



High-resolution electricity generation mixes in building operation: A methodological framework for energy and environmental impacts and the case study of an Italian net zero energy building

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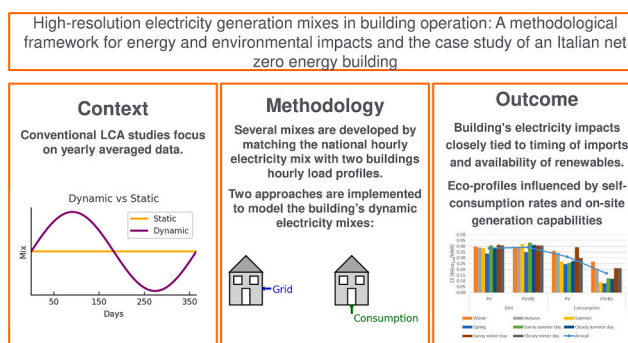
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HIGHLIGHTS

- A framework for high-resolution electric mixes in NZEB operation is created.
- Self-consumption plays a role in varying the electricity import from the grid.
- Eco-profile of hourly electricity mixes varies with generation system and load.
- High-res analysis enables efficient use for electricity and reduce impact.
- High-res mixes refine environmental impact assessment of building use phase.

GRAPHICAL ABSTRACT



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ABSTRACT

Temporal fluctuations of the electricity grid generation composition, variability of electricity consumption in building operation over the year and of the on-site renewable energy systems are factors that should be properly considered, using high-resolution data in the building energy and environmental performance assessment.

In this study a methodological framework is developed to model high-resolution electricity mixes in building operation and to assess the related energy and environmental impacts over the year, by means of a life cycle approach.

For most impact categories, the imported electricity generation mixes, to meet the residual building demand, show impact variations not higher than +20 % and not lower than −38 % at seasonal and daily time compared with the annual average values.

Temporal variations are even more relevant in building consumption electricity mixes, which are significantly characterized by self-consumption and show noticeable reductions compared to the annual electricity generation mix in both assessed scenarios.

As an example, summer and spring energy generation mixes show the best results for climate change (0.09 kgCO_{2eq}/kWh) compared to the annual ones, while in winter and autumn mixes the contribution to climate

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change overcomes the respective annual results. Both summer day-mixes contribute to climate change for about 0.12 kgCO_{2eq}/kWh, with a reduction of nearly 30 % if compared the annual data. Conversely, in the winter day-mixes the contribution to climate change is about 0.20 kgCO_{2eq}/kWh and comes mostly from the grid.

The results highlight that assessed temporal variations are significant through the year for the most assessed environmental indicators. Furthermore, the use of high-resolution electricity generation mixes allows to optimize efficiently the temporal use of electricity in buildings, in sight of energy and environmental impact reduction also thanks to the employment of life cycle oriented approaches. The results also highlight the relevance of the storage system in fulfilling periods of peak demand or low renewable generation.

Nomenclature

ADP _{m&m}	Abiotic Depletion Potential for minerals and metals	E _{PV} (t)	Self-consumed electricity generated by the PV system at hour <i>t</i>
AP	Acidification Potential	EU	European Union
BL	Building Load	EU-ETS	European Union's Emissions Trading System
BS	Battery Storage	G(t)	Electricity generated at hour <i>t</i>
C(t)	Battery energy capacity at the time step (<i>t</i>)	GHG	Greenhouse Gas Emission
CC	Climate Change	GWP	Global Warming Potential
CED _{non-ren}	Cumulative Energy Demand non-renewable	IR	Ionizing Radiation
CO _{2eq}	Equivalent Carbon Dioxide	I _{j,n}	Environmental impact per kWh of electricity supplied to the building over a period of “ <i>n</i> ” hours for the “ <i>j</i> th ” environmental impact category
E(t)	Electricity exported/imported at hour <i>t</i>	LCA	Life cycle assessment
E _{BS} (t)	Self-consumed electricity from battery system at hour <i>t</i>	LCIA	Life cycle impact assessment
E _{BS-BL} (t)	Electricity delivered from the battery system to feed the building load at hour <i>t</i>	I _{k,j}	Contribution, per kWh supplied by the <i>k</i> th electricity generation system, to the <i>j</i> th environmental impact category at midpoint level
E _c (t)	Total electricity consumption at hour <i>t</i>	M _{k,n}	Mix share for the <i>k</i> th electricity generation system in the timestep
E _{c,k} (t)	Amount of electricity supplied from each electricity generation system at hour <i>t</i>	NZEBs	Net zero energy buildings
EF 3.0	Environmental Footprint 3.0	ODP	Ozone Depletion Potential
E _{imp} (t)	Amount of electricity imported from the building at hour <i>t</i>	PED	Positive Energy Districts
E _{imp,k} (t)	Amount of electricity imported from each of the <i>k</i> th electricity generation system at hour <i>t</i>	PM	Particulate Matter
E _{IBS-BL} (t)	Electricity delivered from the battery system to feed the building load at hour <i>t</i>	POCP	Photochemical Ozone Creation Potential
E _{IPV-BS}	Electricity from the photovoltaic system available to charge the battery system	PV	Photovoltaic
ENTSO-E	European Network of Transmission System Operators of Electricity	PV-BS	Photovoltaic system, including a li-ion battery storage system
EN 15804	European Standard for Sustainability of Construction Works	SoC	State of Charge
E _{PFW}	Eutrophication Potential Fresh Water	p _k (t)	Relative share of electricity generated by each <i>k</i> th electricity generation system on the generation mix total at hour <i>t</i>
E _{PM}	Eutrophication Potential Marine	δ _{SoC} (t)	Difference of state of charge at the time step
E _{PT}	Eutrophication Potential Terrestrial	ε(t)	Battery efficiency corresponding at the time step

1. Introduction

The decarbonisation of the building stock is a key priority of the European Union's (EU) climate policies, as approximately 40 % of final energy consumption and 36 % of energy related greenhouse gas (GHG) emissions stem from buildings (European Commission, 2018).

Many of EU buildings are inefficient, with over 40 % of the existing ones constructed before 1960 and 90 % before 1990, thus prior to the implementation of stringent efficiency regulations. Most energy consumption occurs during the service life of a building, required for space heating, hot water supply, cooling, ventilation, lighting, etc., thus representing the highest contribution to the building life cycle CO_{2eq} emissions (Cusenza et al., 2021). This has involved a strong focus on minimizing operating energy demand of buildings (Cusenza et al., 2022). Furthermore, a relevant share of space heating and hot water

supply still relies on fossil heat sources, mainly natural gas (Toleikyte et al., 2023).

In the pathway towards the EU mid-term commitment of 55 %¹ GHGs reduction compared to 1990 levels, and to the climate neutrality target by 2050, the revision process of relevant directives has been started, including the Energy Performance of Buildings Directive (European Union, 2018a), Renewable Energy Directive (European Union, 2018b), and Energy Efficiency Directive (European Union, 2023), as well as comprehensive changes to the EU's emissions trading system (EU-ETS). In parallel, the Renovation Wave of the European Green Deal has been launched in 2020 to trigger the building energy renovation by 2030 (European Commission, 2020).

As outlined in the recent REPowerEU Plan, aimed at making Europe independent from Russian fossil fuels before 2030, renewable energy technologies, heat pumps for heating, and energy efficiency measures in buildings are of paramount importance to contribute to the achievement of the 2030 EU target (European Commission, 2022).

¹ European Climate Law [3].

Due to the increasing electrification of heating systems and the possibility to reach higher efficiencies in electrical equipment than those powered by fossil fuels, electricity has gained an increasingly significant share in the building operating energy demand. Furthermore, although fossil fuels still represent the most exploited sources to produce electricity in Europe, renewable energy sources in electricity generation mixes have been increasing in the last years and will increase further to comply with the climate neutrality target fixed in the European Green Deal by 2050 (European Commission, 2019).

The ongoing push towards carbon neutrality in cities encompasses diversified efforts aimed at reducing the impact climate change might have on the built environment in the coming decades (Beccali et al., 2007). This is exemplified with the Positive Energy Districts plan by the Commission through the Joint Programming Initiative Urban Europe towards the development of 100 PEDs by 2025 as well as with the launch of the two EU missions for 2030 connected to these topics: pushing 100 carbon neutral cities by 2030 - in parallel to the adaptation to climate change one, which aims at supporting climate resiliency by 2030 within 150 European regions.

With the growth of building electricity demand and of renewable sources, temporal changes and variability in electricity generation systems become increasingly significant, depending on which time the energy is generated (Bastos et al., 2023). This is particularly significant for solar and hydro generation systems, which show important hourly variations across the day and from a season to another, with the highest contributions in spring and summer. Electricity production from wind, biomass, and geothermal is slightly fluctuating in a short time view.

Consequently, the composition of the electricity grid is not stationary and can fluctuate significantly, depending on the national context and the timescale (Jorge and Hertwich, 2014). Such a dynamicity involves temporal variations in the environmental impacts per unit of electricity supply as well.

Even the electricity consumption in building operation varies during the year, (Airò Farulla et al., 2020) depending on different factors, such as building specific use (type of occupancy) (Cellura et al., 2011), and the behaviour of users (Negishi et al., 2018). Heating energy use and higher lighting demand in winter, as well as cooling demand in summer are examples of variable consumptions at seasonal level, directly influenced from the above factors. Daily, peaks of consumption occur in the morning and in the evening in residential buildings, while for commercial and office buildings the consumption is higher over the workdays.

All these factors make the interaction between building operation and the electricity generation systems increasingly more complex. Moreover, the growing electrification of the final uses enhances the influence of the electricity supply mix on the energy and environmental performances of the building use as well.

2. Insight from literature review

The above considerations suggest that high-resolution data can give meaningful insights on the variability of building's electricity consumption-related impacts (Cellura et al., 2017). Conventionally Life Cycle Assessment (LCA) studies have overlooked the temporal variations of the electricity mix composition and almost all LCA studies provide yearly averaged data and results (Cuéllar-Franca and Azapagic, 2012; Giordano et al., 2015; Vilches et al., 2017). It is a common practice to apply yearly averaged conversion factors of a national electricity mix.

Furthermore, none of the existing standards and databases for LCA consider the temporal dimension in the building performance assessment but there are some commercial LCA tools that consider the variable "time" in energy and material life cycle inventories.

For example, Electricity Maps (Electricity Maps [WWW Document], 2024) offers a live visualization of electricity sources from ENTSO-E and focuses on the environmental impact considering the carbon intensity of consumed electricity in gCO₂eq/kWh using greenhouse gas emission

from the report the IPCC 2014. The consumption includes the carbon intensity from both imported and exported electricity, with data accessible historically, in real-time and as forecasts. The tool employs a specific method, called the flow tracing methodology (Institution of Electrical Engineers, 1996). This study focuses on the energy mix, which involves evaluating the balance of energy production, import, and export. This approach provides a comprehensive view of the energy sources and allows for better matching of energy data with the impacts as analysed byecoinvent. Although the Ecoinvent database was used to model the impacts generated by every technology available within the energy generation mix in Italy, the share of relevance of each technology was determined at hourly timestep by detailed energy balances.

The flow tracing method, on the other hand, is more about understanding the impact of individual generators or loads on the power system and tracing the flow of electricity in the network. The methodology mainly computes carbon intensity of electricity and IPCC aggregated data for environmental impacts computation.

The EcoDynBat initiative (Padey et al., 2020), focusing on the Dynamic Life Cycle Assessment of buildings (DLCA), carries out an in-depth analysis of how varying time intervals affects the accuracy of environmental impact assessments related to the Swiss electrical grid. This study specifically explores the implications of these intervals on the precision of calculating the environmental footprint of electricity consumed in buildings, utilizing advanced DLCA methodologies. The EcoDynBat model, being tailored to the Swiss energy infrastructure and regulatory environment, uses Model M2 for modeling of the electricity trade rather than the Model M3.

Model M3 (Menard and Gantner, 1998) was adopted in the study rather than M2 as it could allow for a finer tuning of the energy flows concerning import and export to the grid.

The data of EcoDynBat are the main sources of a new tool called the EcoDynElec, aimed at overcoming the limitations of Electricity maps (Lasvaux, 2023). This model enables DLCA calculations using a dynamic life-cycle inventory model and a temporal database. The model was developed to calculate electricity supply mixes on an hourly basis, and to evaluate the Swiss hourly supply mix and DLCA of electricity used in Swiss buildings.

While in such tool the electricity supply mix includes electricity imports alongside domestic electricity production, without distinguishing between the exported electricity and that one which is supplied domestically (Model M2 from (Menard and Gantner, 1998)), in the present study it is assumed that exported electricity originates from domestic power plants, and that imported electricity is exclusively utilized within the importing country's electricity supply (Model M3 from (Menard and Gantner, 1998)).

Other tools are the DyPLCA tool and Temporalis software that present earlier efforts in dynamic LCA.

DyPLCA (DyPLCA Environmental Assessment of Dynamic Processes - Considering Time Dependency in Life Cycle Assessment [WWW Document], 2024) tool enables DLCA calculations, utilizing a dynamic life cycle inventory model and a temporal database. Temporalis is an open source for dynamic LCA (Temporalis: An Open Source Software for Dynamic LCA [WWW Document], 2024) on enhancing the resolution in inventory and emission characterization within LCA. Dynamic models in LCA have appeared recently to face some lacks in conventional static approaches, considering the temporal dimension in each process unit, leading often to different outcomes from the static model application.

Many studies investigate on medium- and long-term scenarios of electricity generation and building energy demand, while few studies are focused on intra-annual variations of operational electricity demand and electricity mix (Collinge et al., 2013). This aspect has been neglected in conventional analyses that generally rely on generic annual average data.

However, considering short-term variations using high-resolution data is relevant to address differences, such as between peak and base load hours, or from one season to another (Kiss et al., 2020). The study

(Peuportier and Roux, 2023) shows that the analysis of French mix using a static approach can lead to an error of up to 40 % in the estimation of greenhouse gas (GHG) emissions. Another study (Romano, 2023) emphasizes the importance of hourly emissions factors to assess the GHG footprint of electricity usages with seasonal profiles. This aspect has been neglected in conventional analyses that generally rely on generic annual average data.

Hourly analysis studies can indeed be utilized for mitigating the impacts of the hourly phase in buildings. In Vuarroz et al. (2018) an energy management procedure (EMP) in buildings is proposed to consider the reduction of the Global Warming Potential (GWP) using hourly conversion factors for grid, renewable source and storage. Our study diverges from the author's approach by concentrating on the specific hourly impacts of individual energy sources, rather than the broader energy grid perspective the author discusses.

Vuarroz (2021) focuses on the life-cycle impacts of energy storage systems in high-performance buildings. He proposes a methodology for determining the balance between the additional environmental impacts of energy storage systems and their operational benefits. The study emphasizes the importance of considering life-cycle aspects when implementing energy storage in buildings, particularly for ensuring sustainability. The approach is tested in a case study of a high-performance building in Switzerland. The study finds that integrating energy storage can mitigate greenhouse gas emissions and primary energy usage, but its economic viability depends on the continual reduction of battery costs. The research contributes to understanding the life-cycle characteristics of energy storage in buildings and their implications for sustainability but the results are strongly influenced by the geographical context.

Karl et al. (2019) points out that the neglect of temporal variations is one of the most relevant drawbacks and shortcomings of LCA. They account for the source variations in electricity production using electricity grid data at high temporal resolutions. The results indicate that the building environmental performances are related to the data resolution of the grid composition and can be overestimated when compared with conventional grid data (annual resolution).

Some studies underline that the most reliable way to assess the environmental performance of a building is to introduce dynamic aspects in order to track the possible variations throughout the building lifetime (Anand and Amor, 2017; Sohn et al., 2017). Asdrubali et al. (2020) highlight that the introduction of dynamic parameters within LCA should be done to properly reflect the effects of electricity production decarbonization in the life cycle impacts of buildings. A crucial aspect of this dynamic approach is the emission factors which, as highlighted by (Balouktsi and Birgisdottir, 2023), need regular updates, ensuring that the LCA reflects current energy production scenarios and policy changes. Furthermore, Malte Schäfer's study (Schäfer, 2023) deepens the discussion on the methodological aspects of calculating national grid emission factors, emphasizing the importance of methodological transparency and the need for standardization in calculating these factors.

In (Herfray and Peuportier, 2012), one of the first studies on this issue, hourly and monthly electricity consumptions of tested buildings are obtained, and the related Global Warming Potential (GWP) is evaluated. Life-cycle inventories linked to electricity production and consumption of a French positive energy building are calculated with a dynamic approach on an hourly time basis. Continuing this research, (Roux et al., 2016) apply the same methodology to three low-energy buildings to assess their environmental performances and acknowledged the discrepancy between static and dynamic LCA results. In this study, taking into consideration temporal variations in the composition of the power grid, the discrepancy between the annual and hourly values results over 30 % for some impact indicators.

In (Vuarroz and Jusselme, 2018) visualization techniques are applied to detect when strategies involving timing optimization of electricity use may be efficient, showing the relevance of hourly impacts

when performing LCA associated to the exploitation of a given building.

Su et al. (2017) propose a theoretical approach on the use of weighting factors, variable over time, in the calculation of the single end-point impact in the life cycle impact assessment step. This approach is applied in (Su et al., 2020) that introduces an innovative model that integrates Building Information Modeling (BIM) with DLCA. This approach aims to provide a more accurate and dynamic evaluation of the environmental impact of buildings, accounting for temporal variations and the entire life cycle. Although primarily focused on the Chinese context and reliant on the accuracy of BIM data, this model is less suitable for studies concentrating only on the operative phase and presents significant insights for the assessment of environmental impacts in NZEBs, enriching the analysis of impacts in a dynamic and integrated context.

Negishi et al. (2018) identified key dynamic characteristics to be considered in building LCA for long-term temporal changes, as technical performances, occupant behaviour, building components, energy production equipment, energy mix, carbon uptake/emission, end of life technologies. They propose a framework, which integrates the time dimension at the level of different steps of LCA, combining existing environmental databases and LCA software with a new dataset enabling temporal behaviours of the building system.

Neves Mosquini et al. (2023) suggest a refined method for enhancing long term DLCA efficiency, focusing on a selective number of dynamic parameters (DPs). This methodology was applied in a specific case study, employing a global Sensitivity Analysis to identify DPs with a significant impact on GWP. The study integrates data from the French environmental product declarations, utilizing this information within the DLCA framework to provide a more streamlined and focused analysis. Literature analysis highlights that few studies are available on LCA dynamic approach, and a very small number of papers concern the building operation impacts related to electricity demand and with short-term changes in consumption and grid composition simultaneously.

Based on the above knowledge, this paper investigates on which electricity generation mix to consider in assessing the energy and environmental performances of buildings' operating step. The main goal is to investigate how high-resolution data can affect the results of LCA studies tailored at energy systems. To this purpose a methodological and data-related approach is provided to model differentiated hourly-based electricity supply mixes to apply in the environmental performance assessment of building use. A Mediterranean NZEB is selected as case study in one reference year of operating phase.

Moreover, the contribution of the paper covers a specific need for complexity within the built environment and specifically to develop definitions, tools and materials to accompany the transition to a decarbonized economy. As pointed out in (Guarino et al., 2023), carbon neutrality and positive energy/negative carbon can have very different meanings and domains of applications/boundaries being investigated. The paper investigates a specific layer of variability of the impact of grid generation on carbon and environmental impacts which is crucial in quantifying the impacts of the urban environment.

Lastly, the paper provides insights on the fluctuations of environmental impacts over time, derived from the electricity demand in building operation, and can support decision makers and researchers in the following fields:

- Strategies for building renovation aimed at enhancing energy efficiency and reducing carbon emissions.
- Load management to achieve a more flexible electricity demand.
- Building sustainability assessments.

3. Materials and methods

A framework to model hourly-based electricity mixes is developed and applied to assess the energy and environmental performances of building operation. A Mediterranean NZEB is selected as case study.

The following subsections describe the implemented methodological framework, which can be recapped in the following steps:

1. Development of dynamic electricity generation mixes (annual, seasonal, and daily), by matching different hourly load profiles of the NZEB under study, with the national hourly electricity mix (Subsection 3.1). Two hourly load profiles are modelled, related to PV plant/battery storage system.
2. To evaluate hourly-based energy and environmental impacts of the above defined mixes by means of a life cycle approach, including a wide set of impact indicators (Subsection 3.2).

3.1. Dynamic electricity mixes

The case study is a residential building in Rome (Italy). It is modelled from Cusenza et al. (2022), from which all the integrated technical systems are taken to be a NZEB in the operation phase and designed to have all electricity end-uses.

As regards the envelope, in the present study the thermal insulation with cellulose fibres is considered. The air conditioning system consists of an air-water heat pump for summer cooling and winter heating demand, and of a heat storage tank. An electric air-water heat pump is installed as auxiliary equipment to the domestic hot water generation system.

The building is equipped with a grid-connected photovoltaic (PV) plant, and the electricity generated from PV, not consumed for the building end uses, is delivered to the grid. Two scenarios of building load profile are modelled:

- Scenario 1 (PV): Electricity consumption for heating, cooling ventilation, lighting, and domestic hot water generation from the grid, and self-consumed electricity generated by a grid connected PV system with a peak power of 10.8 kW.
- Scenario 2 (PV-BS): The same as Scenario 1, including a Li-ion battery storage system, with a nominal capacity of 30 kWh.

Fig. 1 summarizes the main methodological steps, followed in the following paragraphs to analyse the grid-building interaction and to develop the hourly-based electricity mixes for the building load profiles.

3.1.1. Data collection

3.1.1.1. Step 1: Hourly electricity mix. The electricity grid generation mix in Italy is based on thermal power plants fuelled by fossil sources (mainly fossil gas) and renewable energy sources (mainly hydro, solar PV and wind). It still relies on fossil fuels significantly. Specifically, natural gas contributed to about 45 % of the total electricity mix in 2018, whereas renewable energy sources only account on average for 35 %.

The value proposed for GWP is in line with other computations of the GWP for the Italian context, ranging from 0.418 from (Gargiulo et al., 2020) to 0.393 from (Bastos et al., 2023) kg CO_{2eq}/kWh.

For the building electricity generation mixes modelled in this paper, data on the Italian electricity grid with a time resolution of 1 h are gathered from European Network of Transmission System Operators of Electricity (ENTSO-E) platform,² a public online data source for European electricity system data, which provides disaggregated hourly data of the electricity production by energy source (European Commission, 2013).

This allows for the development of a database for Italy of electricity generation mix with an hourly resolution for 2018, which has been

chosen as reference year for reasons of completeness and disaggregation level of energy sources.

The database provides data on national electricity generation for every hour of the year and for different energy sources, such as fossil fuels (coal, natural gas, oil), and renewables (mainly wind, solar, hydro, biomass), and nuclear energy from imports. The hourly share of each energy sources to the grid for each hour is calculated as share from each energy source, dividing the related electricity generation by the total hourly electricity generated by the Italian grid during every hour.

3.1.1.2. Step. 2. Characterization of an instantaneous set of energy generation and consumption data. This step delves into the development of a specific building's energy profile in terms of both its energy consumption and generation. The process involves the following key stages:

- Building Modeling. This stage was performed in (Cusenza et al., 2022).
- Simulation of Energy Systems. The energy systems of the building are simulated over an entire year using TRNSYS, run with 1 h setpoints (Klein et al., 2010). The result is a set of data on electricity generation and consumption, as well as import from the grid, directly from PV and from battery storage system, and export to the grid, at each hour of the year.
- Data Characterization. The data derived from the simulation provides for a granular view of the building's energy profile. Detailed information about how much energy the building generates and consumes at every hour is available.

3.1.2. Computation of the electricity imported from the hourly-based national grid

This procedure is performed on an hourly base, by referring to the specific electricity generation mix at the timestep of interest. Thus, at every timestep, energy balance is carried out between on-site generation, consumption and storage (the last one only in Scenario 2), according to the following equation:

$$E(t) = G(t) - E_c(t) + E_{BS-BL}(t) \quad (1)$$

where:

- $E(t)$ represents the electricity exported/imported at hour t ;
- $G(t)$ represents the electricity generated at hour t ;
- $E_c(t)$ represents the total electricity consumption at hour t ;
- $E_{BS-BL}(t)$ represents the electricity delivered from the battery system to feed the building load at hour t . It is zero in Scenario 1.

The electricity delivered from the battery system is modelled following the procedure described in (Cusenza et al., 2019) in which it is assumed that:

- (1) the PV system always feeds the load first and then, if a surplus is available, the battery system, and lastly the grid;
- (2) the battery storage system cannot be used to feed the grid and vice versa.

The calculation of $E_{BS-BL}(t)$ is described in Eq. (2).

$$E_{BS-BL}(t) = \delta_{SoC}(t) \cdot C(t) \quad (2)$$

where:

- $\delta_{SoC}(t)$ represents the difference of state of charge at the time step (t);
- $C(t)$ represents the battery energy capacity at the time step (t).

If the energy from the photovoltaic system (G) at time ($t - 1$) is lower than the building load (BL) and the state of charge of the battery (SoC) at time ($t-1$) is sufficient to provide an energy flow (E_{BS-BL}) to fully or

² <https://m-transparency.entsoe.eu>.

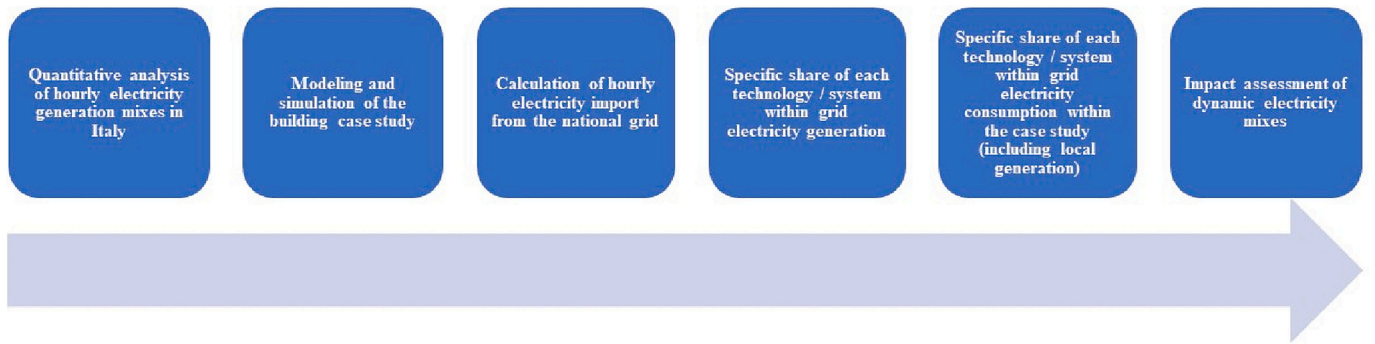


Fig. 1. Main methodological steps.

partially meet the building load, then the state of charge (SoC) is calculated using the Eq. (3):

$$SoC(t) = SoC(t-1) - \frac{El_{BS-BL}(t-1)}{C(t)} \quad (3)$$

where:

- SoC represents the state of charge;
- $El_{BS-BL}(t)$ represents the electricity delivered from the battery system to feed the building load at hour t .

Alternatively, if the energy from the photovoltaic system (G) at time ($t-1$) is greater than the building load (BL), indicating that there is excess energy available to charge the battery system (El_{PV-BL}), and if the state of charge (SoC) at time ($t-1$) is less than the maximum state of charge, then the state of charge (SoC) is calculated using the Eq. (4):

$$SoC(t) = SoC(t-1) + \frac{El_{PV-BL}(t-1) \cdot \varepsilon(t)}{C(t)} \quad (4)$$

where:

- SoC represents the state of charge;
- $El_{PV-BL}(t)$ represents the electricity delivered from the photovoltaic system to feed the battery system;
- $\varepsilon(t)$ represents the battery efficiency corresponding at the time step (t).

Eq. (5), instead, allows the computation of the detailed contributions of the electricity imported from the grid: for every time-step of the analysis the electricity imported is multiplied by the share of each energy generation system on the total electricity generation mix.

$$E_{imp,k}(t) = p_k(t) \cdot E_{imp}(t) \quad (5)$$

where:

- $E_{imp}(t)$ is the electricity imported at hour t and calculated by means of Eq. (1) ($E(t) < 0$);
- $p_k(t)$ is the relative share of electricity generated by each k^{th} electricity generation system on the generation mix total at hour t ;
- $E_{imp,k}(t)$ is the amount of electricity imported from each of the k^{th} electricity generation system at hour t .

This allows to calculate the total share of imported electricity, which is generated by the k^{th} electricity generation system (i.e., solar photovoltaics or fossil gas).

3.1.3. Hourly-based grid electricity mixes

The share of the k^{th} electricity generation system in the imported electricity is calculated by summing all the hourly contributions per the

k^{th} electricity generation system itself and, finally, by dividing the total contribution from each electricity generation system by the total imported electricity in the year. This allows to discern the proportion of energy derived from each electricity generation system in the context of overall imported energy, providing a clear view of the dependency on different electricity generation systems over the course of the year.

The calculation of the relative share of each electricity generation system on the total imported electricity for the case-study at hand is calculated as described before:

$$M_{k,n} = \frac{\sum_{t=1}^n E_{imp,k}(t)}{\sum_{t=1}^n E_{imp}(t)} \quad (6)$$

where:

- $M_{k,n}$ is the energy mix share for the k^{th} electricity generation system in the timestep n .
- $E_{imp,k}(t)$ is the amount of energy imported from each electricity generation system at hour t .
- $E_{imp}(t)$ is the total amount of imported electricity at hour t .
- n is the number of hours, depending on the timestep considered.

This equation allows for determining the hourly-based composition of the electricity mix imported from the grid to meet the residual building demand in a specific interval of time (in the following called building imported electricity mix).

3.1.4. Integrated building/grid electricity generation mix model

This step aims at considering the role of the PV on-site generation and battery storage dynamics in the hourly-based electricity supply mixes used by the case study. To this aim, based on the hourly building simulation on self-consumption and on Eq. (1) results, the total hourly energy consumption $E_c(t)$ at hour t is calculated by means of the following equation:

$$E_c(t) = E_{imp}(t) + E_{PV}(t) + E_{BS}(t) \quad (7)$$

where:

- $E_c(t)$ represents the total energy consumption at hour t ;
- $E_{imp}(t)$ is the amount of electricity imported from the building at hour t .
- $E_{PV}(t)$ is the self-consumed electricity generated by the PV system at hour t .
- $E_{BS}(t)$ is the self-consumed electricity from battery system at hour t .

Summing the contributions of each electricity generation system across a specific time frame within the year, including the onsite electricity generation, both directly from PV system and stored from the battery (Scenario 2) and dividing the sum by the total electricity sup-

plied to the building in that time frame, the electricity share of each electricity generation system is calculated by means of the following equation:

$$M_{k,n} = \frac{\sum_{t=1}^n E_{c,k}(t)}{\sum_{t=1}^n E_c(t)} \quad (8)$$

where:

- $M_{k,n}$ is the mix share for the k^{th} electricity generation system in n hours;
- $E_{c,k}(t)$ is the amount of electricity supplied from each electricity generation system at hour t ;
- $E_c(t)$ represents the total electricity supplied to the building at hour t ;
- n is the number of hours, depending on the timestep considered, varying from 1 to 8760.

Eq. (8) allows for determining the hourly-based composition of the electricity mix supplied to the building (in the following called building consumption electricity mix). Compared to Eq. (6), it includes the shares of the import from the grid at time t , and of the electricity self-consumption from PV and storage systems.

3.2. Energy and environmental impact assessment of the building dynamic electricity mixes

For each electricity mix, the following equation is applied to assess the contribution $I_{j,n}$ to the j^{th} impact category per kWh of electricity supplied to the building in n hours:

$$I_{j,n} = \sum_{k=1}^m I_{k,j} \times M_{k,n} \quad (9)$$

where:

- $I_{k,j}$ (amount/kWh) is the contribution, per kWh supplied by the k^{th} electricity generation system of the electricity mix (see Subsection 3.1), to the j^{th} environmental impact category at midpoint level.
- $M_{k,n}$ is the mix share for the k^{th} electricity generation system in n hours.

Eq. (9) is applied to the electricity mixes in Scenario 1 and Scenario 2. It allows for developing the life cycle energy and environmental impacts of the electricity mixes coupled with building-specific energy production and consumption of equal resolution.

In the context of integrating different energy data sources for Life Cycle Impact Assessment (LCIA), particularly from Ecoinvent and ENTSO-E, the process involves a systematic and analytical approach. Eq. (9) is central to this process, as it evaluates the impact of each kilowatt-hour (kWh) of electricity supplied to a building for the j^{th} environmental impact category. This equation is a crucial link between the energy mix analysis and the LCIA, highlighting the importance of accurately assessing environmental impacts over a specified time frame.

Year 2018 is selected as reference year, aligned with the Ecoinvent v3.8 database, recognized for its detailed and year-specific data. This decision ensures the relevance and accuracy of the analysis, given that the database offers comprehensive information for that particular year.

The integration of data from Ecoinvent and ENTSO-E presents challenges, primarily due to their different approaches in categorizing energy sources. For instance, ENTSO-E generally categorizes biomass and biogas under a single 'biomass' category and does not provide detailed distinctions in cogeneration technologies. To address these discrepancies, the study incorporates detailed data from TERNA, which offers more nuanced categorization, thereby enhancing the quality and

specificity of the analysis.

In terms of photovoltaic energy, Ecoinvent provides data based on installation size and type, such as mono- or polycrystalline. However, TERNA does not supply data segmented by size or type for photovoltaic and wind installations.

This gap necessitates the use of data from GSE (Gestore dei Servizi Energetici), which provides specific information categorized by installation size but does not provide information on energy generation segmented by the type of solar installation. This necessitates an assumption of average values for solar energy to simplify the analysis.

In contrast, for wind energy, the study assumes that data for installations larger than 3 MW is more representative, based on the analysis of GSE.

As regard to the system boundaries, in compliance with the modular structure adopted by the international standards EN 15978:2011 (CEN, 2011) and EN 15804: 2019 (EN, 2019), module B6 is assessed, including all the building energy end-uses. The production step of the building components and plants should be accounted in the modules A1–A3. However, to highlight the role of PV and BS systems, both in terms of positive and negative effects on the building operation impacts, the authors include their production steps in the system boundaries.

Background processes are modelled from international databases and literature data.

The life cycle inventories of the electricity generation systems, contributing to the modelled mixes, are provided by Ecoinvent 3.8, including inventories of grid infrastructure, losses and emissions of distribution and transmission networks.

The dataset Ecoinvent 3.8 "Electricity, low voltage (IT) production, photovoltaic, 3kWp slanted-roof installation, single-Si, panel" dataset is applied to model the PV electricity generation, including the processes related to the production of the PV system components (Wernet et al., 2016). Electricity from PV is directly consumed, stored in battery or exported to the grid.

The BS system is modelled according to (Cusenza et al., 2019). Electricity from battery is only self-consumed by building and not exported to the grid.

Data on grid energy generation mixes and building electricity consumption in 2018 are collected as described in Subsection 3.1. High-resolution data on grid composition are given by ENTSOE. According to reference literature, it is assumed to model electricity mix supply in 2018, including the national hourly production and imports from neighbouring countries³ (Austria, France, Greece, Malta, Slovenia, and Switzerland) minus exports (Frischknecht and Alig, 2021; Itten et al., 2014).

Hourly data on the building electricity consumption cover 1 year-demand for heating, cooling, domestic hot water production, ventilation, lighting, and household appliances.

Based on the most common practice of literature on Life Cycle Impact Assessment (LCIA) of electricity production and on recommendations on LCIA, the energy and environmental midpoint impact categories are assessed by means of the following methods:

- Cumulative Energy Demand non-renewable (CED_{non-ren}), for the calculation of non-renewable primary energy consumption energy (Frischknecht et al., 2007).
- EN 15804 + A2 Method V1.00 for the calculation of environmental impacts, based on the EF 3.0 methodology developed by Fazio et al. (Castellani et al., 2018).

In addition to climate change, the broad set of LCIA indicators are selected and evaluated to avoid the burden shift from one environmental impact category to another. For instance, even if less discussed

³ The breakdown of the energy mix from import into different sources is not considered.

worldwide, the indicator $ADP_{m\&m}$ is particularly relevant in electricity generation from renewable energy sources, particularly in sight of the increasing development of renewables. The assessed impact categories are summarized in Table S1 of Supplementary Material.

4. Results

This section summarizes and discusses the main results, which are structured in the following subsections:

- **Subsection 4.1** presents the dynamic electricity mixes modelled according to the methodology described in **Section 3.1**.
- **Subsection 4.2** describes the energy and environmental impacts induced by the developed electricity mixes per unit of electricity used in 1 year of building operating phase.

4.1. Building dynamic electricity mixes

Annual, seasonal, and daily electricity mixes are developed for the modelled scenarios of building load profile, according to the methodology described in **Section 3.1**.

In order to build a representative dataset for the analysis of grid-building interactions, the following four particular days are statistically identified within an extensive and year-long dataset that contains hourly metrics such as solar radiation and temperature:

- 1) sunny summer day (2018 August 4th) which is the day with the highest solar radiation and temperature;
- 2) cloudy summer day (2018 September 8th), which is the day with the lowest radiation but the highest temperature;
- 3) sunny winter (2018 March 8th), that is the average day with the highest radiation and the lowest temperature;
- 4) cloudy winter day (2018 February 8th) with the lowest radiation and temperature.

Figs. 2 and 3 show, respectively, the hourly-based annual and seasonal electricity mixes used in the two assessed scenarios of building load profile.

On the left of every figure, the building imported electricity mixes, which stem from Eq. (6) (**Section 3.1.4**) are shown. They represent the

hourly-based composition of 1 kWh of the remaining electricity mix imported from the grid for each of the periods considered, net of the self-generation. Such mixes provide insight on the source characterization of the national grid when the building imports from it and are affected from the availability of renewable resources in the imported electricity.

The building consumption electricity mixes, calculated by means of Eq. (8) (**Section 3.1.4**), are shown on the right of **Figs. 2 and 3** and represent the composition of 1 kWh of the annual and seasonal electricity mixes consumed in the building for each of the periods considered. Thus, they highlight the role of the self-consumption from onsite PV generation and of the self-consumption from BS (in scenario 2).

As regard to the building imported electricity mixes, the analysis of the seasonal mixes shows small variations in winter and autumn mixes, compared to the annual mixes (**Fig. 3**).

With regard to the building consumption electricity mixes, self-consumption is always prominent in scenario 2 mixes. In the annual mix it accounts for about 25 % in scenario 1 and 70 % (25 % from PV and 44 % from BS) in scenario 2.

Among the seasonal mixes, the spring and summer ones present the largest shares of self-consumption in both scenarios. In particular, the self-consumption in scenario 2 is about 93 % in summer and 96 % in spring.

In scenario 1 winter and autumn mixes present lower self-consumption shares than the annual ones (11 % and 15 % respectively). As regards to scenario 2, the self-consumption shares for about 40 % (winter) and 54 % (autumn).

In all the examined mixes self-consumption is mostly provided from BS.

The above considerations can be applied to the hourly-based daily mixes, but with more marked variations compared to the seasonal ones, as shown in **Fig. S1** of Supplementary Materials.

4.2. LCIA of the dynamic electricity mixes

4.2.1. LCIA of annual electricity mixes

Table 1 shows the results of the LCIA carried out for the annual electricity mixes in scenario 1 and scenario 2. The impact indicators are calculated according to Eq. (9) and refer to 1 kWh of electricity supplied to the building in 1 year of building operation ($n = 8760$).

The environmental impacts are essentially affected by the fossil fuel components of the electricity mixes presented in the previous section.

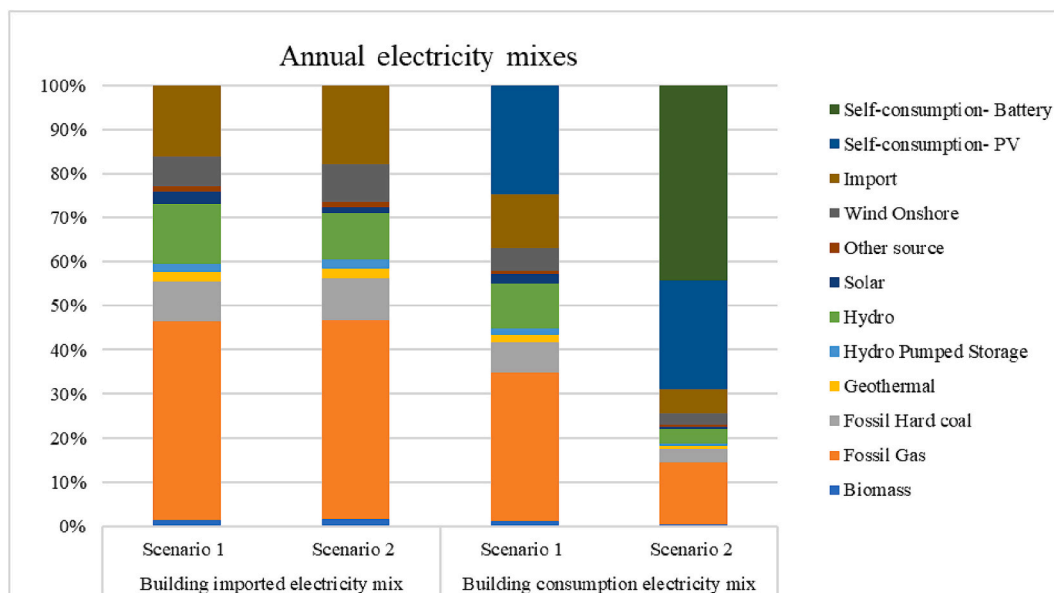


Fig. 2. Hourly based annual electricity mixes.

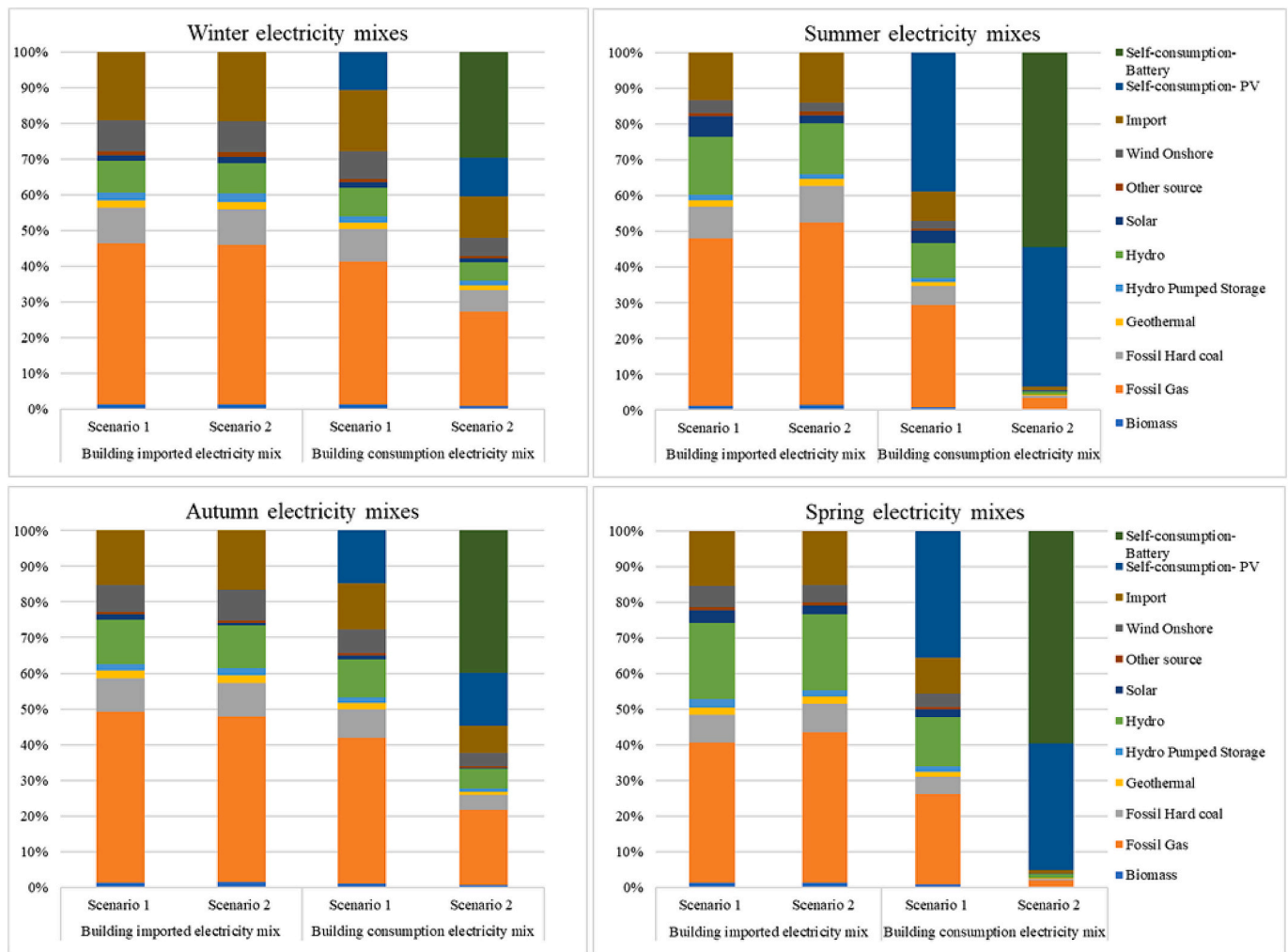


Fig. 3. Hourly based seasonal electricity mixes.

Table 1

Life cycle impacts per kWh of electricity supplied to the building in 1 year.

Impact category	Unit	Building imported electricity mix		Building consumption electricity mix	
		Scenario 1	Scenario 2	Scenario 1	Scenario 2
CC	kg CO _{2eq}	3.84E-01	3.92E-01	3.09E-01	1.67E-01
ODP	kg CFC _{-11eq}	5.40E-08	5.43E-08	4.26E-08	2.02E-08
IR	kBqU ²³⁵ _{eq}	4.96E-02	5.48E-02	3.92E-02	2.23E-02
POCP	kg NMVOC _{eq}	7.96E-04	8.30E-04	6.79E-04	4.25E-04
PM	Disease incidence	4.29E-09	4.52E-09	4.57E-09	4.33E-09
AP	mol H _{eq} ⁺	1.42E-03	1.48E-03	1.22E-03	8.71E-04
EP _{FW}	kg PO _{4eq}	9.35E-05	9.68E-05	8.29E-05	5.41E-05
EP _M	kg N _{eq}	2.40E-04	2.49E-04	2.05E-04	1.28E-04
EP _T	mol N _{eq}	2.51E-03	2.60E-03	2.13E-03	1.32E-03
ADP _{m&m}	kg Sb _{eq}	4.02E-07	3.51E-07	2.14E-06	3.47E-06
CED _{non-ren}	MJ	6.54E+00	6.74E+00	5.20E+00	2.73E+00

As shown in Table 1, all the impact indicators present slight variations from Scenario 1 to Scenario 2 in the residual electricity mixes imported from the grid (the third and the fourth columns). The building electricity consumption mixes (the fifth and the sixth columns) involve significant reduction of almost all the environmental impact indicators in both scenarios, compared to the grid electricity mixes, except for PM and ADP_{m&m} which are related to the production steps of PV and BS

systems.

Here results for CC and CED_{non-ren} are summarized. For each scenario the total value is broken down by energy source in order to identify the share of each of them to the modelled mixes.

In Fig. 4, the contribution to CC of the building annual mixes is shown. In each mix such a contribution is dominated from the fossil sources sharing the mix when the building imports from the grid. In building electricity consumption mixes the contribution of self-consumption arises from the production steps of PV (about 7 % in scenario 1, and 12 % in scenario 2), and from the production step BS system (15 % in scenario 2).

Fig. 5 shows the contribution of the annual electricity mixes to CED_{non-ren}. Due to the similar trend with the contribution to CC, the contribution analysis of seasonal and daily mixes to CED_{non-ren} is shown in Figs. S2 and S3.

Annual imported electricity mixes present similar trend in terms of energy source share. Imports of electricity from abroad contribute to the total CED_{non-ren} for about 20 % in both scenarios. In building consumption electricity mixes CED_{non-ren} from self-consumption accounts for not >5 % of the total CED_{non-ren} in scenario 1 (0.27 MJ/kWh). In scenario 2 it accounts for 24 %, with contributions from PV (10 %) and BS (14 %).

Table 2 presents a comparison between the results obtained from the two DLCA scenarios discussed so far in the paper for the building imported electricity mix (referred to as DLCA Scenario 1 and DLCA Scenario 2) and the standard results that would be obtained using the

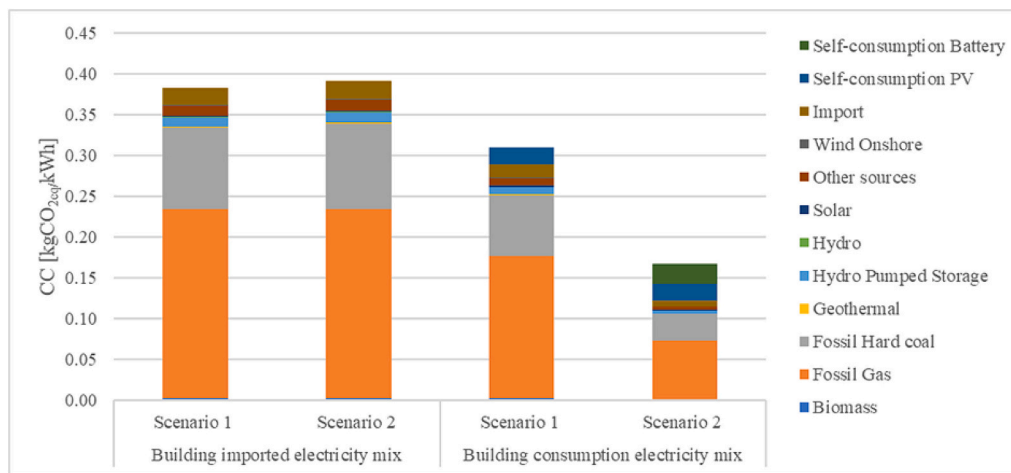


Fig. 4. Climate change of the annual energy generation mixes.

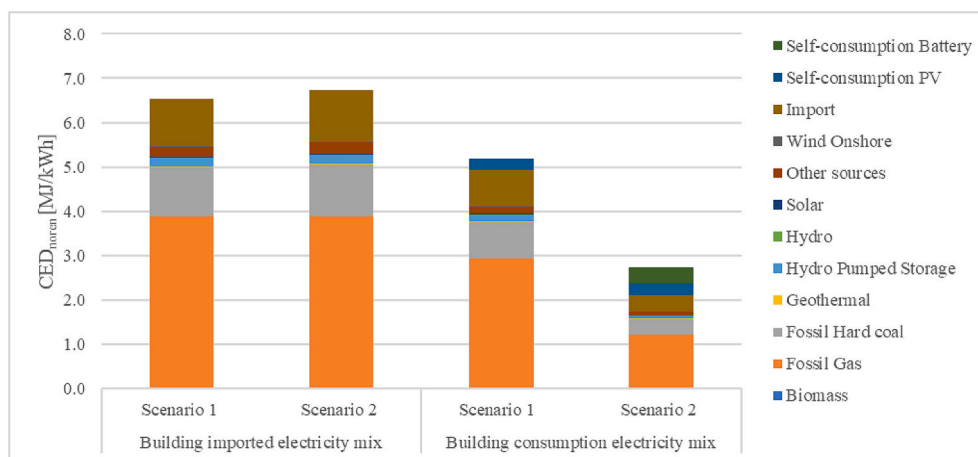


Fig. 5. $CED_{non-ren}$ of the annual energy generation mixes.

Table 2

DLCA and traditional LCA accounting comparison (positive differences imply Scenario standard is higher).

Impact category	Unit	Scenario Standard 1	Scenario DLCA 1	Difference S1	Scenario Standard 2	Scenario DLCA 2	Difference S2
CC	kg CO _{2eq}	3,85E+03	3,83E+03	0,52 %	1,59E+03	1,62E+03	−1,89 %
ODP	kg CFC _{11eq}	5,20E−04	5,39E−04	−3,65 %	2,15E−04	2,25E−04	−4,65 %
IR	kBq U-235 _{eq}	5,22E+02	3,36E+02	35,63 %	2,16E+02	1,42E+02	34,26 %
POCP	kg NMVOC _{eq}	8,64E+00	7,96E+00	7,87 %	3,57E+00	3,43E+00	3,92 %
PM	Disease inc.	7,68E−05	4,29E−05	44,14 %	3,17E−05	1,87E−05	41,01 %
AP	mol H ₂ O _{eq}	1,86E+01	1,42E+01	23,66 %	7,69E+00	6,10E+00	20,68 %
EP _{FW}	kg P _{eq}	9,76E−01	9,34E−01	4,30 %	4,04E−01	4,00E−01	0,99 %
EP _M	kg N _{eq}	2,75E+00	2,40E+00	12,73 %	1,14E+00	1,03E+00	9,65 %
EP _T	mol N _{eq}	3,06E+01	2,51E+01	17,97 %	1,27E+01	1,08E+01	14,96 %
ADP _{m&m}	kg Sb _{eq}	3,73E−02	4,02E−03	89,22 %	1,54E−02	1,45E−03	90,58 %
CED _{non-ren}	MJ	6,24E+04	6,54E+04	−4,81 %	2,58E+04	2,78E+04	−7,75 %

Ecoinvent database.

The Table 2 shows that differences between the standard and the DLCA scenario can be very wide, ranging from very similar results (as seen GWP in scenario 1 with 0.4 % and in scenario 2 with EPFW 0.95 % variations) to the widest differences which can reach up to 90 % (both scenarios for ADPm&m).

4.2.2. Seasonal and daily mixes

Fig. 6 shows the contribution to CC of the seasonal building electricity mixes. The trend observed in the annual imported mixes remains approximatively unchanged in winter and autumn ones, according to

Fig. 3. Higher deviation from the annual value occurs in spring when CC decreases to 0.34 kgCO_{2eq}/kWh in Scenario 1 and to 0.35 kgCO_{2eq}/kWh in Scenario 2. Further, CC reaches the highest value (0.42 kgCO_{2eq}/kWh) in summer in Scenario 2.

The seasonal building consumption electricity mixes are significantly influenced by self-consumption PV and battery storage systems, which involve noticeable reductions compared to the annual mix in both assessed scenarios.

Summer and spring mixes are almost entirely PV-based in scenario 2, which involves lower contribution to CC category impact than scenario 1. The following results are obtained: i) for each scenario there are

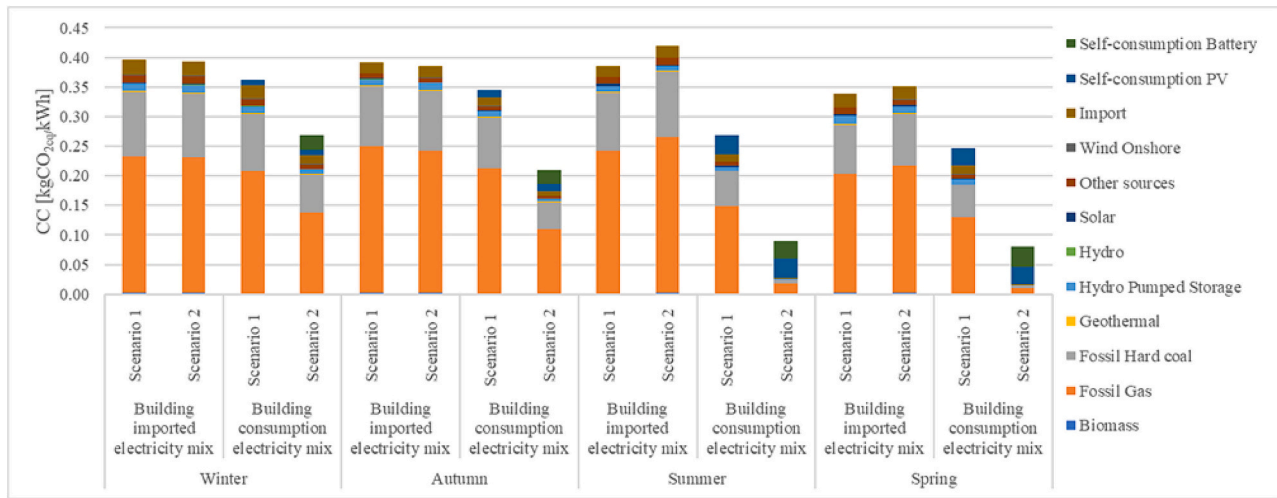


Fig. 6. Climate change of the seasonal energy generation mixes.

significant variations from one season to another and in comparison with the annual building consumption electricity mix; ii) such mixes differ considerably compared to the grid mix ones, with the highest reductions in Scenario 2; iii) the lowest contribution to CC comes from spring and summer mixes in scenario 2 (around 0.09 kgCO_{2eq}/kWh), mostly attributable to the production steps of PV and battery storage system; iv) the highest contribution arises from winter and autumn mixes in scenario 1 (around 0.35 kgCO_{2eq}/kWh), with the closest values to the annual mixes.

In scenario 1, the lowest contribution to CC is around 0.25 kgCO_{2eq}/kWh in spring mix, followed by the CC of the summer mix (0.27 kgCO_{2eq}/kWh). In scenario 2 the summer and the spring mixes present the lowest contributions to CC (<0.1 kgCO_{2eq}/kWh), while winter and autumn mixes display higher values in both scenarios.

Fig. 7 shows the contribution to CC from daily electricity mixes.

The contribution to CC from the building imported electricity mixes overcomes slightly the annual mix in each of the assessed days, showing values around 0.40 kgCO_{2eq}/kWh. This is attributable to the fact that the building imports from the grid when the national electricity mix has higher shares of fossil sources. The two cloudy day-grid electricity mixes present slight increases compared to the annual mix.

The building consumption electricity mixes display the smallest contribution to CC in scenario 2. In particular, the CC impact in both summer day-mixes is about 0.12 kgCO_{2eq}/kWh, to which the production phase of the PV and battery storage systems share for the half.

Conversely, in the winter day-mixes the contribution to CC for scenario 2 (about 0.20 kgCO_{2eq}/kWh) comes mostly from the grid.

Similar considerations can be made looking at the contribution to CED_{non-ren} per kWh of the seasonal mixes and of the daily mixes, which are reported in Figs. S2 and S3 in Supplementary Materials, respectively.

5. Discussion

The framework described and tested in this study offers two approaches to model the building's electricity mixes, including temporal variability of electricity generation and consumption in the related environmental impacts. The first approach allows to consider the share of energy sources in the residual electricity imported from the national grid and puts on evidence that the building electricity induced impacts depend strictly on when electricity is imported and are particularly affected by the discontinuous availability of renewable resources in the national grid when the building imports from it. The second approach, implemented by means of Eq. (8), allows for assessing the correlation between the building's energy demand and time frames of on-site generation and is addressed to provide insights on the role of the self-consumption from PV system (scenario 1) and of the battery storage system (scenario 2) in varying the electricity import from the grid. The application of Eq. (9) provides the eco-profile of the hourly-based electricity mixes, considering the temporal variability of the energy generation systems and the building load throughout the year. It

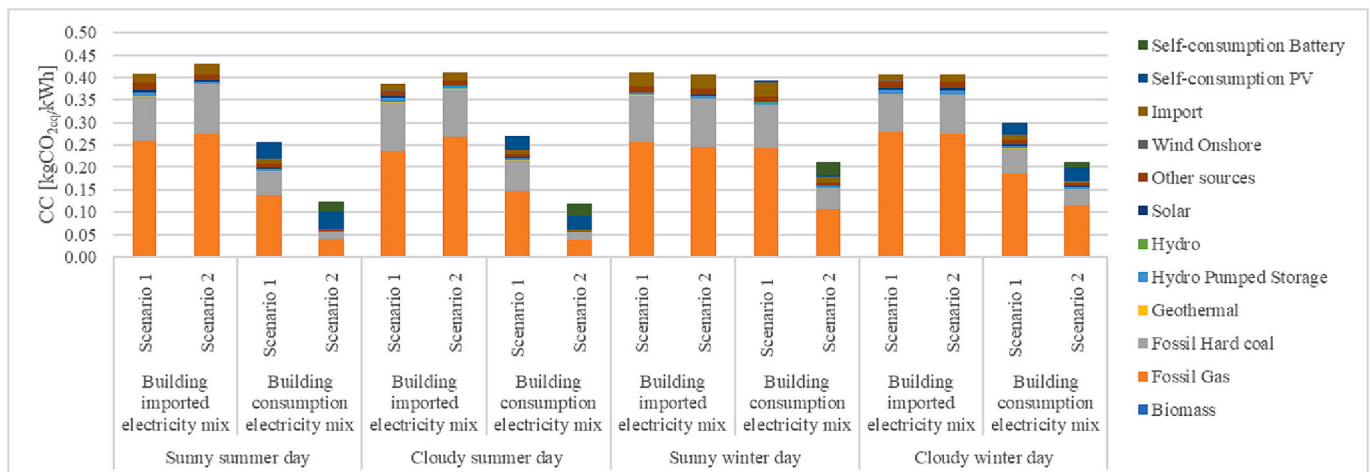


Fig. 7. Climate change of the daily electricity generation mixes.

provides for identifying the entity of the impacts, depending on when electricity is consumed, whether the building relies more on the electricity grid, thus mainly on fossil fuels, or more on the onsite generation.

Tables 3 and 4 give a deeper understanding of the effects of the temporal variations in the eco-profiles of the building electricity mixes, showing the deviation of each environmental impact indicator from the annual score. Scores that are lower than the annual are coloured in green, with different shades of green for the intermediate values. Scores that are much higher than the annual are marked by red. The different shades of light red to pink show intermediate outcomes between the annual and the worst score. The white colour indicates no deviation from the annual score.

For almost all the indicators, the variation trend is similar, except for $ADP_{m\&m}$ and PM.

Building imported electricity mixes present slight differences at seasonal and daily time frames, compared to the annual one, both in terms of energy source shares and of impact scores. This is due to the dominance of fossil sources throughout the year in the national grid composition.

In winter and in autumn, from the building side the PV self-generation is the lowest in the year, and from the grid side, the electricity supplied to the building is mainly based on fossil fuels. In summer and spring, when the onsite self-generation is at the maximum level of the year, the residual electricity is supplied from the grid during the night and the early morning, when the contribution of renewable energy sources comes only from hydro. This is particularly noticeable in seasonal and daily mixes, which delve into the temporal variations of the

renewable energy generation systems and highlight the relevance of the storage system in fulfilling periods of peak demand or low renewable generation.

With regards to CC indicator, the building imported electricity mixes (Table 3) display small increases from the annual one in winter and autumn mixes (3 % in scenario 1 and 0.5 % in scenario 2). Higher deviation from the annual value occurs in spring in (scenario 1: -12 %; scenario 2: -10 %). At daily mix level, the contribution to CC in each of the assessed sunny days overcomes the annual value (sunny summer day: +6 % in scenario 1, and +10 % in scenario 2; sunny winter day: +7 % in scenario 1, and +4 % in scenario 2).

Table 4 shows variations not higher than 20 % and not lower than -38 %, except for $ADP_{m\&m}$, which has the maximum deviation from annual score in cloudy winter day (scenario 1: +48 %; scenario 2: +81 %), essentially attributable to higher solar share in the electricity mix imported from the grid (Fig. S1). In the assessed cloudy winter day, the import occurs mostly during daytime hours, when the share of solar energy source in the grid is higher.

The importance of considering the temporal variations is particularly relevant in building consumption electricity mixes, where the role of self-consumption is pointed out. In such mixes the seasonal analysis allows for highlighting the following considerations. Firstly, for each scenario, summer and spring mixes involve significant reduction of CC and of CEDnon-ren impacts compared to the annual mixes, while in winter and autumn mixes the contributions to CC and to CEDnon-ren overcome the respective annual scores. Secondly, scenario 2 is still the less impacting one in each season. In particular, in spring and summer

Table 3

Deviation in energy and environmental impacts from annual average scores (Building imported electricity mixes).

Scenario 1											
Electricity mix	CC	ODP	IR	POCP	PM	AP	EPFw	EP _M	EP _T	$ADP_{m\&m}$	CED _{non-ren}
Winter	3%	1%	7%	4%	6%	8%	9%	6%	6%	-12%	4%
Autumn	2%	4%	-10%	-3%	-11%	-3%	-11%	-2%	-1%	-16%	1%
Summer	1%	3%	-6%	-2%	-5%	-4%	-3%	-2%	-2%	28%	-1%
Spring	-12%	-12%	9%	-12%	-7%	-10%	-7%	-11%	-11%	3%	-10%
Sunny summer day	6%	10%	-8%	4%	6%	1%	8%	3%	3%	64%	2%
Cloudy summer day	0%	0%	-3%	0%	-3%	-3%	-9%	0%	1%	23%	-5%
Sunny winter day	7%	9%	11%	4%	2%	8%	21%	6%	4%	-36%	5%
Cloudy winter day	6%	17%	-33%	-1%	-3%	-7%	-16%	-4%	-3%	48%	0%
Scenario 2											
Winter	0%	-1%	4%	0%	1%	3%	4%	2%	2%	6%	1%
Autumn	-1%	1%	-5%	-7%	-15%	-6%	-12%	-5%	-4%	-15%	-2%
Summer	7%	11%	-7%	2%	-6%	-2%	-1%	2%	2%	-3%	4%
Spring	-10%	-8%	4%	-14%	-16%	-13%	-12%	-13%	-13%	-2%	-10%
Sunny summer day	10%	14%	-3%	5%	-2%	2%	16%	6%	5%	18%	4%
Cloudy summer day	5%	10%	-8%	-2%	-14%	-7%	-13%	-2%	-3%	-30%	-4%
Sunny winter day	4%	4%	8%	2%	0%	7%	20%	4%	2%	-20%	3%
Cloudy winter day	4%	15%	-38%	-4%	-6%	-8%	-16%	-6%	-5%	81%	-4%

Table 4
Deviation in energy and environmental impacts from annual average scores (Building consumption electricity mixes).

Electricity mix	Scenario 1										
	CC	ODP	IR	POCP	PM	AP	EPF _w	EP _M	EP _T	ADP _{m&m}	CED _{non-ren}
Winter	17%	16%	21%	14%	1%	17%	17%	16%	16%	-48%	19%
Autumn	12%	15%	-1%	4%	-11%	3%	-5%	5%	6%	-35%	12%
Summer	-13%	-13%	-18%	-11%	1%	-12%	-9%	-11%	-12%	50%	-16%
Spring	-20%	-21%	-3%	-16%	-1%	-14%	-11%	-16%	-16%	36%	-20%
Sunny summer day	-17%	-17%	-26%	-13%	9%	-13%	-7%	-13%	-14%	79%	-23%
Cloudy summer day	-12%	-14%	-15%	-9%	1%	-11%	-13%	-9%	-9%	45%	-14%
Sunny winter day	27%	31%	31%	18%	-3%	21%	32%	20%	18%	-69%	28%
Cloudy winter day	-3%	5%	-36%	-7%	0%	-11%	-16%	-9%	-9%	34%	-8%
	Scenario 2										
	CC	ODP	IR	POCP	PM	AP	EPF _w	EP _M	EP _T	ADP _{m&m}	CED _{non-ren}
Winter	56%	67%	53%	38%	1%	32%	35%	40%	41%	-41%	61%
Autumn	25%	34%	19%	12%	-8%	9%	4%	14%	15%	-25%	27%
Summer	-46%	-57%	-42%	-32%	0%	-25%	-26%	-32%	-33%	38%	-51%
Spring	-52%	-65%	-44%	-37%	-2%	-28%	-30%	-37%	-38%	36%	-57%
Sunny summer day	-26%	-31%	-28%	-16%	5%	-15%	-7%	-16%	-17%	40%	-32%
Cloudy summer day	-29%	-36%	-29%	-20%	1%	-17%	-17%	-20%	-20%	29%	-32%
Sunny winter day	27%	32%	28%	15%	-5%	17%	24%	17%	16%	-34%	28%
Cloudy winter day	27%	46%	-16%	15%	4%	6%	6%	14%	15%	4%	22%

periods, when the onsite PV system is at the peak of the production and the electricity imported from the grid is at the minimum level, the CC and CED_{non-ren} reach the lowest scores and show the highest reduction compared to the annual ones. Further, the contribution to such impacts arises in a large extent by the production steps of the PV and BS systems. Conversely, in winter and autumn, when the building's self-consumption is at its lowest and does not meet alone the building electricity demand and the required electricity is supplied from the grid, predominantly running on fossil fuels, scenario 2 presents the highest increases of CC and CED_{non-ren} from annual scores. The analysis of the daily mixes and of the related environmental impacts allows for a more insightful understanding of the interaction between the grid and the building electricity consumption, facilitating the consideration of smaller-scale deviations occurring during the day, as the variations in the imported electricity and the changes in demand of the building from day to night.

Table 4 shows that, for both scenarios almost all the indicators decrease in spring, summer and daily summer mixes, while they grow in autumn, winter and daily winter mixes. In scenario 2 the summer and the spring mixes present the highest reductions in CC compared to the annual mixes (-46 % and -52 %, respectively), while winter and autumn mixes display higher values in both scenarios. This trend is observed also for the other impact indicators, except for ADP_{m&m} and PM.

At daily level, the summer mixes show the highest reduction of CC from the annual values (scenario 1: -17 % in sunny summer day, and

-12 % in cloudy summer day; scenario 2: -26 % in sunny summer day, and -29 % in cloudy summer day).

As regards the winter day mixes, the selected sunny winter day presents the highest import during the hours (late evening and night) when the electricity mix is essentially fossil based, as showed in Fig. 8. This induces, overall, a worse environmental performance respect to the cloudy winter day mix.

PM and ADP_{m&m} follow an opposite trend to the most indicators. While PM presents smaller deviation range from the annual score, ADP_{m&m} has much more significant deviations in both scenarios. The contribution to such an impact category is more relevant in the mixes with higher self-consumption.

From the above results the following findings can be highlighted:

- Hourly resolution data allow for considering periods shorter than one year, so that it is possible to identify the change of electricity mixes in terms of energy source composition, and the effects in the related energy and environmental performances in one day and from a season to another.
- The detected temporal variability of electricity mixes provides more accuracy in the environmental impacts of building operation performances. The assessed temporal variations are significant through the year for the most assessed environmental indicators, thus such variations should be inserted in LCA of buildings.
- The conventional practice to carry out LCA studies is based on yearly averaged data and static inventories, neglecting the temporal

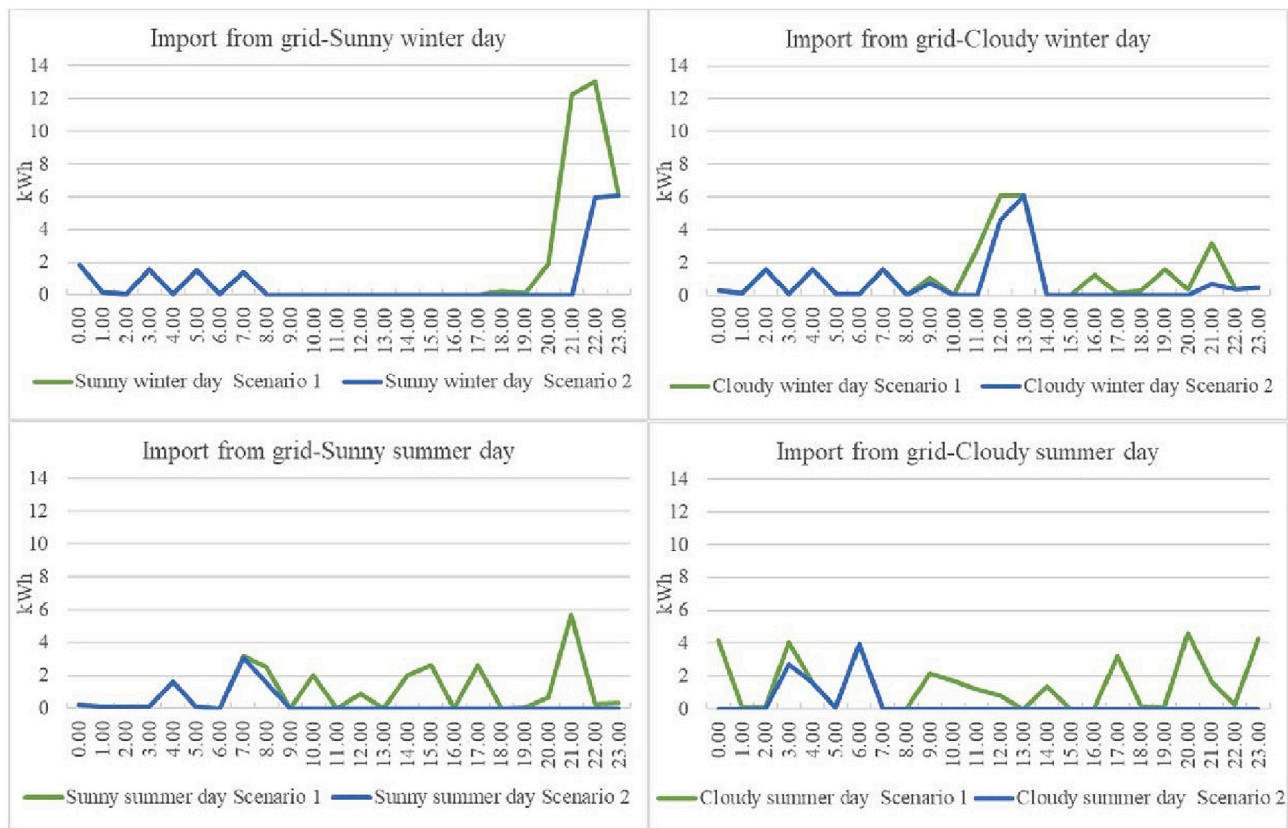


Fig. 8. Daily electricity import from the grid.

fluctuations of the grid composition and the involved unsystematic variations of the electricity-related environmental impacts. The analysis of the eco-profiles of the high-resolution generation mixes allows to identify the effects on the electricity-induced energy and environmental impacts, by aligning them with the actual building electricity mix during a specific time frame.

- The use of high-resolution analysis allows to optimize efficiently the time when using electricity, in sight of energy and environmental impact reduction.

The data presented in Tables 3 and 4 showcase high deviations for each scenario and impact category, emphasizing the necessity of employing hourly data for a precise evaluation of environmental impacts.

In Table 3, variations in $ADP_{m\&m}$ are observed across different days. Specifically, Scenario 1, shows a decrease of 36 %, in sunny winter day mix whereas Scenario 2, shows a substantial increase of 81 % in cloudy winter day mix.

In Table 4, the analysis of $ADP_{m\&m}$ across daily mixes unveils further insights. In Scenario 1, a sunny summer day mix show an increase of 79 %, while there is a decrease of 69 % during sunny winter day within the same scenario. This daily variability highlights the impact of temperature and weather conditions on $ADP_{m\&m}$. Furthermore, in Scenario 2, both winter and spring seasonal mixes exhibit decreases of 61 % and 57 %, respectively.

Finally, the analysis of ODP in Scenario 2 unveils opposite trends across seasons, while winter shows an increase of 67 % in ODP, spring shows a decrease of 65 %. Lastly, investigating dynamic energy generation mixes at the hourly level and integrating them with Life Cycle Assessment (LCA) methodologies marks a pivotal advancement in understanding the intricate interplay between energy consumption and environmental impacts at both the building and grid level. This innovative approach not only offers insights into the temporal variability of

energy generation but also enables a comprehensive evaluation of the environmental footprint associated with different energy sources. Its inherent scalability is however easily clarified by extending beyond individual building assessments to encompass larger spatial scales, including districts.

The utilization of a physics-based mathematical approach in modeling energy flows not only imparts a robust foundation but also underscores significant scalability potential. This adaptability is contingent upon the availability of requisite data, such as smart meters and monitoring devices, thereby positioning the methodology as versatile for broader implementations across varying spatial scales.

Moreover, the conceptual framework seamlessly aligns with the dynamic landscape of Positive Energy Districts (PED) and smart cities. Within this context, the scalability of the methodology emerges as a valuable asset, contributing potentially in a meaningful way to the ongoing discussions on PED definition, in particular to the functional definition of energy and carbon balances to be included in the quantitative assessment of PED performances. As a result, the methodology becomes not only a theoretical construct but a practical and impactful tool for promoting PEDs and the knowledge in the research within the field.

Within the broader scientific domain focused on achieving climate-neutral cities, the methodology assumes a pivotal role in bridging a critical gap. By offering a scientifically sound foundation, it addresses the imperative need to ground environmental impact assessments and city carbon footprint investigations in robust methodologies. As the collective pursuit of climate neutrality gains momentum, the methodology's methodical and rigorous framework could give a quantitative definition of an urban carbon footprint.

6. Conclusions

In this study the proposed methodological framework allows for

detecting the composition of high-resolution electricity mixes in building operating phase, considering the interaction between the grid and the on-site energy generation systems, and for assessing the related energy and environmental impacts throughout the year. High-resolution electricity generation mixes are developed, by matching the national hourly electricity mix with two building hourly load profiles, related to PV plant/battery storage system. The case study is a NZEB, for which high-resolution electricity mixes are developed, starting from the hourly resolution data of the national electricity generation mix and of the case-study energy simulation. Then, life cycle inventories of such electricity generation mixes are modelled, and the related corresponding eco-profiles are assessed,

The methodology outlined is scalable and can be used in different contexts. Key aspects include:

1. Hourly grid electricity mix analysis: The methodology used for analyzing the hourly electricity mix of the grid, including data collection from the ENTSO-E platform and the process of developing a database with hourly resolution, can be applied in any geographical contexts wherever similar data are available, allowing for comparative studies across different geographical locations.
2. Analysis of building energy mixes: The approach to analyse building electricity mixes can be adapted to different grid configurations and building types.
3. Energy and environmental impact assessment: Using Ecoinvent to assess the environmental impacts per kWh of electricity supplied is a method that can be extended to other case studies.

From the comparison with the analysed literature the paper involves original contribution on building dynamic aspects of NZEB operational phase, emission factor utilization, and integration of DLCA with physics-based tools and short term LCA.

The paper presents a common focus on the operational phase with [Vuaroz et al. \(2018\)](#), [Karl et al. \(2019\)](#), [Balouktsi and Birgisdottir \(2023\)](#), [Herfray and Peuportier \(2012\)](#), and [Roux et al. \(2016\)](#). Conversely, studies by [Asdrubali et al. \(2020\)](#), [Su et al. \(2020\)](#), [Negishi et al. \(2018\)](#), [Collinge et al. \(2013\)](#), and [Sohn et al. \(2017\)](#) explore broader life cycle phases, encompassing construction and disposal.

[Su et al. \(2020\)](#), [Karl et al. \(2019\)](#), [Vuaroz et al. \(2018\)](#), [Negishi et al. \(2018\)](#), and [Sohn et al. \(2017\)](#) applied DLCA modeling in standard building, while [Herfray and Peuportier \(2012\)](#) focus on positive buildings and [Roux et al. \(2016\)](#) on low-energy houses.

The use of constant emission factors in the paper aligns with [Schäfer \(2023\)](#), while [Vuaroz et al. \(2018\)](#) explore variable factors, and [Romano \(2023\)](#) and [Balouktsi and Birgisdottir \(2023\)](#) discuss the importance and implications of adopting dynamic factors, highlighting both the potential and uncertainties associated with their implementation.

The presented paper integrates dynamic LCA with physics-based tools while [Su et al. \(2020\)](#) integrate BIM (Building Information Modeling) and dynamic LCA, which proves particularly effective in analyzing life cycle phases beyond the operational phase, such as construction and end-of-life phases.

The paper applies short-term LCA similar to [Peuportier and Roux \(2023\)](#), [Kiss et al. \(2020\)](#), and [Romano \(2023\)](#) while studies like [Negishi et al. \(2018\)](#) and [Moskini et al. \(2023\)](#) adopt long-term approaches.

The study has investigated the potential for detailed insights with the connection to Life Cycle Assessment studies applied to the built environment.

The large variability of the results has highlighted several points of interest which are worth mentioning and discussing for the LCA analysts:

- A building system has several time-related factors to introduce in LCA, among which the composition of the electricity mix consumed in the building itself, depending on the hourly grid composition and

the hourly building load profile. The study reveals that the variations of the building energy and environmental impacts assessed applying high-resolution electricity generation mixes during the year, undetectable in annual average mixes, are not negligible. Such variations highlight the strict connection between the electricity demand from building end-uses and the electricity supply composition available when building consumes.

- While building electricity consumption mixes show eco-profile essentially dependent on self-consumption share and highlight the role of PV and storage systems, the building imported electricity mixes depict the grid composition when building imports the residual electricity from the grid.
- Carbon neutrality is a topic still blurry at the cities and districts implementation level. While the current discussion at the continental level is vibrant and general, some specific points which are often overlooked need further investigation. This is the case for several aspects (e.g., mobility, street lighting, food footprint and industry) as already widely discussed in literature ([Guarino et al., 2023](#)) but for sure the focus on the life cycle perspective is currently lacking. The results highlighted within the paper point out clearly that, when computing environmental analyses of a building, a wider perspective including in-depth variable data on the energy generation at local/grid level, including a life cycle perspective, generates significant variations at the high-resolution level if compared to average data. This should be included in suggestions to stakeholders and be part of the current discussion of climate neutrality at the EU level. This has significant implications also on other domains, specifically to the EU missions for carbon neutrality and even more towards resilience to climate change of regions: energy flexibility applications could be based on similar data to try and explore solutions to minimise environmental impacts by maximizing energy storage when the grid has higher potential impacts. Including also the life cycle perspective is an innovative take on the problem which could be further explored.
- It is a well-known fact that climate change is not the only problem that should concern research in the domain of environmental impacts of the built environment. The paper has clearly highlighted the need for multi-dimensional approaches to the environmental assessment of the built environment: all the indicators proposed had very diverse results which would need specific attention and proposal of tailored solutions to be addressed. These approaches also need to be included in the current debate for carbon neutrality as further discussion elements towards low - impacts cities and districts.
- LCA methodology is often applied as supporting tool in the design of new buildings or of retrofit actions. To support the decarbonisation strategies, dynamic LCA could aid to early assess of different options considering the variations of the parameters influenced by time, such as type of occupancy, energy production equipment, building components, energy mixes. Further, in terms of future research, since buildings have a lifetime of many decades, it should be relevant to assess the variation of the building eco-profile, as consequence of different scenarios of electricity mix for medium and long time horizon.

In considering future directions for this research, several key avenues emerge that can significantly contribute to the advancement of our understanding of dynamic energy generation mixes and their environmental impacts. Firstly, the scale of our methodology will be expanded, transitioning from building-level assessments to comprehensive applications at the district level, particularly within the Positive Energy Districts framework. This extension will not only validate the applicability of our approach but also contribute valuable insights for sustainable urban planning and development.

Secondly, future research endeavors should place a strong emphasis on implementing long-term modifications to the energy generation mixes. This involves accounting for evolving energy systems and

considering climate resilience factors. The adaptability of our methodology to accommodate changes in energy infrastructure over time is essential for providing practical and forward-looking insights into the dynamics of urban energy consumption and its environmental repercussions.

Furthermore, evolution in the field of LCA data represents a crucial area for future exploration. Incorporating variable characterization factors will enhance the accuracy of our environmental impact assessments, providing a more nuanced understanding of the sustainability implications associated with different energy generation sources.

Lastly, future research should delve into the connection between our methodology and energy flexibility considerations.

CRediT authorship contribution statement

Marina Mistretta: Writing – review & editing, Writing – original draft, Validation, Methodology, Formal analysis, Data curation, Conceptualization. **Alberto Brunetti:** Writing – review & editing, Writing – original draft, Validation, Methodology, Formal analysis, Data curation, Conceptualization. **Maurizio Cellura:** Writing – review & editing, Writing – original draft, Validation, Methodology, Formal analysis, Data curation, Conceptualization. **Francesco Guarino:** Writing – review & editing, Writing – original draft, Validation, Methodology, Formal analysis, Data curation, Conceptualization. **Sonia Longo:** Writing – review & editing, Writing – original draft, Validation, Methodology, Formal analysis, Data curation, Conceptualization.

Declaration of competing interest

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

Data availability

Data will be made available on request.

Appendix A. Supplementary data

Supplementary data to this article can be found online at <https://doi.org/10.1016/j.scitotenv.2024.172751>.

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