.46	1.56	7.25	0.338	13.79	31
Energy water	EC	53.51	6.91	20.55	0.384	7.74	74
Energy water	HEC	0.33	0.02	0.11	0.338	13.79	31
Agro	HC	1,956.91	241.98	718.96	0.367	8.09	39
Agro	EC	423.24	106.69	213.57	0.505	3.97	574
Textile	HC	7,277.90	358.89	1,843.19	0.253	20.28	12
Textile	EC	664.31	167.45	335.21	0.505	3.97	574
Mineral	HC	4,904.26	355.65	1,657.40	0.338	13.79	31
Mineral	EC	62.11	10.70	28.18	0.454	5.81	528
Chemistry	EC	6,267.01	1,079.25	2,843.01	0.454	5.81	528
Steel	HC	3,548.36	257.32	1,199.17	0.338	13.79	31
Steel	EC	1,932.77	332.85	876.80	0.454	5.81	528
Metallurgy	HC	91.34	6.62	30.87	0.338	13.79	31
Metallurgy	EC	51.41	8.85	23.32	0.454	5.81	528
Other Industry	HC	65.62	3.24	16.62	0.253	20.28	12
Other Industry	EC	2.51	1.40	1.86	0.742	1.79	1880

Table 5. Load-duration characteristics of modelled building-energy profiles. Peak load is the maximum annual hourly load. Base load is represented by the 5th percentile of the annual hourly load distribution. Load factor is the ratio of mean annual hourly load to peak load. The peak-to-base ratio is peak load divided by the 5th-percentile base load. Peak-duration hours are the number of hours with load ≥ 90% of the annual peak. Values are derived from the 8,760 hourly profiles used to construct the load-duration curves.

SD = 107.02 kWh), whereas cooling demand (CED) remains comparatively limited, varying from 5.88 to 25.80 kWh (Mean = 13.02 kWh, SD = 6.52 kWh). The annual profiles indicate a strong seasonal dependence of thermal demand, reflecting the combined effects of space heating and temperature-sensitive food processing operations.

Chemical industries constitute by far the most energy-intensive industrial category. HC varies between 641.70 and 21,528.36 kWh (Mean = 7,275.51 kWh, SD = 4,581.16 kWh), while HD ranges from 586.70 to 19,683.08 kWh (Mean = 6,651.90 kWh, SD = 4,188.49 kWh). Electricity consumption reaches exceptionally high levels, ranging from 897.87 to 6,267.01 kWh (Mean = 2,843.01 kWh, SD = 1,613.11 kWh), accompanied by cooling demand varying between 43.10 and 300.82 kWh (Mean = 136.47 kWh, SD = 77.43 kWh). These very large energy requirements reflect the continuous operation of reactors, distillation units, pumps, compressors and process heating systems characteristic of chemical manufacturing. Among all industrial categories, chemistry exhibits the highest overall thermal demand.

Mineral industries also display very large heating requirements but comparatively limited electricity consumption. HC ranges from 146.18 to 4,904.26 kWh (Mean = 1,657.40 kWh, SD = 1,043.61 kWh), while HD varies between 133.23 and 4,469.71 kWh (Mean = 1,510.54 kWh, SD = 951.14 kWh). Electricity demand remains relatively modest, varying from 8.90 to 62.11 kWh (Mean = 28.18 kWh, SD = 15.99 kWh), whereas cooling demand is almost negligible (0.009–0.062 kWh, Mean = 0.028 kWh, SD = 0.016 kWh). This behaviour indicates

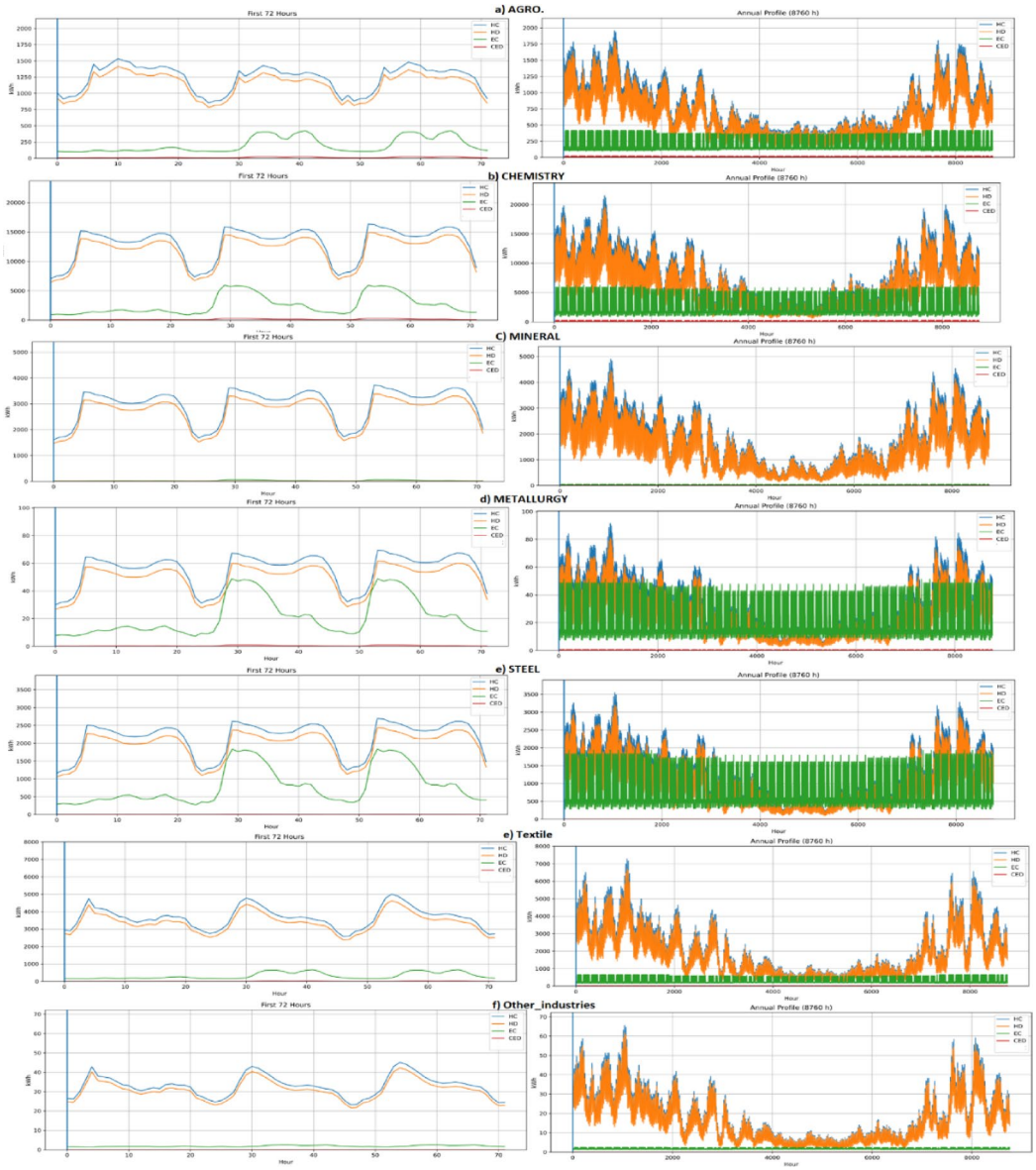


Fig. 5. Average hourly profiles (left) and seasonal evolution of hourly industrial energy demand (right) for HC(t), HD(t), EC(t), and CED(t) for industrial building categories: (**a**) Agro-food, (**b**) Chemistry, (**c**) Mineral, (**d**) Metallurgy, (**e**) Steel, (**f**) Textile, and (**g**) Other Industries. HEC was not modelled for industrial categories. Overview characteristics are given in Supplementary Table S5.

that mineral industries are dominated by thermal processing operations such as kilns, furnaces and drying systems, with very limited mechanical cooling requirements.

Metallurgical industries exhibit moderate and relatively balanced thermal and electrical loads. HC ranges from 2.72 to 91.34 kWh (Mean = 30.87 kWh, SD = 19.44 kWh), while HD varies between 2.42 and 81.20 kWh (Mean = 27.44 kWh, SD = 17.28 kWh). Electricity consumption ranges from 7.37 to 51.41 kWh (Mean = 23.32 kWh, SD = 13.23 kWh), accompanied by limited cooling demand (0.132–0.922 kWh, Mean = 0.418 kWh, SD = 0.237 kWh). The similarity between thermal and electrical loads suggests production processes relying simultaneously on electrically powered equipment and moderate heat generation.

Steel manufacturing presents substantially larger energy requirements than general metallurgy. HC ranges from 105.77 to 3,548.36 kWh (Mean = 1,199.17 kWh, SD = 755.08 kWh), while HD varies between 95.79 and 3,213.61 kWh (Mean = 1,086.04 kWh, SD = 683.84 kWh). Electricity consumption reaches 876.80 kWh on average (SD = 497.49 kWh) and varies between 276.91 and 1,932.77 kWh, whereas cooling demand remains relatively small (0.554–3.865 kWh, Mean = 1.754 kWh, SD = 0.995 kWh). The simultaneous importance of thermal and electrical loads reflects the intensive use of electric arc furnaces, rolling mills and continuous casting equipment.

Textile industries exhibit highly variable thermal loads associated with drying, washing and finishing operations. HC ranges from 209.26 to 7,277.90 kWh (Mean = 1,843.19 kWh, SD = 1,368.18 kWh), while HD varies between 193.40 and 6,726.54 kWh (Mean = 1,703.55 kWh, SD = 1,264.53 kWh). Electricity demand remains moderate, varying from 151.36 to 664.31 kWh (Mean = 335.21 kWh, SD = 167.97 kWh), whereas cooling demand ranges from 4.69 to 20.59 kWh (Mean = 10.39 kWh, SD = 5.21 kWh). The high variability observed throughout the year reflects batch production cycles and temperature-dependent industrial processes.

Finally, the Other Industry category exhibits the lowest industrial energy demand. HC varies between 1.89 and 65.62 kWh (Mean = 16.62 kWh, SD = 12.34 kWh), while HD ranges from 1.77 to 61.52 kWh (Mean = 15.58 kWh, SD = 11.57 kWh). Electricity consumption remains very limited (1.31–2.51 kWh, Mean = 1.86 kWh, SD = 0.35 kWh), with almost negligible cooling demand (0.018–0.035 kWh, Mean = 0.026 kWh, SD = 0.005 kWh). These characteristics are representative of small-scale industrial facilities with limited process heating and low equipment density.

Overall, the industrial sector exhibits considerably larger energy demands than both the residential and tertiary sectors. Chemistry represents the most energy-intensive industrial activity, with average heat consumption exceeding 7,275 kWh, followed by textile (1,843 kWh), mineral (1,657 kWh) and steel (1,199 kWh) industries. Conversely, metallurgy and miscellaneous industries remain comparatively less energy-intensive. Cooling electricity demand is generally much smaller than thermal demand across all industrial categories, except in chemical industries where process cooling becomes significant. Heating Electricity Consumption (HEC) was not estimated for industrial buildings because the available regional energy statistics did not provide sufficiently detailed subsector-specific information to distinguish electricity used for process heating from other industrial electricity end uses. This exclusion should not be interpreted as evidence that industrial heating is entirely non-electric; rather, it reflects the data resolution available for the present regional modelling framework. Accordingly, HEC values are not reported for industrial categories. Table S5 (appendix) summarizes the descriptive statistics of the hourly industrial energy profiles used to construct Fig. 5. The statistics include the mean, standard deviation (SD), standard error (SE), minimum and maximum values computed from the 8,760-hour average profiles for each industrial sub-sector. Heating Electricity Consumption (HEC) was not calculated for the industrial sector.

Load duration curve analysis of residential, tertiary and industrial buildings

Figure 6 presents the annual load duration curves (LDCs) of heat consumption (HC), heat demand (HD), electricity consumption (EC), cooling electricity demand (CED) and heating electricity consumption (HEC) for the residential, tertiary and industrial building categories. Unlike the hourly profiles presented in "Hourly energy profiles of residential building typologies"–"Hourly energy profiles of industrial buildings" sections, load duration curves rank the 8,760 hourly loads from the highest to the lowest values, thereby providing valuable information regarding peak demand, base loads and the operational characteristics of different building categories. Such curves are widely used for energy system sizing, district heating design, electricity infrastructure planning and peak-load management.

The residential sector exhibits smooth and continuously decreasing load duration curves for all four dwelling categories (Detached, Semi-detached, Terraced and Apartment). Heat consumption (HC) remains the dominant energy component throughout almost the entire year, followed closely by heat demand (HD), whereas electricity consumption (EC), cooling demand (CED) and heating electricity consumption (HEC) remain considerably lower. Apartments display the highest annual thermal loads, followed by detached dwellings, while semi-detached and terraced houses present comparatively lower load levels. The gradual decline of the HC and HD curves, together with their load-factor and peak-duration characteristics, indicates that residential heating demand is distributed over a substantial proportion of the year rather than being concentrated exclusively in a few extreme peak hours. This behaviour reflects the strong dependence of residential energy demand on outdoor climatic conditions and continuous household occupancy.

The tertiary sector demonstrates substantially greater diversity in load duration characteristics because of the heterogeneity of building functions. Educational and cultural buildings exhibit steep HC and HD curves with moderate electrical loads, confirming that space heating remains the principal energy end-use. In contrast, administrative buildings, banks, transport facilities and energy infrastructure display remarkably high EC curves that exceed thermal loads over much of the year, indicating the predominance of office equipment, information technologies, pumps, ventilation systems and continuously operating electrical installations. Transportation facilities exhibit the highest electrical base loads among all tertiary categories, while commercial buildings

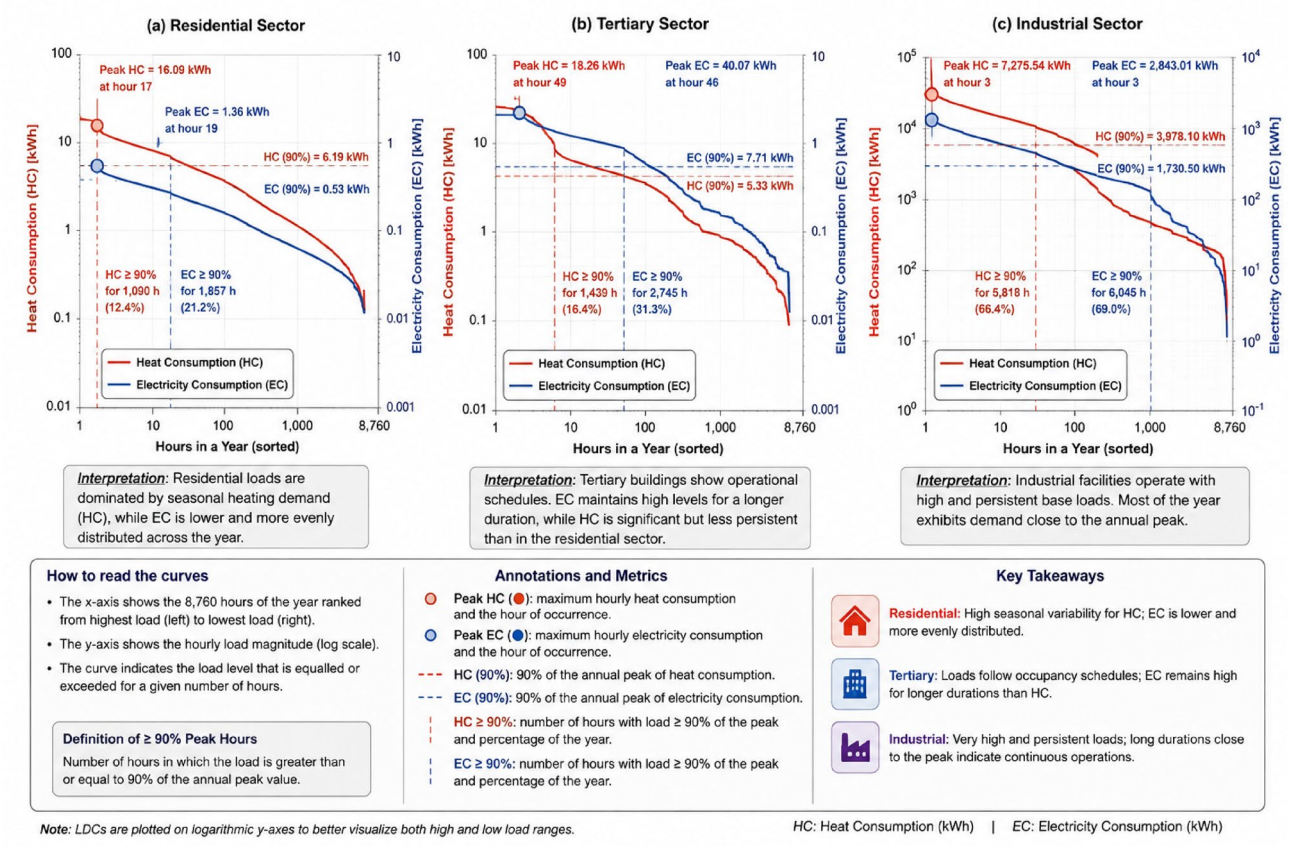


Fig. 6. Load-duration curves of hourly heat and electricity consumption across residential, tertiary, and industrial sectors in Wallonia.

present intermediate characteristics with balanced thermal and electrical requirements. The relatively flat EC duration curves observed for administration, transport and energy facilities demonstrate that electricity demand remains significant throughout most hours of the year, suggesting limited operational flexibility and continuous equipment utilisation.

Industrial buildings present the largest load duration curves of the entire Walloon building stock. Chemistry, textile, mineral and steel industries exhibit exceptionally high modelled HC and HD loads. These differences primarily reflect their category-specific annual energy intensities and reconstructed floor areas, combined with the assigned BDEW temporal archetypes. The resulting high base-load characteristics should therefore be interpreted as features of the standardized modelled profiles rather than as direct evidence of continuous plant-level production.

Steel and textile industries similarly display sustained thermal requirements, although at lower magnitudes. Agro-food industries occupy an intermediate position, whereas metallurgy and miscellaneous industries exhibit considerably smaller load duration curves. Electricity demand becomes particularly important in chemistry and steel production, where industrial equipment, compressors, furnaces and process machinery operate continuously. Cooling electricity demand remains relatively limited in most industrial sectors, except for chemistry where process cooling contributes noticeably to the total energy profile. Heating Electricity Consumption (HEC) is not presented for industrial buildings because no industrial HEC coefficient was derived in the annual energy-estimation framework. This exclusion reflects the lack of sufficiently detailed subsector-specific data required to distinguish electricity used for process heating from other industrial electricity end uses and should not be interpreted as an absence of industrial heating electrification. The quantitative LDC indicators further characterize the concentration and persistence of demand. Peak load, base load, load factor, peak-to-base ratio and peak-duration hours provide complementary information on peak intensity and load persistence, while the peak-to-average ratio, equivalent full-load hours and P95/P50 ratio provide additional measures of demand concentration.

A comparison among the three major sectors reveals distinct energy-use patterns. Residential profiles exhibit strong seasonal concentration of reconstructed thermal loads, while tertiary profiles show more pronounced schedule-related temporal variation. Industrial profiles display relatively flat reconstructed load-duration curves and high base loads. These characteristics are partly determined by the temporal structure of the assigned BDEW archetypes. Tertiary buildings exhibit highly diversified load duration characteristics governed by building function and occupancy schedules, resulting in strong variations between educational, commercial and infrastructure-related activities.

Industrial facilities display the highest modelled peak and base loads in the atlas. However, because several industrial subsectors share common BDEW archetypes, these load-duration characteristics should be interpreted as standardized temporal reconstructions rather than direct evidence of plant-level production continuity or process-specific operating schedules. Plant-level production schedules and measured industrial load profiles would be required to resolve such process-specific temporal variability. Consequently, industrial energy systems require substantially larger installed capacities than residential and tertiary buildings.

From an energy system perspective, the load duration curves highlight considerable opportunities for demand-side management and infrastructure optimisation. Residential buildings offer significant flexibility for thermal storage and heat pump scheduling because a relatively small number of hours account for the annual peak loads. Tertiary buildings provide opportunities for intelligent building control and occupancy-based demand response, particularly in educational and administrative facilities. Industrial sectors, especially chemistry and steel manufacturing, require strategies focused on process optimisation, waste heat recovery and industrial energy integration rather than simple peak shaving because of their persistently high base loads. Overall, Fig. 6 demonstrates that load duration analysis provides complementary information to hourly energy profiles and constitutes an essential tool for designing resilient, low-carbon and economically efficient energy systems at the regional scale. The Table 5 shows the load-duration characteristics of modelled building-energy profiles.

To complement the visual interpretation of the load-duration curves, five indicators were calculated from the 8,760 hourly values used to construct the curves: peak load, base load, load factor, peak-to-base ratio and peak-duration hours. Base load was defined as the 5th percentile of the annual hourly load distribution, while peak-duration hours correspond to the number of hours during which the load remained above 90% of the annual peak. These indicators reveal marked differences in the temporal persistence of the modelled energy profiles across building categories. For residential HC, apartment buildings exhibited a peak load of 51.92 kWh, a load factor of 0.357, a peak-to-base ratio of 12.54 and 28 peak-duration hours, compared with 16.09 kWh, 0.292, 25.93 and 7 h, respectively, for detached houses. In the tertiary sector, HC load factors ranged from 0.201 for transport to 0.338 for energy-and-water facilities, while peak-to-base ratios ranged from 13.79 to 61.13, indicating substantially different load persistence across service activities. Industrial HC profiles exhibited much larger absolute loads. For electricity consumption, load factors were generally higher than for HC, ranging from 0.543 for residential profiles to 0.238 for education and administration, while industrial chemistry exhibited a load factor of 0.454 and 528 h above 90% of its annual peak.

These metrics should be interpreted as characteristics of the modelled hourly profiles rather than as direct measurements of observed operational behaviour. Because BDEW standard load profiles are used for temporal disaggregation, buildings within some categories share common normalized temporal shapes, while their absolute magnitudes differ according to category-specific annual energy intensities, reconstructed floor areas and building-stock composition. Accordingly, differences in load factor, peak-to-base ratio or peak-duration hours between categories sharing the same archetype should be interpreted primarily as consequences of the imposed profile shape and scaling, rather than as independently observed operational behaviour. The resulting load-duration metrics therefore provide a consistent basis for comparing the temporal structure represented by the atlas, while further validation against Belgian smart-meter observations would be required to quantify real-world behavioural variability.

LDC also provide a direct interface between the building-energy model and energy-system applications. Peak load and peak-duration hours can inform capacity sizing, while the load factor and peak-to-base ratio provide information on the relative importance of base-load and peak-load resources. At the territorial scale, the same indicators can be used to compare alternative infrastructure configurations and identify areas where network reinforcement, flexible demand or storage may provide greater system value.

Discussion

Residential building typology as the dominant driver of hourly heating demand

The present study identifies residential building typology as an important determinant of the magnitude of modelled hourly energy demand. However, the temporal shape of the profiles is partly prescribed by the assigned BDEW archetypes: detached, semi-detached and terraced dwellings share the EFH heat profile, whereas apartments use the MFH profile, while all residential categories use the H0 electricity profile. Consequently, the differences reported here primarily reflect variations in annual energy intensity, reconstructed floor area and building-stock composition rather than independently inferred behavioural or morphological temporal patterns. In the real building stock, such differences may be influenced by variations in building compactness, envelope characteristics, occupancy and thermal inertia; however, these mechanisms are not independently resolved by the present archetype-based temporal model. Such conclusions are fully consistent with recent European investigations demonstrating that building morphology remains one of the strongest predictors of residential energy demand under temperate climatic conditions[45–47]. Detached dwellings exhibit the largest thermal requirements among individual residential buildings, with an average hourly heat consumption of 4.698 kWh compared with 3.333 kWh for semi-detached houses. The corresponding Mean Relative Difference (MRD) reaches − 29.1%, indicating that semi-detached houses require almost one-third less heating energy than detached dwellings. Similar reductions are obtained for heat demand (MRD = −29.2%). The 29.1% reduction in mean HC between detached and semi-detached dwellings in the present study falls within the 20–35% range reported in previous European analyses of shared-wall effects[38–40]. This difference is therefore quantitatively consistent with the expected thermal benefit of increased compactness. Belgian building-stock studies have likewise shown that building geometry and stock description substantially influence estimated heating demand[36]. However, direct numerical comparison should be treated cautiously because these studies differ in building typologies, construction periods, floor-area assumptions, simulation methods and temporal

boundary conditions. The physical explanation is straightforward. Detached houses expose all façades, roofs and ground-contact surfaces directly to outdoor climatic conditions, thereby increasing conductive, convective and radiative heat losses throughout the heating season. Semi-detached dwellings eliminate one exposed façade, while terraced houses reduce external exposure even further through two shared party walls. Consequently, the effective heat-transfer area decreases significantly without reducing useful floor area, leading to improved thermal performance. Similar mechanisms have been described in detail by the International Energy Agency (2023)[47], which identifies compact residential forms as among the most cost-effective passive energy-efficiency measures for temperate climates. Within the present model, the HC intensity of semi-detached buildings is 20.2% lower than that of detached buildings (154.5 versus 193.6 kWh m^{-2} yr^{-1}), whereas terraced buildings show an intensity only 1.4% lower than detached buildings (190.9 versus 193.6 kWh m^{-2} yr^{-1}). These normalized differences are substantially smaller than the differences observed in aggregate building-level loads, confirming that floor area and the number of dwelling units are major contributors to the absolute-load differences.

Interestingly, terraced houses consume slightly more electricity (Mean EC = 0.949 kWh) than semi-detached dwellings (Mean EC = 0.867 kWh), corresponding to an MRD of approximately + 9.5%. The difference in modelled electricity consumption between terraced and semi-detached dwellings should not be interpreted as direct evidence of differences in occupancy behaviour or appliance use, because all residential categories share the same H0 temporal electricity archetype. Instead, the difference primarily reflects the category-specific annual electricity-intensity coefficients and reconstructed floor areas. Actual behavioural differences may further contribute to observed electricity-use variability and should be investigated using Belgian smart-meter data. Numerous studies have shown that residential electricity consumption depends strongly on behavioural factors, particularly occupancy schedules and socio-economic characteristics, whereas heating demand remains primarily controlled by envelope thermal performance[8,10,45]. This distinction highlights the importance of combining building renovation with behavioural energy-efficiency measures in future decarbonisation strategies.

Apartment buildings exhibit substantially larger absolute energy requirements than all other residential typologies, with mean HC reaching 18.533 kWh, approximately 295% higher than detached houses (MRD = + 294.5%). Mean HD follows the same tendency (15.299 kWh versus 3.822 kWh). At first glance, these values could suggest poorer thermal performance. However, such an interpretation would be misleading. Apartment buildings aggregate numerous dwelling units within a single structure, and the reported hourly profiles correspond to the entire building rather than to individual apartments. Previous European analyses consistently report that apartment buildings generally exhibit lower heating demand per dwelling because of superior compactness, reduced surface-to-volume ratios and significant heat exchange between adjacent apartments[48–51]. Therefore, the higher total energy demand observed in the present study primarily reflects building size and occupancy rather than reduced thermal efficiency. When normalized by floor area, the modelled HC intensities are 193.6 kWh m^{-2} yr^{-1} for detached, 154.5 kWh m^{-2} yr^{-1} for semi-detached, 190.9 kWh m^{-2} yr^{-1} for terraced and 230.9 kWh m^{-2} yr^{-1} for apartment buildings. These values should be compared with previous Belgian stock studies using the same normalization basis rather than with aggregate hourly loads.

Another notable finding concerns cooling electricity demand. For all residential typologies, CED remains extremely small compared with heating demand. Mean CED varies only between 0.013 kWh for detached houses and 0.061 kWh for apartment buildings, representing less than 2% of average heat consumption. The modelled results indicate that cooling electricity demand remains substantially lower than heating demand under the present annual energy-intensity assumptions. However, because CED is temporally distributed using a standardized electricity profile rather than an explicitly weather-dependent cooling profile, these results should be interpreted primarily as an estimate of the relative magnitude of annual cooling demand rather than as a fully weather-resolved representation of hourly cooling operation. Similar conclusions have recently been reported by the IPCC (2022)[1], which nevertheless predicts a progressive increase in cooling demand across north-western Europe under future climate warming scenarios. Consequently, although cooling currently represents only a minor fraction of residential energy consumption, future building regulations should progressively integrate passive cooling strategies, solar protection and natural ventilation to improve long-term resilience. The differences among residential typologies should be interpreted as differences in the magnitude and temporal structure of the modelled profiles rather than as inferential evidence based on independent hourly observations. The standardized BDEW archetypes constrain the temporal shape, while category-specific energy intensities, reconstructed floor areas and building-stock composition determine the magnitude of the resulting profiles. Real-world variability associated with occupant behaviour, construction age, renovation status and heating-system characteristics is therefore not fully represented. Comparable explanatory powers have been reported in large-scale building stock simulations conducted in Belgium, Germany and Sweden[46,47,49].

Overall, the residential analysis confirms that envelope compactness remains one of the most effective passive strategies for reducing heating demand. Consequently, future regional renovation policies should prioritise detached houses for deep envelope retrofits, façade insulation and roof improvements, whereas apartment buildings should focus on optimising collective heating systems, district heating integration and large-scale heat pump deployment. Such differentiated strategies are fully aligned with the objectives of the European Green Deal and the revised Energy Performance of Buildings Directive[52].

The principal contribution of the present study is not the confirmation of established relationships between building morphology and heating demand or between industrial activity and energy intensity. Rather, it is the transformation of annual regional energy information into a spatially explicit and temporally resolved representation covering approximately 1.69 million buildings. Conventional annual inventories can quantify how much energy is consumed within a territory, but they do not directly indicate when demand occurs, how long peak conditions persist, or whether high annual consumption is associated with concentrated peaks or persistent base loads. The present atlas adds this temporal dimension by reconstructing 8,760 hourly profiles for five complementary energy indicators and linking them to multiple territorial scales.

Functional use dominates energy behaviour in tertiary buildings

Unlike residential buildings, where energy demand is primarily controlled by building morphology and climatic conditions, tertiary buildings are characterised by highly diverse hourly energy profiles governed principally by functional use, occupancy schedules and operational requirements. The eight tertiary categories analysed in this study exhibit markedly different balances between thermal and electrical demand, illustrating the dominant influence of building activity on annual energy behaviour. Similar conclusions have recently been reported by the International Energy Agency (2023)[47], which identifies operational schedules as the primary determinant of energy use in non-residential buildings.

Educational buildings represent a typical example of occupancy-driven energy demand. Mean heat consumption reaches 15.737 kWh, whereas average electricity demand remains limited to 3.990 kWh, producing an HC/EC ratio close to 4:1. Compared with detached residential buildings, educational facilities consume approximately 235% more heating energy (MRD = + 235%), reflecting their larger conditioned volumes, higher ventilation requirements and continuous daytime occupancy. The pronounced weekday peaks followed by significant reductions during weekends and holidays are consistent with observations reported across European school buildings, where heating demand closely follows academic calendars[47,53]. These findings demonstrate that occupancy-based heating control and demand-responsive ventilation remain among the most effective energy-saving strategies for educational infrastructure.

Administrative buildings display a fundamentally different energy signature. Although their average heating demand (HC = 16.472 kWh) remains comparable to educational facilities, electricity consumption increases dramatically to 20.317 kWh, representing an MRD of approximately + 409% relative to educational buildings. This sharp increase primarily reflects the intensive use of computers, office equipment, lighting systems, servers and mechanical ventilation. Similar electrical dominance has been documented in recent analyses of European office buildings, where information technology now constitutes one of the fastest-growing electricity end uses[28,51]. The relatively high standard deviation observed for electricity demand (SD = 24.416 kWh) further suggests considerable variability associated with occupancy intensity and operational schedules.

One of the most striking findings concerns transportation facilities, which exhibit the highest electricity demand among all tertiary categories (Mean EC = 40.072 kWh). Compared with commercial buildings (Mean EC = 5.962 kWh), transportation infrastructure consumes approximately 572% more electricity (MRD = + 572%). This behaviour reflects the continuous operation of lighting systems, escalators, signalling equipment, mechanical ventilation and safety infrastructure, which remain active throughout most hours of the year irrespective of outdoor climatic conditions. Similar electrical profiles have been reported for railway stations and airport terminals across Europe, where operational continuity produces relatively constant base loads[32,47].

Conversely, Culture and Sport facilities exhibit the highest thermal demand among tertiary buildings (Mean HC = 18.263 kWh), exceeding commercial buildings by nearly 180%. Large conditioned volumes, elevated ventilation rates and intermittent occupancy explain these substantial heating requirements. Such observations agree with previous investigations highlighting the energy intensity of sports halls, theatres and cultural centres because of their high ceiling heights and strict indoor comfort requirements[54]. Despite these high heating loads, electricity demand remains relatively modest, confirming that thermal conditioning rather than equipment use dominates overall energy consumption.

A particularly interesting observation concerns Banks and Financial Services. Despite relatively modest heating requirements (HC = 4.362 kWh), average electricity demand reaches 21.442 kWh, almost five times larger than heating demand. This imbalance clearly illustrates the growing influence of digital infrastructure within modern service economies. Continuous operation of data centres, ATMs, security systems and communication equipment generates substantial internal gains while simultaneously increasing cooling requirements. Similar transitions towards electricity-dominated energy profiles have been reported in commercial office buildings worldwide as digitalisation accelerates[47].

Delghust et al. (2021) used a bottom-up district-energy modelling framework for the Belgian building stock, providing an important methodological benchmark for the present regional-scale approach[45].While, Reynders et al. (2022) similarly demonstrated the importance of building-stock representation for residential energy and flexibility assessment in Belgium[36]. The present study extends these approaches by applying category-specific energy intensities to approximately 1.69 million cadastral buildings and generating continuous 8,760-hour profiles across residential, tertiary and industrial sectors. The infrastructure relevance of the atlas arises from the combination of magnitude, timing and persistence. A territory with a high annual demand but a relatively low load factor represents a different infrastructure challenge from a territory with a similar annual demand and a high load factor. The former may be dominated by a limited number of peak-demand periods and may therefore offer opportunities for storage, demand response or peak management, whereas the latter implies a more persistent requirement for network or generation capacity. Annual inventories cannot distinguish these two situations without an explicit temporal reconstruction. The atlas therefore provides the temporal boundary conditions required for subsequent infrastructure assessment rather than replacing detailed network or techno-economic models.

Industrial energy demand: implications for process-intensive buildings

The industrial sector exhibits energy characteristics that differ fundamentally from those observed in residential and tertiary buildings. Whereas residential energy demand is primarily governed by climatic conditions, building envelope characteristics and household occupancy, and tertiary buildings are largely driven by operational schedules and functional use, industrial categories exhibit the highest modelled loads and relatively persistent reconstructed profiles. Because several industrial subsectors share common BDEW archetypes, these patterns should not be interpreted as evidence of continuous plant-level production. Consequently, industrial buildings

display the largest thermal and electrical loads, the highest base-load demand and the smallest relative daily variability among all sectors investigated. This behaviour is consistent with recent global assessments indicating that industrial processes account for nearly one-third of worldwide final energy consumption, with process heating representing the dominant end use in heavy industries[1,47,54]. Similar conclusions have been reported by Hasanbeigi and Price[53], who demonstrated that industrial energy demand is primarily governed by production technologies rather than building characteristics.

The chemical industry represents by far the most energy-intensive industrial activity within the Walloon building stock. Average hourly heat consumption reaches 7,275.5 kWh, compared with 718.9 kWh for the agro-food sector, corresponding to a Mean Relative Difference (MRD) of + 912.0% (Mean difference = 6,556.6 kWh; SD = 4,636.8 kWh). Electricity consumption also increases dramatically, rising from 213.6 kWh in agro-food industries to 2,843.0 kWh in chemical industries (MRD = + 1,231%). These high modelled energy requirements are consistent with the energy-intensive nature of chemical manufacturing; however, the specific contribution of individual processes such as reactors, distillation columns, compressors or heat-exchange systems is not explicitly represented in the present model and should therefore be considered as plausible interpretations rather than directly demonstrated causal mechanisms. According to the International Energy Agency (2023)[47], chemical manufacturing is among the largest industrial consumers of both thermal and electrical energy because numerous production steps simultaneously require high-temperature process heat, steam generation and continuous electrical operation. Similar observations have been reported by (Fleiter et al. (2018), Arens et al. (2020) and Madeddu et al. (2020))[55,56], who estimated that process heating alone generally represents more than 70% of total energy use within European petrochemical complexes.

Compared with the chemical industry, the mineral sector exhibits considerably lower electricity demand but remains highly dependent on thermal energy. Mean HC reaches 1,657.4 kWh, while average EC remains limited to 28.2 kWh, resulting in an HC/EC ratio approaching 59:1. Such behaviour is consistent with the predominance of energy-intensive thermal processes reported for mineral industries; however, these individual process contributions are not explicitly resolved in the present building-stock model. The extremely low cooling demand further confirms that thermal energy is almost entirely consumed for process heating rather than space conditioning. Comparable energy distributions have been reported for European cement industries, where kiln operations account for between 70% and 90% of total plant energy consumption[47,57]. These observations also explain why decarbonisation strategies in the mineral sector increasingly focus on low-carbon fuels, carbon capture technologies and electrified clinker production rather than conventional building energy retrofits.

Steel manufacturing constitutes another highly energy-intensive industrial activity. Although its average HC (1,199.2 kWh) remains substantially below that of the chemical sector, electricity consumption reaches 876.8 kWh, approximately 31 times larger than that observed in mineral industries. The relatively balanced thermal and electrical loads are consistent with the energy characteristics reported for steel manufacturing, although specific process contributions such as electric arc furnaces, rolling mills and continuous casting are not explicitly represented in the model. Such behaviour illustrates the progressive electrification of steel production currently observed throughout Europe as industries gradually replace blast furnaces with electric arc technologies powered by low-carbon electricity and green hydrogen[57–59], who demonstrated that industrial electrification constitutes one of the principal pathways towards achieving carbon neutrality in steel manufacturing.

The textile industry exhibits distinctive hourly behaviour characterised by pronounced temporal variability. Mean HC reaches 1,843.2 kWh, whereas EC averages 335.2 kWh. The corresponding standard deviations (HC SD = 1,368.2 kWh; EC SD = 168.0 kWh) are among the highest observed in this study, indicating large fluctuations associated with batch production, washing, bleaching, dyeing, drying and finishing operations. Compared with the agro-food sector, textile industries exhibit an HC MRD of approximately + 156.4%, demonstrating substantially larger thermal requirements. Previous investigations similarly reported that textile factories display greater operational variability than continuous-process industries because production is organised into discontinuous batches rather than uninterrupted manufacturing lines[60,61]. Consequently, textile facilities may offer considerably greater opportunities for demand-side management, thermal storage and flexible production scheduling than continuously operating chemical plants.

Metallurgical industries display intermediate energy characteristics. Mean HC (30.9 kWh) and EC (23.3 kWh) remain relatively close, producing one of the smallest thermal-to-electrical ratios among all industrial categories. This balanced behaviour indicates that electrically driven machinery, induction furnaces, hydraulic systems and moderate thermal processes contribute simultaneously to overall energy demand. By contrast, the category Other Industries records the smallest energy requirements (HC = 16.6 kWh; EC = 1.86 kWh), reflecting the heterogeneous composition of smaller manufacturing facilities characterised by relatively limited process heating and lower equipment density. Similar observations have been reported in European industrial energy surveys, where miscellaneous manufacturing industries consistently exhibit lower energy intensities than heavy process industries[47,62].

From a statistical perspective, the variability among industrial sectors greatly exceeds that observed within residential buildings. Mean HC ranges from only 16.6 kWh (Other Industries) to 7,275.5 kWh (Chemistry), corresponding to an MRD exceeding 43,600%. Likewise, electricity demand varies from 1.86 kWh to 2,843.0 kWh, illustrating an EC MRD greater than 152,000%. Such extraordinary variability confirms that industrial energy demand cannot be represented using a single generic load profile. Instead, sector-specific modelling remains indispensable for regional energy planning, demand forecasting and industrial decarbonisation strategies. Similar conclusions were reached by Fleiter et al. (2018)[55], who demonstrated that industrial process diversity represents one of the largest sources of uncertainty in regional energy system models.

The absence of Heating Electricity Consumption (HEC) within industrial simulations deserves particular attention. Unlike residential and tertiary buildings, industrial thermal processes are predominantly supplied by fossil-fuel combustion systems, steam networks, waste heat recovery units, biomass boilers or direct process

heating rather than electric space heating. Consequently, HEC was intentionally excluded from the simulation framework, and its omission does not affect the interpretation of industrial thermal behaviour. Nevertheless, future industrial decarbonisation pathways are expected to increase the role of electrically driven heat pumps, resistance heating and hydrogen-based technologies, particularly for medium-temperature industrial processes[10].

Overall, the industrial analysis clearly demonstrates that manufacturing processes dominate energy consumption to a much greater extent than building envelope properties. Consequently, industrial decarbonisation policies should prioritise process optimisation, waste heat recovery, industrial heat pumps, fuel switching, electrification of high-temperature processes, green hydrogen deployment and carbon capture technologies rather than conventional building retrofit measures. These priorities are fully consistent with the objectives of the European Green Deal, the Fit-for-55 Package and the Net-Zero Industry Act, all of which identify industrial decarbonisation as a critical component of achieving climate neutrality by 2050[47,52]. These process-level explanations should therefore be interpreted as literature-supported contextual interpretations rather than causal mechanisms identified by the model. This distinction is particularly important because several industrial subsectors share the same BDEW temporal archetype, meaning that their differences in hourly load magnitude primarily arise from their annual energy-intensity coefficients and reconstructed floor areas rather than independently modelled production processes. The spatial dimension of the atlas also changes hotspot detection from a purely annual ranking to a spatiotemporal problem. A municipality can be identified as a hotspot because of its annual energy magnitude, its winter peak, its persistent electricity base load, or the duration of high demand. These definitions need not identify the same territories. By preserving hourly information while aggregating the building stock across municipalities, arrondissements and provinces, the atlas enables these different forms of hotspot to be distinguished. This distinction is particularly relevant for infrastructure planning because a spatial concentration of annual energy consumption does not necessarily imply the same infrastructure requirement as a concentration of short-duration peak loads.

Distinguishing Walloon-specific information from inherited BDEW behaviour

One of the major scientific contributions of the present study lies in the simultaneous characterization of hourly energy demand across the residential, tertiary and industrial building stocks using a unified bottom-up modelling framework and identical climatic boundary conditions. Previous studies have generally focused on individual sectors or specific building typologies, whereas integrated analyses combining the complete urban building stock at an hourly resolution remain relatively scarce[8,45,47]. Consequently, the Wallonia Energy Atlas developed in this work provides a unique opportunity to compare sector-specific energy behaviour under homogeneous modelling assumptions.

The comparative analysis clearly demonstrates that the three sectors exhibit fundamentally different energy regimes driven by distinct physical and operational mechanisms. The reconstructed profiles exhibit distinct temporal patterns across sectors. Residential profiles show stronger seasonal variation, tertiary profiles show more pronounced schedule-related patterns, and industrial profiles show relatively persistent loads. These differences arise from the combination of Walloon annual energy-intensity coefficients, reconstructed floor areas, building-stock composition and the temporal structure of the assigned BDEW archetypes. They should therefore not be interpreted as direct evidence of causal differences in occupant behaviour, equipment operation or industrial production schedules. Similar sectoral distinctions have been highlighted by the International Energy Agency (2023)[47], which identifies building operation and industrial production as the principal determinants of energy demand variability at the national scale.

From a quantitative perspective, remarkable differences are observed among the three sectors. Average hourly heat consumption increases from 4.70 kWh for detached residential buildings to 18.26 kWh for culture and sport facilities and reaches 7,275.5 kWh for chemical industries. Relative to detached houses, the chemical industry exhibits a Mean Relative Difference (MRD) of approximately + 154,800%, illustrating the enormous scale difference between domestic space heating and industrial process heating. Likewise, average electricity consumption rises from 0.738 kWh in detached houses to 40.07 kWh in transportation facilities and 2,843.0 kWh in chemical industries, corresponding to an EC MRD exceeding + 385,000% between detached dwellings and chemical plants. These exceptional differences confirm that industrial energy demand is several orders of magnitude larger than residential demand and cannot be managed using identical energy planning strategies[1,47].

Another important finding concerns the dominant end-use of energy within each sector. In residential buildings, heat consumption consistently exceeds electricity consumption because space heating remains the principal energy service under the temperate climatic conditions of Wallonia. Cooling electricity demand represents only a very small fraction of total annual energy use, confirming that the regional climate remains strongly heating-dominated. Similar conclusions have been reported for north-western European countries, including Belgium, Germany and the Netherlands, where heating generally accounts for more than 60% of final residential energy consumption[47,50,51]. By contrast, several tertiary sub-sectors including administration, banking, energy infrastructure and transportation display electricity-dominated profiles resulting from intensive use of information technologies, lighting, ventilation systems and continuously operating equipment. Industrial facilities, however, remain overwhelmingly dominated by process heating, particularly within chemical, mineral and steel industries where high-temperature thermal processes represent the largest share of total energy demand.

The load duration curves presented in Fig. 6 provide additional insight into sector-specific energy behaviour. Residential buildings exhibit relatively steep curves, indicating that high thermal loads occur during a limited number of winter hours, whereas lower loads dominate the remainder of the year. This behaviour reflects the strong influence of seasonal outdoor temperatures and confirms that residential heating demand remains highly weather-sensitive. Conversely, tertiary buildings display intermediate load duration characteristics, combining occupancy-dependent electricity peaks with moderate seasonal thermal variations. Industrial facilities present

the flattest load duration curves and the highest base loads among all sectors, demonstrating that industrial production continues almost continuously throughout the year with limited operational interruption. Comparable observations have been reported in previous industrial energy analyses, where continuous process industries such as chemicals and steel maintain high load factors exceeding those observed in commercial and residential sectors[55,56,63].

These sectoral differences have important implications for energy system flexibility. Residential buildings provide considerable opportunities for demand-side management through thermal storage, smart thermostats, demand-response programmes and heat-pump scheduling because a relatively small proportion of annual hours contributes to peak heating demand. Tertiary buildings offer additional flexibility through intelligent Building Energy Management Systems (BEMS), occupancy-based HVAC control, adaptive lighting and predictive ventilation strategies. In contrast, industrial flexibility is inherently more constrained because manufacturing processes often require continuous operation to maintain production quality and equipment performance. Consequently, flexibility within industrial facilities should primarily rely on process integration, waste heat recovery, industrial thermal storage, electrification of low- and medium-temperature processes and optimized production scheduling rather than conventional peak-shaving approaches[47,63,64].

The present results also have direct implications for regional decarbonisation policies. The residential sector should primarily focus on deep envelope renovation, heat pump deployment and district heating integration in order to reduce space-heating demand. Within the tertiary sector, priority should be given to improving operational efficiency through intelligent control systems, LED lighting, high-efficiency ventilation and occupancy-based energy management. Industrial decarbonisation, however, requires fundamentally different approaches centred on process optimisation, fuel switching, industrial electrification, waste heat utilisation, green hydrogen and carbon capture technologies. Such differentiated strategies are fully consistent with the objectives of the European Green Deal, the REPowerEU Plan, the revised Energy Performance of Buildings Directive and the Net-Zero Industry Act, all of which emphasise the necessity of sector-specific pathways towards climate neutrality[51,52,64]. Beyond its scientific contribution, the Wallonia Energy Atlas developed in this study represents a practical decision-support tool for regional authorities, energy utilities and urban planners. Unlike conventional annual energy inventories, the atlas provides spatially explicit hourly information for more than one million buildings, allowing the identification of temporal demand peaks, regional energy hotspots and opportunities for renewable energy integration. Such information is essential for optimising district heating networks, sizing renewable energy systems, planning electricity distribution infrastructure and designing future Positive Energy Districts (PEDs). Similar digital energy atlas initiatives have recently emerged across Europe, although very few currently integrate residential, tertiary and industrial sectors simultaneously at hourly temporal resolution[8,35,37]. A comparison of the three sectors is presented in Table 6.

Overall, the cross-sector comparison demonstrates that building function and industrial processes exert a stronger influence on hourly energy behaviour than climatic conditions alone. While climate remains the principal driver of residential heating demand, operational schedules dominate tertiary buildings and manufacturing processes govern industrial facilities. Consequently, future regional energy policies should move beyond generic building renovation programmes towards sector-specific decarbonisation strategies capable of addressing the distinct physical mechanisms controlling energy demand in each part of the built environment. Such integrated approaches will be indispensable for achieving the European Union's objective of climate neutrality by 2050 while maintaining secure, reliable and economically efficient regional energy systems. Unlike conventional static maps, the proposed Wallonia Energy Atlas is available through an interactive web platform, enabling users to dynamically explore spatial and temporal energy demand across the Walloon building stock. This functionality considerably enhances the practical applicability of the proposed methodology for researchers, energy planners and policy makers(Nematchoua and Reiter,2026)[44,65]. A comparison between the present study and selected previous frameworks is provided in Table 7.

An important distinction is required when interpreting the hourly patterns generated by the atlas. The spatial magnitude of the estimated demand is predominantly determined by Walloon-specific information, including cadastral building characteristics, reconstructed floor areas, sectoral classification and energy-intensity coefficients derived from the Walloon Regional Energy Balance. The temporal shape, however, is partly inherited from the standardized BDEW archetypes used for temporal disaggregation. Consequently, the atlas provides Walloon-specific spatial and annual energy information combined with standardized temporal representations, rather than fully empirical Walloon hourly behaviour. This distinction is particularly important for cross-category comparisons. Where two Walloon building categories are assigned the same BDEW archetype, differences in their hourly load magnitudes arise from their Walloon annual energy estimates and building characteristics, whereas their normalized temporal shape is imposed by the common BDEW profile. Therefore, similarities

Sector	Dominant load	Typical hourly magnitude	Temporal behaviour	Cooling importance	Main driver
Residential	Space heating	Low-moderate	Strong daily & seasonal	Very low	Outdoor temperature & occupancy
Tertiary	Heating or electricity depending on use	Moderate-high	Working-hour dependent	Moderate	Building function & occupancy
Industrial	Process heat and electricity	Very high	Continuous production	Generally low (except Chemistry)	Industrial processes

Table 6. Overall comparison of residential, tertiary and industrial sectors.

Study/platform	Spatial extent	Buildings	Temporal resolution	Sectors	Modelling approach	Validation	Public accessibility
Fonseca & Schlueter (2015)[36]	City district, Zug, Switzerland	1392	Hourly	Residential + commercial + industrial	Hybrid dynamic UBEM + GIS	Measured data + peer model	Research platform/limited
CityBES/ San Francisco application	6 city districts, USA	940	Dynamic simulation	Office + retail	EnergyPlus-based UBEM	Scenario/application-based	Public web platform
EU Building Stock Observatory[38]	European/ national	Aggregated stock	Statistical/ annual indicators	Residential + service	Building-stock database/statistical	Cross-country data harmonisation	Public interactive platform
TABULA/ EPISCOPE	European countries	Building-stock archetypes	Mainly annual	Residential	Archetype/stock modelling	Stock-level comparison	Public database/ reports
Belgian building-stock UBEM studies	Belgium	Regional/ national residential stock	Sub-hourly/ hourly depending study	Mainly residential	Bottom-up dynamic modelling	Calibration against Belgian load profiles	Research datasets/models
Wallonia Energy Atlas (this study)	Regional → municipal → arrondissement → provincial	~ 1.69 million	8,760 h	Residential + tertiary + industrial	Hybrid top-down/ bottom-up + cadastral GIS + standardized hourly profiles	Regional energy balance + validation analysis	Interactive public web platform

Table 7. Quantitative benchmarking of representative UBEM and urban energy-atlas studies.

in daily or seasonal timing between such categories should not be interpreted as independently observed behavioural similarities. Conversely, differences in absolute load magnitude remain informative because they reflect the Walloon-specific energy-intensity and building-stock information incorporated into the model.

Implications for energy system design and operation

District heating system design and operation

The hourly heat profiles generated by the Wallonia Energy Atlas provide several elements directly relevant to district heating (DH) planning and operation. First, the spatial distribution of Heat Consumption (HC) and Heat Demand (HD) can be used to identify areas with sufficiently concentrated and temporally compatible heating loads to justify district heating development. High-density residential areas, particularly those containing apartment buildings and clusters of buildings with high and persistent thermal demand, represent potential priority zones for network assessment. Conversely, dispersed detached housing areas may require greater network length per unit of delivered heat and may therefore present less favourable conditions for conventional district heating expansion. Second, the 8,760-hour profiles allow network capacity to be assessed against both annual energy requirements and short-duration peak loads. The annual maximum hourly HD can be used as an initial estimate of the required peak thermal capacity, whereas the load-duration curve provides information on the number of hours for which peak or near-peak capacity is required. This distinction is important because a district heating system designed solely according to annual energy demand may be oversized if a very high peak occurs only during a limited number of hours. The atlas can therefore support the separation of base-load and peak-load supply requirements and the preliminary assessment of alternative heat-generation portfolios. Recent studies on energy-system optimisation, renewable-storage integration, machine-learning approaches and building-to-district digital twins provide complementary methodological directions for future extensions of the Wallonia Energy Atlas (Refs. 66–69; Supplementary Table S6, appendix).

Renewable energy integration: photovoltaic generation and heat pumps

The hourly electricity profiles also provide a basis for evaluating renewable-electricity integration. In particular, the EC profiles can be compared with the expected temporal production of photovoltaic (PV) systems to identify periods of potential coincidence or mismatch between electricity generation and building demand. Building categories with substantial daytime electricity consumption, such as administration, transportation and energy-infrastructure facilities, may offer greater opportunities for direct PV self-consumption than demand profiles dominated by evening or winter peaks. Conversely, strong temporal mismatches between PV generation and electricity demand would indicate a greater need for electrical storage, demand shifting or grid interaction. Heat pumps introduce an important coupling between the thermal and electrical energy systems. The simultaneous availability of HD and HEC profiles makes it possible to examine the additional electricity demand associated with electrically driven heating and its temporal alignment with the heating requirement. In a future energy-system application, the atlas could therefore be coupled with heat-pump performance models and temperature-dependent coefficients of performance to estimate the resulting electricity demand, assess winter peak impacts and evaluate the extent to which heat pumps can be coordinated with renewable generation, thermal storage or flexible electricity tariffs.

The hourly profiles can also support preliminary storage assessment by quantifying the duration, magnitude and recurrence of demand peaks. Thermal storage is particularly relevant for heating-dominated residential and tertiary loads because heat demand is strongly seasonal and concentrated in a limited number of high-load hours. A storage system could be evaluated by identifying periods in which heat production exceeds instantaneous demand and subsequently shifting this energy towards periods of higher demand. Similarly, electrical storage

can be assessed by comparing hourly EC profiles with PV generation or other renewable-electricity profiles. The atlas does not directly optimise storage capacity in the present study; however, its 8,760-hour demand series provide the temporal boundary conditions required for subsequent techno-economic optimisation of battery and thermal-storage systems.

The same temporal information can be used to assess demand-side flexibility. Residential buildings offer flexibility primarily through thermal inertia, heat-pump scheduling, thermostatic control and domestic thermal storage. Tertiary buildings provide additional flexibility through occupancy-based HVAC control, ventilation management, lighting and building-energy-management systems. The atlas can identify candidate flexibility periods by combining peak-load hours, load-duration characteristics and sector-specific temporal patterns. In particular, the steep residential load-duration curves indicate that a relatively limited number of high-demand hours contribute disproportionately to peak thermal requirements, suggesting opportunities for peak shaving and load shifting. For tertiary buildings, flexibility can be targeted around occupancy-dependent operating schedules, whereas industrial flexibility requires a more cautious approach because process continuity can constrain load shifting. In industrial applications, the atlas is therefore more appropriate for identifying persistent base-load requirements, potential waste-heat sources and periods of high electricity demand than for assuming unrestricted demand response. Future integration with production schedules, process models and industrial storage systems would be required to quantify economically feasible industrial flexibility. These considerations reinforce the importance of interpreting building-energy indicators within an evidence-based policy framework that explicitly recognises data quality, modelling uncertainty and the limits of performance indicators[66–70].

Strengths, limitations and future research

Several methodological strengths distinguish the present study from previous regional energy analyses. First, the work integrates 1.69 million buildings, covering the complete Walloon building stock within a unified simulation framework. Second, hourly profiles were generated continuously over 8,760 h, allowing the representation of seasonal and daily variability. Third, residential, tertiary and industrial buildings were analysed simultaneously using harmonised modelling assumptions, thereby enabling direct cross-sector comparisons that remain relatively uncommon in regional-scale energy assessments. Finally, all simulation results have been incorporated into an interactive GIS-based Wallonia Energy Atlas capable of supporting regional energy planning and policy development. Nevertheless, several limitations should be acknowledged. The temporal disaggregation of annual energy estimates relies on BDEW standard load profiles rather than on measured smart-meter observations. Although these profiles provide a standardized and reproducible representation of typical temporal behaviour, they were developed for the German energy context and may not fully capture Belgian- or Walloon-specific occupancy patterns, working schedules, appliance-use behaviour, heating-system operation, commercial practices, or other cultural and operational characteristics. No country-specific behavioural recalibration of the BDEW profiles was performed in this study. Instead, their application was constrained by Walloon building categories, cadastral characteristics, regional energy-intensity coefficients, and Walloon climatic data. The resulting hourly profiles should therefore be interpreted as standardized, sector-representative temporal distributions constrained by Walloon annual energy estimates, rather than as building-specific measured load curves. This approach ensures consistency and computational scalability across the entire building stock, but it may smooth local behavioural variability and introduce uncertainty into the temporal distribution of energy demand.

The validation results provide evidence that the framework can reproduce representative temporal energy-demand patterns across the major building functions; however, the number of monitored buildings remains limited relative to the approximately 1.69 million buildings represented in the regional model. Therefore, the validation should not be interpreted as demonstrating building-level predictive accuracy for the entire Walloon building stock, but rather as supporting the suitability of the framework for regional-scale and statistically representative energy modelling. Future validation using larger samples of Belgian smart-meter observations and measured end-use data would provide a stronger basis for assessing the robustness of the hourly profiles. Cooling demand also remains relatively small under the climatic conditions represented in the present study; however, future climate change may substantially modify cooling requirements during the coming decades. Industrial energy modelling represents an additional source of uncertainty. Industrial Heating Electricity Consumption (HEC) was not explicitly estimated because the available regional statistics did not provide sufficiently detailed subsector-specific information to distinguish electricity used for process heating from other industrial electricity end uses. This should not be interpreted as an absence of industrial heating electrification, particularly given the ongoing transition toward electrified industrial processes. In addition, the industrial energy-intensity coefficients represent regional subsector averages and therefore cannot capture plant-level differences in production volume, process technology, equipment efficiency, operating schedules and energy-management practices. Future research should incorporate plant-level energy data, process-specific electricity shares and measured industrial load profiles to improve the representation of industrial energy demand.

These limitations should be considered when interpreting the spatial and temporal energy patterns generated by the atlas. The framework is potentially transferable to other regions, but such transferability should not be interpreted as a plug-and-play application. Adaptation to other national or regional contexts requires sufficiently detailed building-stock inventories, compatible building classifications, regional energy statistics, climatic data, administrative boundaries, and appropriate sector-specific energy-intensity coefficients. In particular, temporal load profiles may require local calibration where occupancy patterns, building regulations, heating technologies, energy-use practices, or cultural behaviours differ substantially from those underlying the BDEW profiles. Thus, the proposed framework is best regarded as a transferable modelling architecture that requires regional adaptation and, where possible, local calibration.

The sensitivity assessment further indicates that uncertainty in category-level energy intensities and corrected floor area primarily controls the magnitude of annual energy estimates, whereas uncertainty in standardized temporal profiles primarily affects hourly characteristics such as peak load and load duration. The present deterministic sensitivity analysis provides first-order uncertainty envelopes for the parameters for which defensible perturbation ranges could be specified. However, these envelopes should not be interpreted as probabilistic confidence intervals. A full Monte Carlo or global sensitivity-analysis framework, using empirically derived probability distributions for energy-intensity coefficients, floor-area reconstruction errors, classification uncertainty, weather variability and temporal-profile selection, would enable formal uncertainty intervals to be propagated to building, statistical-sector, municipal, provincial and regional scales. This represents an important direction for future development of the Wallonia Energy Atlas. Accordingly, the atlas outputs should be interpreted as deterministic regional estimates accompanied by sensitivity ranges, rather than as probabilistic forecasts with formal confidence intervals. A specific limitation concerns the temporal representation of cooling electricity demand. In the present framework, CED is distributed according to a standardized electricity profile rather than a temperature- and solar-driven cooling profile. Consequently, the model does not explicitly capture the activation of cooling systems in response to outdoor temperature, solar gains, internal heat gains or occupancy. This assumption may influence the simulated timing and magnitude of cooling peaks, particularly during summer periods. Future work should therefore develop and validate weather-dependent cooling profiles using hourly outdoor temperature, cooling-degree hours and, where available, occupancy and building-system information.

Future development should prioritize four methodological improvements. First, Belgian smart-meter datasets should be incorporated at hourly or sub-hourly resolution, with separate electricity end-use measurements where available, to recalibrate BDEW temporal profiles and quantify behavioural variability. Second, dynamic occupancy and operational schedules should be incorporated for residential and tertiary buildings, while plant-level production schedules and process-specific electricity shares should be developed for industrial facilities. Third, future climate assessments should use multiple climate projections, including representative CMIP6-based scenarios such as SSP1-2.6, SSP2-4.5 and SSP5-8.5, to quantify changes in heating and cooling demand. Fourth, probabilistic uncertainty propagation and machine-learning approaches could be used to update energy-intensity coefficients and temporal profiles as new observations become available. Machine-learning models could be trained using monitored hourly electricity and heat-demand observations together with building attributes, weather variables, occupancy proxies and building-use categories. The trained models could then be used to calibrate temporal profiles or predict category-specific intensities while preserving the regional energy-balance constraints of the present top-down/bottom-up framework. For district-heating applications, the hourly HD and HC profiles could be coupled with network optimisation models to determine candidate network zones, pipe capacities, peak-generation requirements, thermal-storage capacities and operating strategies. Spatial clustering of buildings with high and temporally coincident heat demand could first identify priority areas, after which hydraulic and techno-economic optimisation could be performed using the atlas-derived hourly demand profiles as inputs. For renewable-energy planning, the hourly EC profiles could be coupled with independent solar-PV and wind-generation profiles to evaluate temporal coincidence, self-consumption potential, grid-import reduction and renewable-energy curtailment. The atlas itself does not determine optimal PV or wind capacity; rather, it provides the spatially resolved demand profiles required as inputs to subsequent renewable-siting and capacity-optimisation models.

From an implementation perspective, long-term maintenance represents an additional challenge. The usefulness of the atlas will depend on the continued availability and periodic updating of cadastral records, regional energy statistics, building classifications, climatic data and energy-intensity coefficients. Building-stock changes caused by new construction, demolition, renovation and changes in building use may progressively reduce the representativeness of a fixed baseline dataset. A sustainable operational version of the atlas would therefore require a defined update protocol, including periodic data ingestion, quality control, recalculation of affected energy indicators and versioning of the published datasets. Rather than recalculating the entire regional model whenever a minor input changes, future implementations could use incremental updating procedures that identify and recompute only affected buildings or spatial entities. Integration into institutional decision-making would also require alignment with existing regional GIS and energy-planning workflows. The atlas could be used as an exploratory and analytical layer alongside existing cadastral, demographic, energy-network and planning databases, providing spatially consistent energy indicators and hourly demand profiles for scenario development and infrastructure assessment. However, institutional adoption may require interoperability with existing GIS platforms, standardised data formats, documented metadata, clear responsibility for data updates and validation, and procedures for communicating uncertainty to decision-makers. Effective use by non-specialist users represents another implementation requirement. Although the web interface reduces the need for programming expertise, users must understand the meaning of the five energy indicators, the spatial aggregation levels, the distinction between annual and hourly quantities, and the principal assumptions underlying the model. Future deployment should therefore be accompanied by concise user documentation, metadata, training materials and practical use cases for local and regional authorities. Such capacity-building would help prevent inappropriate interpretation of modelled values as building-specific measurements or deterministic predictions. Data privacy and security should also be considered in any future operational deployment. Although the underlying modelling framework uses detailed cadastral information, the public atlas is structured around aggregated administrative levels rather than direct disclosure of individual-building energy records. Maintaining this distinction is important because building-level energy information may become sensitive when combined with property characteristics or other datasets. Future extensions providing finer spatial resolution should therefore apply appropriate aggregation, anonymisation, access-control and data-governance procedures in accordance with applicable institutional and legal requirements. These measures would allow the scientific value of high-resolution energy modelling to

be retained while reducing risks associated with the public dissemination of potentially sensitive information. A limitation of the present approach is that facility-level industrial process energy could not be explicitly represented because detailed production and process-energy data are not consistently available at the building scale. Future work should therefore integrate sector-specific production statistics and facility-level energy data to improve the representation and validation of industrial energy demand.

The energy-system applications discussed above should nevertheless be interpreted as screening and planning applications rather than as direct optimisation results. The present atlas provides demand-side boundary conditions but does not explicitly model district heating network hydraulics, generator dispatch, photovoltaic production, heat-pump coefficient-of-performance variations, battery degradation, thermal-storage dynamics, electricity-market prices or network constraints. Consequently, infrastructure capacities derived from the atlas would require subsequent coupling with dedicated energy-system models and techno-economic optimisation frameworks. This distinction is particularly important because uncertainty in the BDEW temporal profiles primarily affects peak magnitude, peak timing and load-duration characteristics, which are critical variables for infrastructure sizing and flexibility assessment. Future work should specifically evaluate alternative Belgian temporal archetypes for residential, tertiary and industrial categories and quantify how replacing standardized BDEW profiles with locally measured profiles changes peak magnitude, peak timing, load factor and load-duration characteristics.

Conclusion

To address the lack of region-wide, multi-sector and temporally resolved building-energy information, this study developed a high-resolution Walloon energy atlas covering approximately 1.69 million buildings, 8,760-hour archetype-based temporal reconstructions, five complementary energy indicators, and multiple nested administrative scales. The resulting atlas provides an interactive decision-support resource for scientific research, regional energy planning and evidence-based policy development, while its long-term operational value will depend on periodic data updates, institutional integration, user capacity-building and appropriate data-governance procedures. The results demonstrate substantial differences in the magnitude and temporal structure of the reconstructed profiles across building typologies and functional categories. Within the residential sector, detached houses exhibited an average HC of 4.70 kWh, whereas apartment buildings reached 18.53 kWh, approximately four times higher because of their larger aggregated floor area and occupancy. In the tertiary sector, transportation facilities recorded the highest electricity consumption (40.07 kWh), while culture and sport buildings presented the highest average heat consumption (18.26 kWh). Industrial buildings displayed by far the largest energy requirements, with the chemical industry reaching average hourly values of 7,275.5 kWh for HC and 2,843.0 kWh for EC, several orders of magnitude greater than those observed in residential and tertiary buildings. The reconstructed profiles exhibit distinct sectoral temporal patterns, including stronger seasonal variation in residential thermal demand, schedule-related patterns in tertiary profiles, and relatively persistent loads in industrial profiles. These patterns are partly inherited from the assigned BDEW temporal archetypes. The load duration curve analysis further revealed three distinct operational regimes. Residential buildings were characterized by climate-driven thermal peaks concentrated during the heating season, tertiary buildings by occupancy-dependent electricity demand, and industrial facilities by relatively persistent reconstructed base loads. These industrial patterns should not be interpreted as direct evidence of continuous plant-level production because standardized BDEW profiles are used for temporal reconstruction. These findings clearly demonstrate that sector-specific characteristics dominate hourly energy behaviour and therefore require differentiated energy efficiency and decarbonisation strategies. Beyond its scientific contribution, the Wallonia Energy Atlas provides a regional-scale demand-side foundation for energy-system planning. The 8,760-hour HC, HD, EC, CED and HEC profiles can support preliminary district-heating assessment, renewable-energy integration, heat-pump electrification analysis, storage screening, electricity-network planning and demand-side flexibility assessment. By linking spatial demand concentrations with peak, base-load and load-duration characteristics, the atlas provides the temporal boundary conditions required for subsequent energy-system simulation and techno-economic optimisation. By providing hourly energy information from the building scale to municipalities, arrondissements, provinces and the entire Walloon Region, the atlas offers an operational framework for identifying energy hotspots and supporting evidence-based investment decisions.

Future work should prioritize the integration of Belgian hourly smart-meter and measured end-use data to locally recalibrate temporal profiles, together with plant-level industrial production data and process-specific electricity shares. Multi-scenario climate simulations based on SSP1-2.6, SSP2-4.5 and SSP5-8.5 should be used to quantify changes in heating and cooling demand. The resulting hourly atlas profiles could then be coupled with hydraulic and techno-economic optimisation models for district-heating network design, thermal-storage sizing, renewable-energy siting, battery operation and demand-response assessment. Machine-learning methods could further support continuous recalibration of energy-intensity coefficients and temporal profiles as new monitoring data become available.

Data availability

The datasets generated during the current study are available in the Zenodo repository at https://doi.org/10.5281/zenodo.20342580. The cadastral datasets used during the current study are not publicly available because of institutional data-sharing policies but are available from the corresponding author upon reasonable request.

Code availability

Kameni Nematchoua, M., & Reiter, S. (2026). Code-Article-A high-resolution urban energy atlas reveals the spatiotemporal dynamics of 1.69 million buildings. Zenodo. https://doi.org/10.5281/zenodo.21101858. The

code repository includes the scripts required for data preprocessing, annual energy estimation, temporal profile generation, spatial aggregation and visualization. The accompanying documentation specifies the expected input variables, building-category classification, energy indicators and output structure required to reproduce the modelling workflow.

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Author contributions

Author Contributions: Modeste Kameni Nematchoua (M.K.N.) conceived the study, designed the methodology, performed the data collection, energy modelling, simulations, geospatial analysis, interactive dashboard development, data visualization, interpretation of the results, and wrote the original manuscript. Aoife Houlihan Wiberg (A.H.W.), Jose A. Orosa (J.A.O.), Shadi Attia (Sh.A.), Njomo Donatien (N.D.), David MacLeod (D.M.), Somayeh Asadi (So.A.), Gholamreza Roshan (G.R.), and Sigrid Reiter (S.R.) contributed to the conceptualization of the study, interpretation of the results, scientific discussion, and critical revision of the manuscript. Sigrid Reiter (S.R.) also supervised the research. All authors have read and approved the final version of the manuscript.

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Declarations

Ethics statement

This study did not involve human participants, human biological materials, identifiable personal information, or animal experiments. The analyses were performed exclusively using building-level cadastral information, aggregated administrative statistics, geospatial datasets, and regional energy-balance statistics. Consequently, ethical approval and informed consent were not required.

Competing interests

The authors declare no competing interests.

Additional information

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