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D7.2.2 Report on the Sustainability impact

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Abstract for dissemination (PU)

When parked, the batteries of electric vehicles (EVs) can provide grid services and help integrate higher shares of renewable energy, playing a key role in the energy transition. By leveraging these existing batteries, the need for stationary battery electric storage (BESS) may be reduced, avoiding the environmental impacts of manufacturing new BESS. However, most studies neglect the impacts of EV battery production when assessing discharging services.
This study evaluates the environmental performance of uni-directional and smart charging in distributed electricity systems in Belgium, with and without BESS. A comparative life cycle assessment (LCA) is integrated with a multi-energy system model featuring an optimization algorithm. Two use cases are assessed: a micro-level household and a mezzo-level industrial site. Four system configurations are analyzed, combining uni-directional or smart charging with or without BESS. The assessment covers climate change (CC), additional midpoint impact categories from the Environmental Footprint 3.1 method, and grid dependency (GD).

At the micro-level, smart charging with BESS reduces CC impacts by up to 60\%, from 165 to 66 gCO_2eq/kWh. In the mezzo-level system, characterized by high shares of photovoltaic (PV) and wind power, CC impacts are lower overall (34–41 gCO_2eq/kWh), and the benefits of smart charging are less pronounced. GD is reduced from 97% to as low as 17% with smart charging and BESS. Monte Carlo simulations and discernibility analysis confirm result robustness, while sensitivity analysis highlights the importance of system lifetime and grid consumption.

Beyond climate impacts, the analysis reveals burden shifts toward PV and wind technologies, underscoring the need for multi-impact assessments and cleaner upstream processes.

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List of abbreviations

aFRR	Automatic Frequency Restoration Reserve
AF	Allocation factor
ALCA	Attributional LCA
BESS	Stationary battery electric storage
CAPEX	Capital expenditure
CC	Climate change
CCB	Climate change: biogenic
CCF	Climate change: fossil
CCL	Climate change: land use and land use change
CI	Confidence interval
CLCA	Consequential life cycle assessment
CV	Coincidence of variance
DOF	Design optimization framework
EF v3.1	Environmental Footprint version 3.1
EoL	End-of-life
ERR	Energy resources: non-renewable
ESM	Energy system model
ETF	Ecotoxicity: freshwater
EUF	Eutrophication: freshwater
EUM	Eutrophication: marine
EUT	Eutrophication: terrestrial
EV	Electric vehicle
EVB	Electric vehicle battery
GD	Grid dependency
GHG	Greenhouse gas
HTC	Human Toxicity: Carcinogenic
HTCI	Human Toxicity: Carcinogenic, Inorganics
HTCO	Human Toxicity: Carcinogenic, Organics
HTN	Human Toxicity: Non-carcinogenic
HTNI	Human Toxicity: Non-carcinogenic, Inorganics
HTNO	Human Toxicity: Non-carcinogenic, Organics
IPCC	Intergovernmental Panel on Climate Change
IR	Ionising radiation: human health
LCA	Life cycle assessment
LCI	Life cycle inventory
LCIA	Life cycle impact assessment
LFP	Lithium-ion batteries with a cathode made of lithium iron phosphate
LIB	Lithium-ion batteries
LT	Lifetime

LU	Land use
MRM	Material Resources: Metals/Minerals
NCA	Nickel cobalt aluminum oxide
NMC	Lithium-ion batteries with a cathode made of lithium nickel manganese cobalt as cathode material
OD	Ozone Depletion
PLCA	Prospective life cycle assessment
PM	Particulate Matter Formation
POF	Photochemical Ozone Formation: Human Health
PV	Photovoltaic
RES	Renewable energy sources
SF	Sensitivity factor
V2G	Vehicle-to-grid
WT	Wind turbine
WU	Water use

1. Introduction

Electrifying the transport sector is a key strategy adopted by many EU member states to reduce greenhouse gas (GHG) emissions and consequently limit global warming [1]. Over the past decade, electric vehicle (EV) and plug-in hybrid vehicle adoption has steadily increased, representing an increase from below 1 % in 2014 up to 20 % in 2024 [2]. However, most passenger EVs are typically parked and unused for approximately 95 % of the day [3]. This underutilized capacity presents an opportunity to support the energy transition towards a system based on renewable energy sources (RES).

Simultaneously, the decarbonization of the energy sector relies increasingly on variable RES, such as solar and wind, whose intermittent generation presents integration challenges [4]. EVs, with their growing battery capacities, can play a critical role in addressing this variability [5]. Their electricity demand is often flexible and does not need to be met immediately upon plugging in, allowing charging to be shifted to periods of high renewable generation or low electricity prices.

In this context, EVs serve not only as transport mode but also as mobile energy storage, capable of absorbing surplus renewable electricity and allow to introduce flexibility on the demand side. Most EVs remain plugged in for extended periods after arrival, enabling charging strategies that could help guaranteeing security of supply of a larger energy system.

This study investigates two charging strategies: uni-directional and smart charging, with the latter offering flexibility services. Uni-directional charging initiates as soon as the EV is plugged in and continues until the battery reaches full state-of-charge. Smart charging, in contrast, allows for deferring the charging process to a later time, based on predefined criteria such as low electricity prices, renewable overproduction, or off-peak hours [6]. Additionally, smart charging enables electricity discharge from the EV battery back to the grid, a concept referred to as vehicle-to-grid (V2G) [7]. These strategies can enhance renewable integration and reduce electricity system costs [8], [9].

Importantly, the ability of EVs to discharge electricity may provide similar system services as BESS, potentially influencing energy system design. If EVs can substitute for BESS in providing flexibility, the need to install additional BESS may be reduced, thereby lowering overall environmental impacts, given the high burdens associated with BESS production. While many studies assess the technical potential of EV flexibility from a macro-perspective, relatively few evaluate its environmental implications using LCA.

Existing studies primarily focus on assessing the impacts of EVs providing flexibility services at a macro-level, analyzing national or large-scale energy systems. Some of these studies apply LCA in a limited manner, relying on secondary data or lacking detailed reporting [10]. Transparent and comprehensive LCA studies on EV charging strategies exist [11], but they exhibit some gaps. Rovelli et al. (2021) employ an ESM coupled with consequential LCA (CLCA) but focus solely on uni-directional charging, omitting other charging potential. In contrast, Zhao and Baker (2022) evaluate the environmental impact of EV flexibility services but do not integrate an ESM. Wohlschlager et al. (20224) advances the field by considering both macro- and micro-level implications, particularly the impact on EV batteries [12]. A full literature review is presented in the first version of this deliverable "D7.2. Life Cycle Assessment Data Provision".

Despite progress in assessing environmental impacts of EVs providing flexibility services, current research overlooks the fact that different services benefit different user groups and cannot be fully understood at a macro level. A key limitation is the absence of a comprehensive, comparative methodology that evaluates environmental impacts across multiple scales while adjusting scopes to capture actual impacts.

As a consequence, this article investigates, to the authors' knowledge, for the first time a novel, comparative framework to assess the environmental impacts of EVs providing uni-directional and smart charging. This framework is applied to two different scales: first, a micro-level use case, representing a household with PV installations, BESS and EV charging and second, at macro-level size, the system includes PV installations and wind turbines (WT) supported with and without BESS. To capture the full advantage of various charging strategies, the hourly electricity grid mix for Belgium is calculated and integrated in the LCA. Additionally, to explore further the robustness of which charging strategy is preferable, this study complements a Monte Carlo simulation the evaluation assessing background uncertainty. Next to CC impacts, other impact categories are assessed in order to avoid burden shifting. Besides environmental impacts, the study extends the scope to assesses the reliability on grid electricity as an evaluation criteria of the different charging strategies and complementing the comparative framework beyond environmental impacts.

Therefore, this study addresses the four following research questions:

1. How can a comparative framework be defined to support the evaluation of different charging strategies?

2. How can temporally refined life cycle inventory (LCI) data in assessing flexibility services be included?
3. What are the environmental impacts of uni-directional and smart charging strategies provided at different scales?
4. Considering background uncertainty, which charging strategy is favorable?

2. Methods

LCA is a standardized method to quantify environmental impacts of products or services. According to the ISO standard, in an iterative process, it is conducted in five phases: i) goal and scope definition, ii) life cycle inventory analysis, iii) life cycle impact assessment, iv) life cycle impact assessment and v) interpretation [13]. The Section is structured following the first four phases described above.

2.1. Goal and scope definition

The aim of this study is to conduct two different LCAs for revealing the environmental impacts of an energy systems where EVs provide flexibility services. To quantify the environmental impacts related to the flexibility services EVs could provide, two different use cases are defined, taking into account different scales and scopes: a) a micro-level use case, and b) a mezzo-level use case (see Figure 1).

An ALCA is used to evaluate the micro- and mezzo-level use cases. While system-level changes, such as the adoption of smart charging, can potentially influence environmental impacts even at small scale (e.g., by encouraging PV installation), the study models system design from scratch using an optimization algorithm. In this context, all decisions, including PV installation, EV acquisition, and charging strategies, are made simultaneously and are treated as independent inputs to the optimization. Therefore, the analysis does not aim to capture causal relationships or market-mediated effects but rather to quantify the environmental performance of internally consistent system configurations. Furthermore, given the limited scale of the systems analyzed, changes in grid electricity demand of the investigated use cases do not significantly affect the composition of the national Belgian electricity grid mix. The use of ALCA is thus appropriate for the defined decision context. Further background on ALCA and other LCA types is available in [14], [15].

A cradle-to-grave approach comprising raw material extraction, component manufacturing, installation, use and EoL is selected. Figure A7 outlines the research design for the conducted assessment. To quantify the two charging strategies applied at different systems, hourly dispatch data from assets of different nature is investigated applying the design and optimization framework, a Python-based virtual platform developed at the Vrije Universiteit Brussel [16]. In the next step, a cradle-to-grave environmental assessment is conducted using the output data of the framework.

Following the order of Figure Figure A7, the system boundaries, depicted with a grey background, are further detailed in Section 2.1.1. A detailed description of LCI and other data required for the design and optimization framework (DOF) and the LCA is provided in Section 2.2. Section 2.3 outlines the applied LCIA indicators. The method chapter closes with a description on assessments beyond that of static LCA in Section 2.4.

2.1.1. System boundaries

In the micro-level use case, one EV is charged or discharged at four-person Belgian household with a PV installation supported by electricity consumption from the national Belgian electricity mix as visible on the left box of Figure 1. At the micro-level, the EV is providing peak shaving and valley filling service with the objective to increase the self-consumption of PV generated electricity.

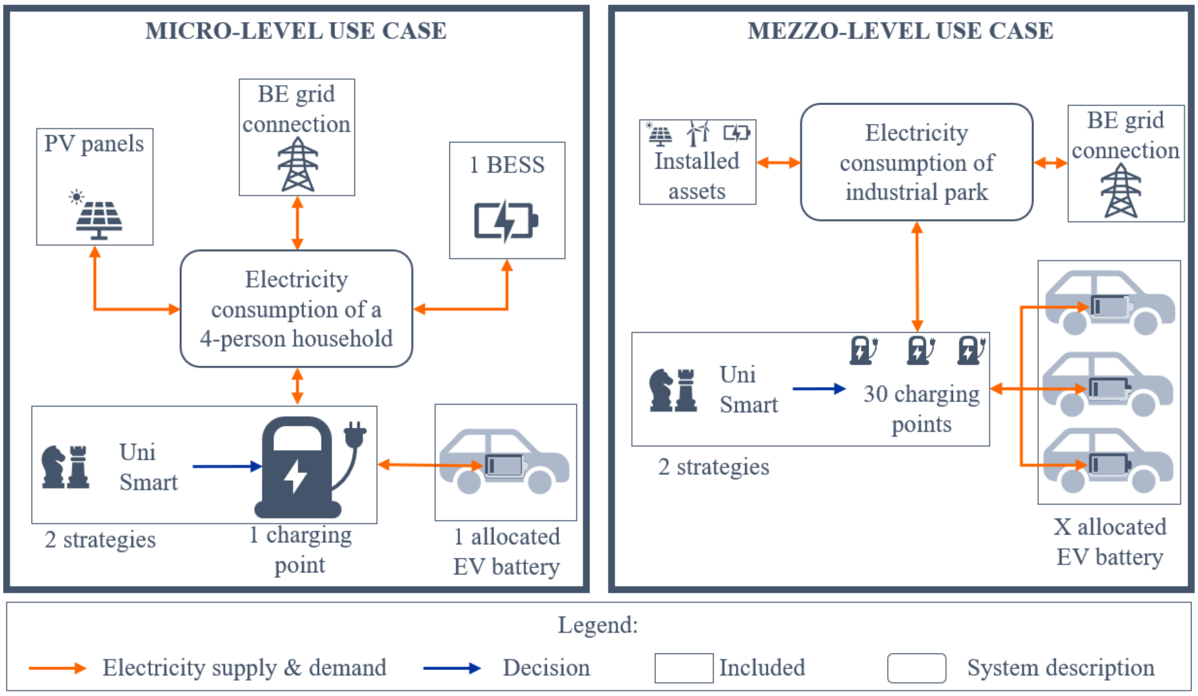

Figure 1: System boundaries to assess flexibility of the micro-level (left side) and mezzo-level use case. (PV = Photovoltaic; BESS = Stationary battery electric storage; ESM = Energy system model; BE = Belgium; LCA = Life cycle assessment; CC = Climate change; EF v3.1 = Environmental Footprint version 3.1; LCIA = Life cycle impact assessment).

As providing the services is technologically already feasible, the year 2023 is selected as time scope. In particular, this means that some electricity normally consumed from the national Belgian electricity mix could be replaced by electricity supplied from the EV. As one potential consequence, at the micro-level, the consumption of national Belgian electricity mix could be reduced and instead more self-generated PV electricity would be consumed, stored in the battery of the EV. Four system configurations with different flexibility services are analysed:

- Uni-directional charging without BESS,
- Uni-directional charging with BESS,
- Smart charging without BESS,
- Smart charging with BESS.

In theory, the described systems are rather simple and so should be the classification of the environmental impacts: there are two systems with and two without a BESS. Logically, the system without BESS should result in lower environmental impacts compared to systems with BESS. However, the interaction between BESS, the EVs and performed charging strategies is more complex, and also directly influences the size of other assets and the grid consumption.

The mezzo-level use case represents an industrial site in Belgium, the VUB's research park located in Zellik, where the electricity supply is, apart from PV installations and national Belgian electricity mix, supported by an additional WT and BESS. Similar to the micro-level use case, the time scope in the mezzo-level use case refers to 2023. At the mezzo-level, the same four charging strategies are investigated, but now at a larger scale with the objective to reveal the importance of scale. Instead of modelling a single EV, 30 charging points are considered at the industrial site, accessible to the public, summarized in the right box of Figure 1. Furthermore, those different charging strategies will result in different system layouts and thus, turn out in different environmental impacts. Hence, to identify whether the environmental impacts of one charging strategy outstand the others, each charging strategy is evaluated considering the environmental impact of the entire system. Therefore, a functional unit of one kWh of generated electricity of four different energy system configurations is chosen.

2.1.2. Allocation

Providing flexibility services does not come for free: an EV is required, in particular its battery to provide the service next to its main purpose to power the vehicle. This multi-functional process presents a challenge in LCA, as those environmental impacts of the process have to be divided between the two services, namely supplying electricity for driving and for energy storage purposes. The ISO 14040 presents solutions to address the problem of environmental impacts of multi-functional processes, among them economic and physical allocation, substitution or system expansion [13].

At the micro-level use case, a physical allocation based on delivered electricity for stationary storage and driving over the battery's lifetime is determined. This allocation factor allows to account for the environmental burden of manufacturing the battery in an EV when modelling systems where smart charging of EVs is performed. Data of electricity charged and discharged is obtained from the framework described in Section 2.2.1. The allocation factor is computed with Equation 1:

$$AF_{flex} \frac{E_{stat}}{E_{stat} + E_{mobile}} \qquad 1$$

Where:

- AF_{flex}: allocation factor for providing flexibility services (\%),
- E_{stat}: discharged electricity for providing flexibility services from the EV battery (kWh/year),

- E_{mobile}: discharged electricity for powering the EV (kWh/year).

The allocation of EV battery impacts at the mezzo-level use case is more complex: Every charging session in theory can be initiated with another EV. The charging points in this use case are public leaving the type of EV and the frequency of charging with the same EV unknown. Thus, summing up the discharged and charged electricity per charger is not feasible in the mezzo-level use case. Instead, the battery manufacturing impacts across a all charging sessions is allocated per unit of electricity discharged. The total electricity charged is calculated for every EV individually based on assumptions and national statistics. Each recorded charging session represents a unique EV. Battery chemistries are assigned stochastically based on 2024 EV sales market shares (LIB with a cathode made of lithium iron phosphate (LFP): 11 %, lithium-ion battery with lithium nickel manganese cobalt as cathode material (NMC) ($LiNi_{0.1}Mn_{0.1}Co_{0.1}O_{0.1}$ (NMC111): 13 %, NMC811 ($LiNi_{0.8}Mn_{0.1}Co_{0.1}O_{2}$) (NMC811): 38~\%, nickel cobalt aluminium oxide (NCA): 38 %), and battery capacities range from 40 to 100 kWh [17]. Each chemistry–capacity pair is linked to a specific manufacturing impact ($kgCO_2eq$). Energy consumption per kilometer is capacity-dependent (own approximations: 0.15–0.18 kWh/km), and a total lifetime millage of 139,587 km is assumed [18]. These inputs allow calculation of a lifetime energy throughput per EV, over which the battery impact is allocated, yielding a normalized value in $kgCO_2eq/kWh$. This value is then multiplied by hourly discharged electricity to attribute impacts dynamically. The compilation of all impacts has already been extensively described in the first deliverable entitled "D7.2 Life Cycle Assessment Data Provision".

2.2. Inventories of small and medium scales

2.2.1. Design and optimization framework

To model the four different system configurations at the micro- and mezzo-level use case, the size and optimization is simulated using a VUB internally developed DOF. The framework aims to simulate and optimize the design and operation of an energy system, based on different electric assets and quantifying its technical, economic and environmental performance. The core of the virtual framework builds an optimization algorithm to reproduce assets modelled based on state-of-the-art from literature and specifically developed models. First, the framework identifies the optimal size of each assets by investigating the power dispatch during the given time. As part of this optimization, various key performance indicators can be selected.

In this study, the minimization of total cost, including investment and operation costs, is selected as objective function. A comprehensive explanation is published by [16], [19]. Additionally, an initial version of this work has already been published, containing further information on the individual methodologies, but also their integration [20]. While more detailed explanations on the framework within the scope of this work is not provided, the following Section 2.2.2 and 2.2.3 describe the input data to simulate the micro- and mezzo-level use case with the framework.

2.2.2. Micro-Level Assessment

The micro-level use case describes a residential, four-person household in Belgium. Example household consumption data on a 15 minutes time resolution for 2022 are obtained from smart meters of a randomly extracted profiles for Flanders, provided by Fluvius [21]. Profiles without heat pumps, EV charging and PV panels are selected to feed the profile as input data into the DOF. The electricity consumption of the selected household is 3,898 kWh per year [21], representing well the average household consumption of 3,500 kWh/year in Belgium [22]. For the micro-level use case, a random consumption profile is extracted out of 1,300 quarter-hourly consumption profiles from the Belgian network operator Fluvius [21]. Additionally, it is assumed, that one EV is charged at the micro-level use case with a battery capacity of 80.3 kWh with an 11 kW charger assuming a 95 % charging efficiency. This charging profile is extracted from [23].

The electricity supply in the micro-level use case is provisioned by PV installations, consumption from the national grid or, in the case BESS is available or smart charging is performed, electricity discharged from the BESS or EV battery. The PV installation is simulated over a lifetime of 25~years, available at a capital expenditure (CAPEX) of 1,000.00 EUR/kWp and has operating costs of 7.50 EUR/kWh. The price of one kWh grid electricity is 0.40 EUR/kWh [24] and has an annual average CC impact of 152.49 gCO_2eq/kWh (source: own calculations). In the case of BESS installations, the price per kWh capacity is 433.00 EUR and a charge/discharge efficiency of 95 % is used [25]. In the micro-level use case, only one BESS based on a LFP chemistry is assumed.

2.2.3. Mezzo-Level Assessment

The mezzo-level use case represents a larger area, comparable to an industrial or commercial site. Data are obtained as described in [20] and sum up to an annual consumption of about 3.4 GWh. Those data do not represent all entities located at the Green Energy Park, but is only selection of available data, which can not be shared due to confidentiality. Instead of a single EV, the simulation assumes 30 charging stations, which are accessible to the public and not restricted to certain EV drivers. While some input data specified in the micro-level use case remained equal in the mezzo-level use case, others are modified and presented hereafter. A lower CAPEX for the PV installation of the mezzo-level use case is used, in particular 850 EUR/kWp [26]. Furthermore, in the mezzo-level use case a lower electricity price of 0.30 EUR/kWh based on average prices for commercial costumers in Flanders [24]. Additionally, a WT is foreseen in the mezzo-level use case with a rated power of 2~MW, a hub height of 78 meters and a rotor diameter of 80 meters. Its CAPEX is set to 2.2 million EUR, with 5 % operating costs of the CAPEX. Its operation is expected to produce electricity over 25 years. Next to the CAPEX of the BESS, a maximum capacity limit of 400 kWh is set for both stationary batteries at the Green Energy Park. Variation of the input data on the DOF output is not part of this work and has already been demonstrated previously [19], and is therefore considered out of scope. Instead, the variation in charging strategies in combination with BESS is resulting in different asset capacities and hence, different electricity generation and supply. The most important input parameters are summarized in Table 1.

Table 1. Common parameters used in the LCA and DOF to simulate the micro- and mezzo-level use case across four system configurations. Presented values are identical for every system configuration (BESS = Stationary battery electric storage; PV = Photovoltaic; WT = Wind turbine; LT = Lifetime; EVB = EV battery; LFP = Lithium-ion batteries with a cathode made of lithium iron phosphate; NMC = Lithium-ion batteries with a cathode lithium nickel manganese cobalt oxide).

Parameter	Unit	System configuration
PV LT	Years	25
WT LT	Years	25
EVB capacity	kWh	80.30
EVB capacity	Kg	518.00
Density – LFP	kWh/kg	0.12

Density – NMC	kWh/kg	0.14
EV LT	Years	9.75
Project LT	Years	25
Lifetime LFP	Years	19
Lifetime NMC	Years	18

2.3. Life cycle impact assessment (LCIA)

Published and coordinated by the European Commission in 2021, the Environmental Footprint version 3.1 (EF v3.1) represents the most up-to-date impact assessment method [27]. It is highly regarded and officially recommended for calculating the Product Environmental Footprint. With 25 impact categories, ranging from climate change and various forms of toxicity to human health, water use, land use, and resource depletion, it enables a more comprehensive representation of environmental impacts than, for example, the climate change category of the Intergovernmental Panel on Climate Change (IPCC) report.

As an initial indication of environmental impacts, this study presents results in the EF v3.1 midpoint impact category climate change. The environmental impacts of different EV charging services are assessed using EF v3.1. A ranking score between 0 and 1 is assigned, where 1 represents the charging case with the highest environmental impact and 0 represents the lowest. Apart from CC impacts, the following impact categories are applied in this study: acidification (AC), climate change: biogenic (CCB), climate change: fossil (CCF), climate change: land use and land use change (CCL), ecotoxicity: freshwater (ETF), energy resources: non-renewable (ERR), eutrophication: freshwater (EUF), eutrophication: marine (EUM), eutrophication: terrestrial (EUT), human toxicity: carcinogenic (HTC), human toxicity: carcinogenic, inorganics (HTCI), human toxicity: carcinogenic, organics (HTCO), human toxicity: non-carcinogenic (HTN), human toxicity: non-carcinogenic, organics (HTNO), human toxicity: non-carcinogenic, inorganics (HTNI), ionising radiation: human health (IR), land use (LU), material resources: metals/minerals (MRM), ozone depletion (OD), particulate matter formation (PM), photochemical oxidant formation: human health (POF), water use (WU).

For a holistic evaluation of the flexibility services, another metric is introduced, namely GD (see Equation 2). This indicator helps to determine how independent the investigated entity is from the national electricity g rid. It is defined as following:

$$GD = \frac{C_{Grid}}{\sum C_{HH/GEP}, C_{BESS}, C_{EV_C}} \qquad 2$$

Where:

- GD = GD (\%)
- C_{Grid} = Grid electricity consumption of the household or the Green Energy Park (kWh)
- $C_{HH/GEP}$ = Electricity consumption of the household or the Green Energy Park (kWh)
- C_{BESS} = Electricity used to charge the stationary battery electric storage (kWh)
- C_{EV_C} = Electricity used to charge the EVs (kWh)

2.4. Uncertainty evolution

To assess the robustness of the developed LCA results, this study employs both uncertainty and sensitivity analyses. These approaches address variability stemming from background data (e.g., inventory databases) and from assumptions in foreground system modeling.
Background uncertainty arises from the use of generic LCI databases, such as ecoinvent. This type of uncertainty is addressed through Monte Carlo simulations with dependent sampling. Due to the reduced modeling complexity in the LCI foreground of energy systems where flexibility services are provided, computational performance allows for 10,000 Monte Carlo iterations. As the re-modelled hourly grid electricity mix does not contain any uncertainty data, for the Monte Carlo simulation it is replaced by the ecoinvent dataset "*market for electricity, low voltage"* for Belgium, enabling the inclusion of uncertainty data. Apart from allowing a holistic Monte Carlo simulation of all activities required per system configuration, exchanging the electricity dataset enables also to draw some conclusions about the influence of using temporally refined LCI, represented by the re-modelled electricity grid mix, and an annual average value, as represented in the ecoinvent dataset. The following statistical descriptors are used to evaluate the results:

- Mean environmental impact
- Standard deviation
- Coincidence of variance (CV)
- 95% confidence interval (CI)

Additionally, minimum, maximum, and percentile values are considered. Given the large sample size and the need for detailed configuration comparisons, a discernibility analysis is applied. Discernibility analysis is a post-hoc, pairwise comparison method used to assess whether observed differences between simulation outcomes are meaningful in light of background uncertainty [28]–[30]. Unlike classical hypothesis testing, this approach does not rely on additional indicator calculation, such as p-values or F-statistics. Instead, the results from Monte Carlo simulations are compared iteratively against a baseline configuration. For each iteration, performance differences that fall within a threshold are considered statistically indistinguishable. The discernibility thresholds (±50 and ±5 gCO_2eq/kWh) are defined by the authors based on the magnitude of total climate change impacts observed in each use case. The highest impact values (~165 gCO_2eq/kWh for the utility-scale case and ~41 gCO_2eq/kWh for the residential-scale case) are rounded up to 200 and 50 gCO_2eq/kWh, respectively. Thresholds are then manually defined as ±50 and ±5 gCO_2eq/kWh to reflect a reasonable margin of discernibility relative to the scale of each system. This allows for identifying configurations that consistently outperform others, as opposed to those whose advantages are masked by uncertainty.

While variance-based methods such as analysis of variance are common in classical statistics, they are less applicable in model-driven LCA contexts, where results often exhibit non-normal distributions and complex interdependencies. In contrast, pairing Monte Carlo simulations with discernibility analysis maintains the full distributional structure of the data and emphasizes practical rather than formal statistical significance.

Complementary to the evaluation of the background uncertainty, foreground uncertainty refers to assumptions made during system modeling and parameterization. This uncertainty is explored using both one-at-a-time sensitivity analysis and perturbation analyses, depending on system complexity. Perturbation analysis is used to assess how marginal changes in parameters influence the model output [28]. Key input parameters are modified by ±10 %, and sensitivity is expressed using a sensitivity factor (SF):

$$SF = \frac{\frac{\Delta R}{R_0}}{\frac{\Delta P}{P_0}} \qquad (3)$$

Where:

- ΔR = change in result
- R_0 = baseline result
- ΔP = change in parameter
- P_0 = baseline parameter

SFs typically range between -1 and 1. Values approaching or exceeding |0.8| indicate high influence and warrant prioritization in future model calibration. For the modeling of flexibility services, a total of 12 parameters modified by ±10 % are tested. Table A6 presents the mapping of micro- and mezzo-level parameters per sensitivity.

3. Results

3.1. Electricity supply

The micro-level use case includes systems with a PV capacity between 2.3 and 2.7 kWp and, in some configurations, a BESS of up to 10.1 kWh.

Figure A12 illustrates the seasonal interaction between PV generation, grid supply, and household demand. In spring and winter, when PV output is low, peak demand is primarily met by grid electricity (top and bottom rows of the subplots). In contrast, summer and autumn exhibit higher PV generation, allowing more demand to be covered locally, particularly in systems equipped with BESS (middle rows).

Table 2. Capacities obtained from the design optimization framework (DOF) for the micro- and mezzo-level use cases and their respective grid dependency (PV = Photovoltaic; BESS = Stationary battery electric storage; source: DOF output and own calculations).

Charging service	PV (kWp)	Wind (kW)	BESS_1 (kWh)	BESS_2 (kWh)	Grid dependency (%)
			MICRO-LEVEL		
Uni – no BESS	2.7	0	0	0	97.0
Uni – BESS	2.7	0	9.5	0	45.7
Smart – no BESS	2.6	0	0	0	89.1
Smart – BESS	2.3	0	10.1	0	36.9
			MEZZO-LEVEL		
Uni – no BESS	1,190.9	2,000	0	0	22.8
Uni – BESS	1,319.8	2,000	300	300	17.2
Smart – no BESS	586.5	2,000	0	0	21.9
Smart – BESS	580.1	2,000	300	300	17.0

The integration of BESS combined with smart charging reduces both peak demand and grid supply during those peaks. Consequently, GD is strongly influenced by the inclusion of BESS. Without BESS, grid reliance remains high, 97.0 % for uni-directional charging and 89.1 % for smart charging. When BESS is introduced, these values drop to 45.7 % and 36.9 %, respectively (see Table 2).

In the uni-directional system without BESS, 226.03 kWh/year of PV-generated electricity must be curtailed. Introducing BESS, especially when combined with smart charging, not only reduces GD and avoids curtailments but also enhances the effective use of installed PV capacity. Full energy balances are provided in Appendix, Table A7.

A key difference in the mezzo-level configurations is the higher PV capacity. Systems with uni-directional charging have 1,191 and 1,320 kWp of PV (without and with BESS, respectively), while smart charging systems have 587 and 580 kWp. All configurations include a 2 MW WT and, in case a BESS is included, its capacity mounts up to 600 kWh per system, equally divided between LFP and NMC chemistries.

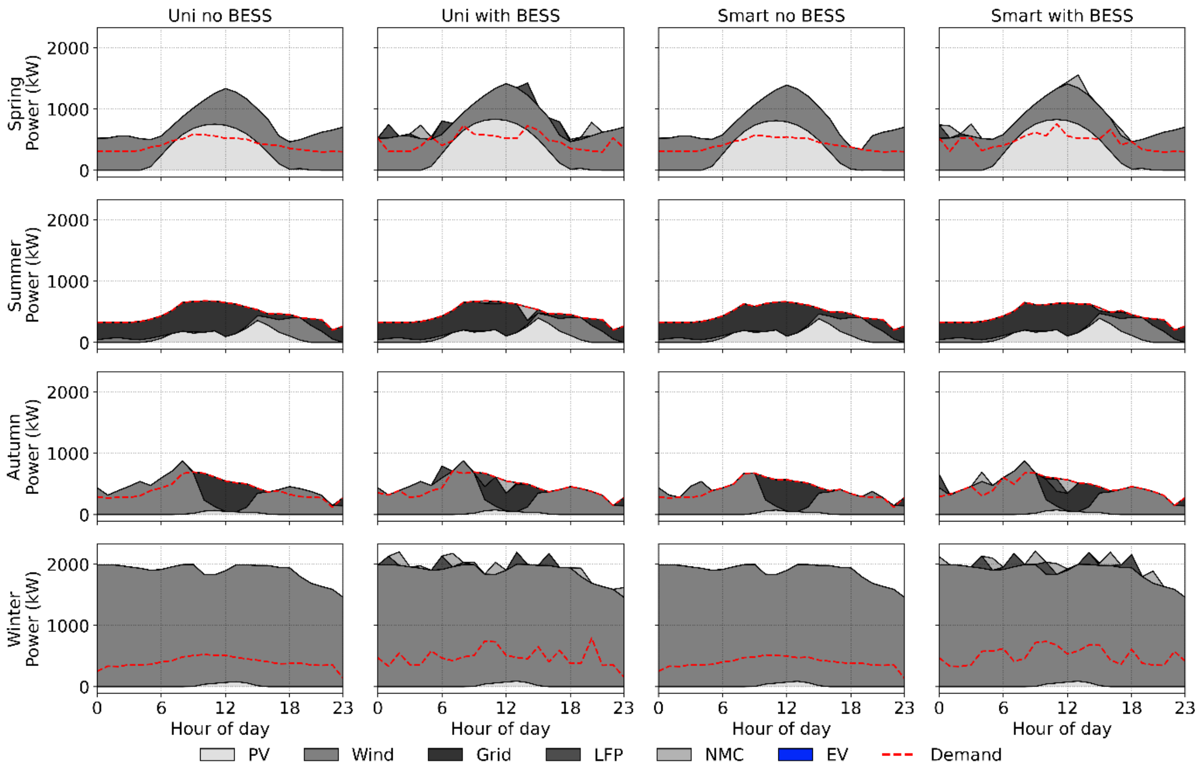

Figure 2: Hourly electricity supply and demand of the GEP in the mezzo-level use case for four representative days in spring (2023-03-20), summer (2023-07-17), autumn (2023-10-09), and winter (2023-12-15) (GEP = Green Energy Park; BESS = Stationary battery electric storage; PV = Photovoltaic; LFP = Lithium-ion batteries with a cathode made of lithium iron phosphate; NMC = Lithium-ion batteries with a cathode made of lithium nickel manganese cobalt oxide; EV = Electric vehicle).

Figure 2illustrates the complementary nature of wind and solar generation across seasons. In spring and autumn, high wind output leads to renewable electricity surpluses. During summer, reduced wind availability in off-peak hours is offset by high daytime PV production. In winter, limited solar irradiation and low wind availability result in higher grid imports. Notably, EV batteries are only little or not at all discharged on the selected day.

Due to the combined RES capacity, mezzo-level systems exhibit considerably lower GD than micro-level systems. The highest observed value is 22.8 % (uni-directional without BESS), while smart charging without BESS performs similarly at 21.9 %. Adding BESS reduces GD further to 17.2 % and 17.0 % for uni-directional and smart charging systems, respectively (see Table 2).

However, in the smart charging case without BESS, curtailment of wind-generated electricity reaches up to 66,855.95 kWh/year. By incorporating a BESS in the same system, curtailment is reduced to 2,776.34 kWh annually. This indicates that smart charging at sites with high RES potential, particularly when supported by BESS, not only minimizes curtailments but also results in the lowest GD. Although the inclusion of BESS reduces curtailment, the GD sees a more modest reduction. This is because the curtailed electricity represents only a small fraction of the site's total electricity demand, limiting the potential for curtailment recovery to offset grid imports completely. A complete overview of electricity generation and supply is provided in Appendix, Table A9.

This analysis reveals great differences in energy self-sufficiency between micro- and mezzo-level systems. Micro-level configurations are heavily influenced by seasonal PV variability and show substantial reductions in GD only when BESS is integrated. In contrast, mezzo-level systems benefit from the synergies of wind and solar power, achieving lower GD overall. Moreover, these systems exemplify a pathway toward highly decarbonized energy systems. Smart charging and BESS improve performance across both scales, underlining their importance in enhancing system flexibility and grid resilience. The results of the improved LCI data is described in the Appendix.

3.2. Contribution analysis

In the micro-level use case, the CC impact per kWh of electricity generated is highest for the configuration using uni-directional charging without BESS, reaching 165 gCO_2eq/kWh (Figure 3). Introducing smart charging reduces CC impacts by over 22 %. Across all charging strategies, grid electricity remains the main contributor, accounting for 76-90 % of total CC impacts. The second-largest contributor is PV installations, though their contribution is substantially lower. In the system with BESS, PV contributes up to 13 gCO_2eq/kWh. The impacts from BESS and EV batteries together represent only 4-6 % of total CC impacts.

Despite the added emissions from battery production, installing a BESS leads to overall reductions in CC impacts due to decreased reliance on grid electricity. The lowest CC impact (65 gCO_2eq/kWh) occurs in the configuration combining smart charging with BESS. This represents a 60 % reduction compared to the uni-directional, no-BESS baseline. For context, the average CC impact of the Belgian electricity grid is 153 gCO_2eq/kWh, indicating that a PV-coupled system with uni-directional charging performs worse than the existing grid. In contrast, combining smart charging and BESS can lower impacts by up to 61 %, highlighting the environmental advantage of flexible, storage-supported configurations.

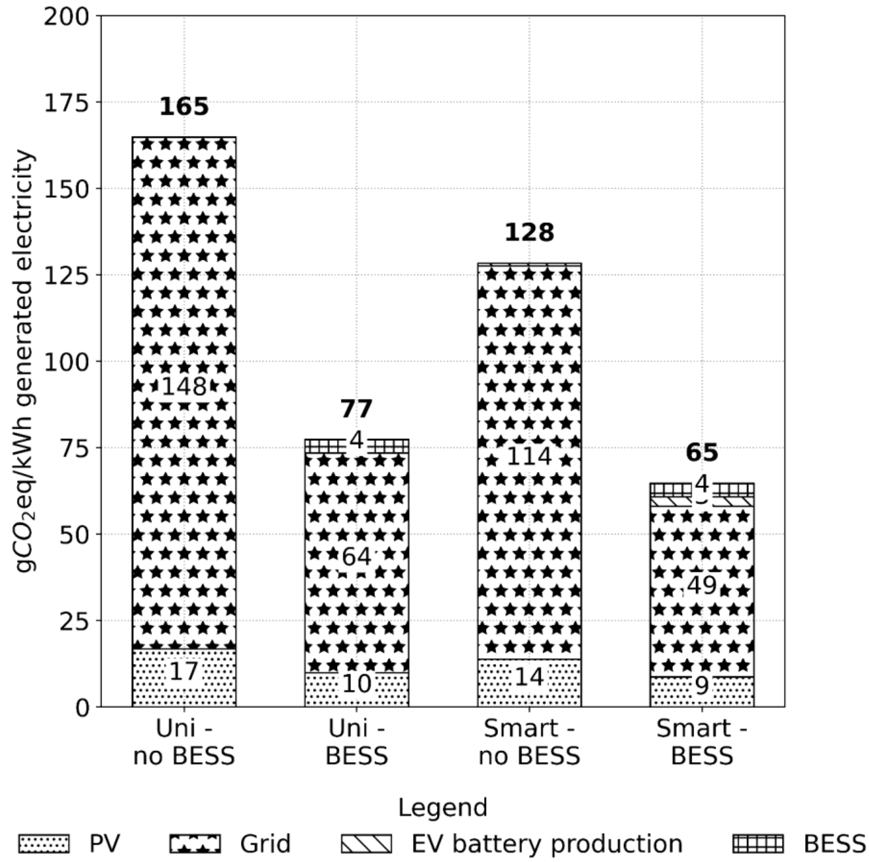

Figure 3: Contribution to climate change impact of assets at a micro-level electricity system in Belgium (PV = Photovoltaic installations; EV = Allocated impact of manufacturing a battery for an electric vehicle; BESS = stationary battery electric storage).

Compared to the micro-level use case, CC impacts are lower across all system configurations at the mezzo level. For instance, uni-directional charging without BESS results in 41 gCO_2eq/kWh, compared to 165 gCO_2eq/kWh at the micro level. Additionally, the variation in CC impacts across configurations is relatively small, ranging from 32 to 41 gCO_2eq/kWh, indicating lower performance variability. Among the configurations, smart charging with BESS performs best, achieving a 21~\% reduction in CC impacts relative to the baseline (uni-directional without BESS). Smart charging without BESS and uni-directional charging with BESS both result in 36 gCO_2eq/kWh, representing 13 % and 12 % reductions respectively. While BESS integration introduces additional emissions from battery production, its impact remains limited. An analysis of the contributions to CC impacts confirms that the electricity grid remains the dominant source (Figure A18). In the smart charging configuration without BESS, grid electricity contributes 69 %, followed by wind (20 %) and PV (11 %). With BESS, the grid share declines to 65 %, while wind and PV contributions rise to 23 % and 11 %, respectively. BESS technologies (LFP and NMC) together contribute around 1 % or less. In the uni-directional with BESS configuration, PV and wind each contribute around 21 % and 20 %, with the grid reduced to 58 %. Without BESS, grid consumption increases to 62 %, with PV and wind each contributing 19 %. EV battery contributions remain negligible across all configurations.

Benchmarking these results against the average Belgian grid mix (153 gCO_2eq/kWh), all configurations yield substantial environmental improvements, reducing impacts by over 110 gCO_2eq/kWh. These findings highlight the environmental benefits of the proposed energy system designs, even without BESS integration.

3.3. Uncertainty evaluation

3.3.1. Global uncertainty assessment

For the Monte Carlo simulation, the re-modelled hourly grid mix was substituted with the ecoinvent dataset "*market for electricity, low voltage*" for Belgium, enabling the inclusion of uncertainty data. The results confirm the trend observed in the static LCA: systems with uni-directional charging and no BESS exhibit the highest mean CC impact (230 gCO_2eq/kWh). Adding BESS lowers this to 104 gCO_2eq/kWh, the lowest among all configurations. Switching to smart charging reduces the impact to 178 gCO_2eq/kWh (without BESS) and 146 gCO_2eq/kWh (with BESS).

Only the uni-directional, no-BESS configuration exceeds the mean CC impact of the current Belgian electricity mix (206 gCO_2eq/kWh); all others perform better. Standard deviations range from 5 to 12 gCO_2eq/kWh, with *Uni - no BESS* showing the highest variability (SD = 12), and *Uni - BESS* the lowest (SD = 5). Despite these standard deviations, the 95 % CI remain narrow, typically within ±1 gCO_2eq/kWh (Figure A13).

The Monte Carlo mean values are 25-50 gCO_2eq/kWh higher than the corresponding static LCA values. While this difference could stem from model structure, a more likely explanation lies in the electricity dataset: the static model uses hourly values, whereas average ecoinvent dataset is included in the Monte Carlo simulation, which differs 50 gCO_2eq/kWh. Given the dominance of grid electricity in micro-level systems, this substitution likely explains the divergence.

Additionally, normalization per kWh compresses the output variance, resulting in artificially narrow CI. This effect is clarified by comparing normalized and unnormalized distributions (Figure A15), which show a broader spread in absolute (unnormalized) terms.

Because the distributions of different configurations partly overlap, their environmental performance cannot be fully distinguished in the Monte Carlo plot in Figure A13. To address this, a discernibility analysis is conducted, using a threshold of ±50 gCO_2eq/kWh to assess whether performance differences between configurations are statistically meaningful (see Figure 4).

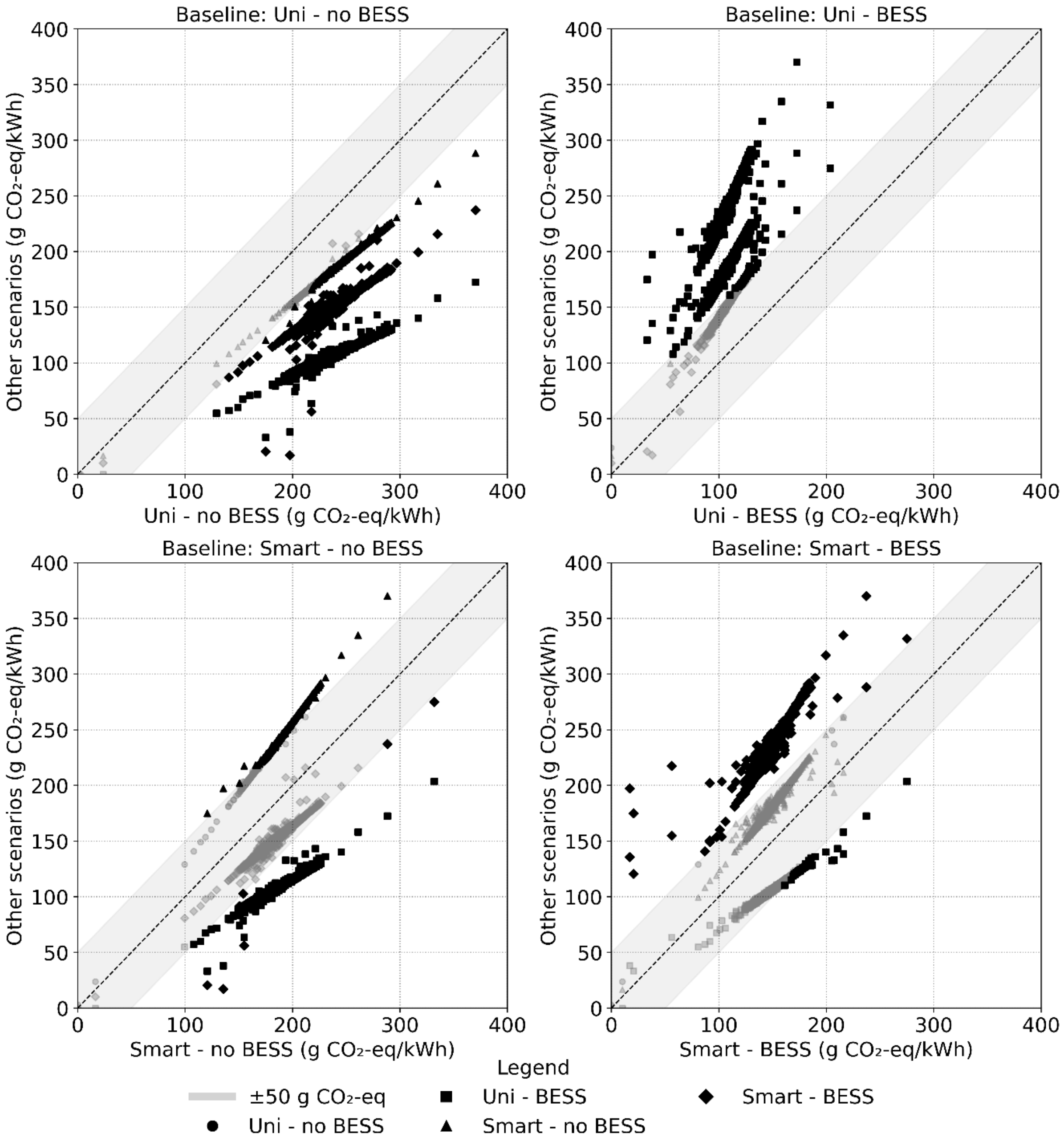

Figure 4: Discernibility analysis comparing climate change impacts (g CO_2eq/kWh) across four flexibility configurations in a micro-level electricity system in Belgium. Each point represents one of 10,000 Monte Carlo iterations. The diagonal line indicates equal performance; the grey band (±50 gCO_2eq/kWh) marks the threshold for discernible differences. Each subplot uses a different configuration as the baseline on the x-axis (BESS = Stationary battery electric storage).

In summary, while the normalized Monte Carlo results support the static model findings, confirming that smart charging with BESS performs best, further analysis is required to assess the smaller differences. To this end, a discernibility analysis is conducted to test whether observed differences are statistically meaningful.

Based on the discernibility analysis presented in Figure 4 and Table 3, the following conclusions can be drawn:

- Baseline: **Uni – no BESS**
    - *Uni – BESS* has lower CC impacts in 99.9% of cases.
    - *Smart – no BESS* has lower CC impacts in 69.0% of iterations and similar impacts in 31.0%.
    - *Smart – BESS* has in almost all iterations lower CC impacts, in particular 99.9% and in 0.1% similar CC impacts.
- Baseline: **Uni – BESS**
    - *Uni – no BESS* has in 99.9% of cases higher CC impacts.
    - *Smart – no BESS* has in 99.9% of iterations higher CC impacts and in only 0.1% of iterations similar.
    - *Smart – BESS* is statistically indistinct, with 99.1% of iterations resulting in similar CC impacts and 0.9% of iterations in lower CC impacts.
- Baseline: **Smart – no BESS**
    - *Uni – no BESS* has in 69.0% of iterations higher CC impacts and in 31.0% of iterations similar CC impacts.
    - *Uni – BESS* shows strong improvement, with 99.9% of the iterations resulting in lower CC impacts.
    - *Smart – BESS* results in largely similar CC impacts, with 99.9% of iterations within the discernibility band.
- Baseline: **Smart – BESS**
    - *Uni – no BESS* has in 99.9% of all iterations higher CC impacts.
    - *Uni – BESS* results in 99.1% of all iterations in similar CC impacts and slightly lower CC impacts in 0.9% of iterations.

- *Smart – no BESS* is yielding similar CC impacts in almost all iterations (99.9%), with 0.1% of iterations resulting in higher CC impacts.

The discernibility analysis at the micro level shows that **Smart – BESS** consistently provides the lowest CC impacts, outperforming *Uni – no BESS* in all cases and surpassing *Uni – BESS* and *Smart – no BESS* in about 99% of iterations. *Uni – BESS* also results in lower CC impacts compared to *Uni – no BESS*, while *Smart – no BESS* shows only partially lower CC impacts, outperforming *Uni – no BESS* in around 69% of cases but being statistically indistinct from *Uni – BESS*. Comparisons of CC impacts between *Uni – BESS* and *Smart – no BESS* are fully within the discernibility threshold, suggesting equivalence. Overall, the analysis confirms that **Smart – BESS** offers a robust advantage at the micro level, while differences between *Uni – BESS* and *Smart – no BESS* are not statistically meaningful.

Table 3. Overview of discernability quantification for the micro-level use case. Results are based on the outcome of the Monte Carlo simulation (source: own calculation).

Baseline	Compared scenario	Better than default (%)	Similar (±50 g) (%)	Worse than default (%)
Uni – no BESS	Uni – BESS	99.90	0.00	0.00
	Smart – no BESS	69.00	31.00	0.00
	Smart – BESS	99.90	0.10	0.00
Uni – BESS	Uni – no BESS	0.00	0.00	99.90
	Smart – no BESS	0.00	0.10	99.90
	Smart – BESS	0.00	99.10	0.90
Smart – no BESS	Uni – no BESS	0.00	31.00	69.00
	Uni – BESS	99.90	0.10	0.00
	Smart – BESS	0.10	99.90	0.00
Smart – BESS	Uni – no BESS	0.00	0.10	99.90
	Uni – BESS	0.90	99.10	0.00
	Smart – no BESS	0.00	99.90	0.10

Overall, the micro-level analysis confirms that integrating smart charging and/or BESS consistently reduces CC impacts, with *Smart - BESS* offering the most robust performance.

For the mezzo-level use case, Figure A19 shows the normalized outcomes: smart charging with BESS achieves the lowest mean impact (35 gCO_2eq/kWh), followed by smart charging without BESS and uni-directional with BESS (both 40 gCO_2eq/kWh), and uni-directional without

BESS (45 gCO_2eq/kWh). These trends are consistent with the static LCA results (Section 3.2). However, none of the static results fall within the 95 % CI. One likely reason for this could be the use of a different electricity dataset in the simulation: the ecoinvent "market for electricity, low voltage" (BE), which results in higher impacts than the modeled hourly mix.

The narrow CI (e.g., [40, 40] or [34, 35]) suggest an artificially high level of certainty. One reason for this could be due to normalization per kilowatt-hour, which compresses output variability. Consequently, the CI presented in Figure A19 do not reflect the full system-level uncertainty. To address this, unnormalized CC impact distributions are also evaluated (Figure 5 and Figure A20), which show greater variation. Standard deviations remain substantial (13-14 gCO_2eq/kWh), and the overlap in means (e.g., 40 gCO_2eq/kWh for both smart no BESS and uni-directional with BESS) confirms these configurations are statistically indistinct. Both normalized and unnormalized results of the mezzo-level use case are visualized in Figure 5.

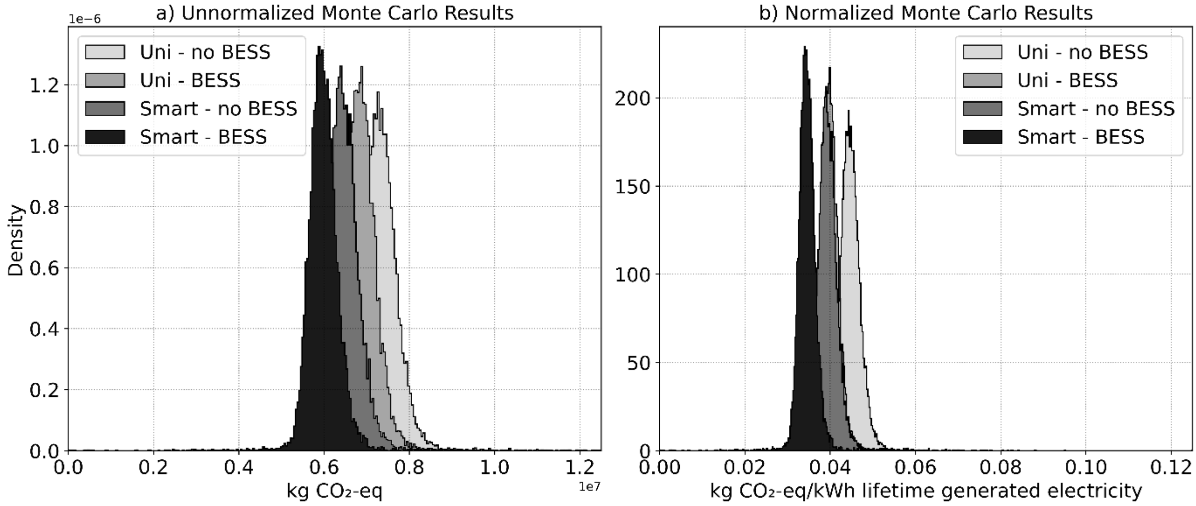

Figure 5: Comparison of normalized (per kWh) and unnormalized (total) distributions of climate change impact for four flexibility configurations in a mezzo-level electricity system in Belgium. Results are based on 10,000 Monte Carlo simulations.

Descriptive statistics of the mezzo-level use cases are presented in Table A10. Notably, the Monte Carlo simulation produces some negative values, indicating net environmental benefits. While this may stem from inaccurate uncertainty data, further investigation is beyond the current scope.

In summary, while the normalized Monte Carlo results support the static model findings, confirming that smart charging with BESS performs best, further analysis is required to assess the smaller differences. To this end, a discernibility analysis is conducted to test whether observed differences are statistically meaningful.

Based on the discernibility analysis presented in Figure A22 and Table 4, the following conclusions can be drawn:

- Baseline: **Uni – no BESS**
    - *Uni – BESS* shows similar results in 69.7% of cases and performs better in 30.3%, indicating no clear advantage.
    - *Smart – no BESS* shows a strong improvement, performing better in 87.6% of iterations and similar in 12.4%.
    - *Smart – BESS* outperforms, with 99.9% of results better than the baseline.
- Baseline: **Uni – BESS**
    - *Uni – no BESS* is largely indistinguishable, with 69.6% of results falling within the similarity band and 30.3% worse.
    - *Smart – no BESS* is statistically indistinct, with 100% of results within the similarity threshold.
    - *Smart – BESS* performs better in 83.2% of iterations and is similar in 16.8%, confirming improvement.
- Baseline: **Smart – no BESS**
    - *Uni – no BESS* performs worse in 87.6% of cases, with limited similarity (12.4%).
    - *Uni – BESS* is statistically indistinct, with 100% of results within the similarity band.
    - *Smart – BESS* shows improvement in 27.7% of cases and similarity in 72.2%, suggesting no strong advantage.
- Baseline: **Smart – BESS**
    - *Uni – no BESS* is almost always worse (99.9%).
    - *Uni – BESS* performs worse in 83.2% of cases and is similar in 16.8%.
    - *Smart – no BESS* performs worse in 27.7% of iterations and is similar in 72.2%.

The discernibility analysis confirms that **Smart – BESS** consistently achieves the lowest CC impacts, outperforming *Uni – no BESS* in nearly all cases and showing improvement over *Uni – BESS* in more than 80% of iterations. *Smart – no BESS* also performs better than *Uni – no BESS* in most comparisons, but its advantage over *Uni – BESS* is statistically indistinct. Comparisons between *Uni – BESS* and *Uni – no BESS* are inconclusive, with results falling mostly within the similarity band. Overall, while the differences between the two unidirectional configurations and between *Smart – no BESS* and *Uni – BESS* are not statistically meaningful, the analysis confirms that **smart charging with BESS** provides a clear and robust environmental improvement. Where CC impact differences are not discernible, other environmental indicators or decision criteria should guide strategy selection.

Table 4. Overview of discernability quantification for the mezzo-level use case. Results are based on the outcome of the Monte Carlo simulation (source: own calculation).

Baseline	Compared scenario	Better than default (%)	Similar (±50 g) (%)	Worse than default (%)
Uni – no BESS	Uni – BESS	30.30	69.70	0.00
	Smart – no BESS	87.60	12.40	0.00
	Smart – BESS	99.90	0.00	0.00
Uni – BESS	Uni – no BESS	0.00	69.60	30.30
	Smart – no BESS	0.00	100.00	0.00
	Smart – BESS	83.20	16.80	0.00
Smart – no BESS	Uni – no BESS	0.00	12.40	87.60
	Uni – BESS	0.00	100.00	0.00
	Smart – BESS	27.70	72.20	0.00
Smart – BESS	Uni – no BESS	0.00	0.00	99.90
	Uni – BESS	0.00	16.80	83.20
	Smart – no BESS	0.00	72.20	27.70

3.3.2. Sensitivity assessment

The perturbation analysis is conducted on the configuration with smart charging and BESS, as it includes all relevant parameters. Following Heijungs and Kleijn (2001), parameters with a SF above 0.8 are considered highly influential [28].

For the micro-level use case, Figure A16 identifies only three criterion: SEN_5 and SEN_6 (system lifetime) and SEN_19 (grid consumption). These parameters affect the functional unit (lifetime electricity output) and are expected to show high sensitivity. While lifetime is fixed across configurations, grid electricity varies depending on charging strategy. All other parameters, including PV/BESS lifetimes, capacities, and EV battery characteristics, yield SF values below 0.2. This indicates that the model is generally robust to most technical assumptions, with lifetime and grid reliance being the most critical inputs.

Results from the perturbation analysis of the mezzo-level use case confirm the micro-level finding: system lifetime is the most influential parameter (see SEN_5&_6 in Figure A23). Longer lifetimes increase impacts due to component replacement and prolonged grid consumption, while shorter lifetimes reduce both. This finding aligns with previous studies ([20]).

Following Heijungs and Kleijn (2001), only system lifetime shows strong sensitivity (SF: 0.91 and 1.11). Other parameters, including WT lifetime (0.21-0.25), turbine capacity (0.23-0.24), and grid electricity consumption (0.60-0.68), show moderate influence. Most other variables, such as battery properties and PV capacity, have sensitivity factors below 0.2, indicating minimal influence. Overall, the model is robust to uncertainty in most technical parameters, but assumptions about lifetime must be carefully validated, ideally supported by primary data.

3.4. Other impact categories

In the micro-level use case, using the ecoinvent electricity dataset instead of hourly grid data leads to a shift in the ranking of configurations. Unlike the CC impact results using hourly mixes, where *Smart - BESS* performed best, the modified model identifies *Uni - BESS* as the lowest-impact configuration across all EF v3.1 midpoint categories (Figure A17). *Smart - no BESS* and *Smart - BESS* rank second and third worst, respectively. Despite variation in absolute values, this relative ranking remains consistent across categories. Grid electricity remains the dominant contributor in all scenarios, followed by PV installations (see Figure 6). In ETF, PV systems contribute over 50 % of total impacts, regardless of configuration. BESS contributions remain moderate, reaching up to 20 % in select categories.

These results confirm that in the micro-level use case smart charging and BESS offer benefits across multiple impact categories. However, they also highlight how background dataset choice can affect the relative ranking of system configurations. While *Smart - BESS* performs best in models using hourly grid data, *Uni - BESS* emerges as the top performer under the average mix assumptions.

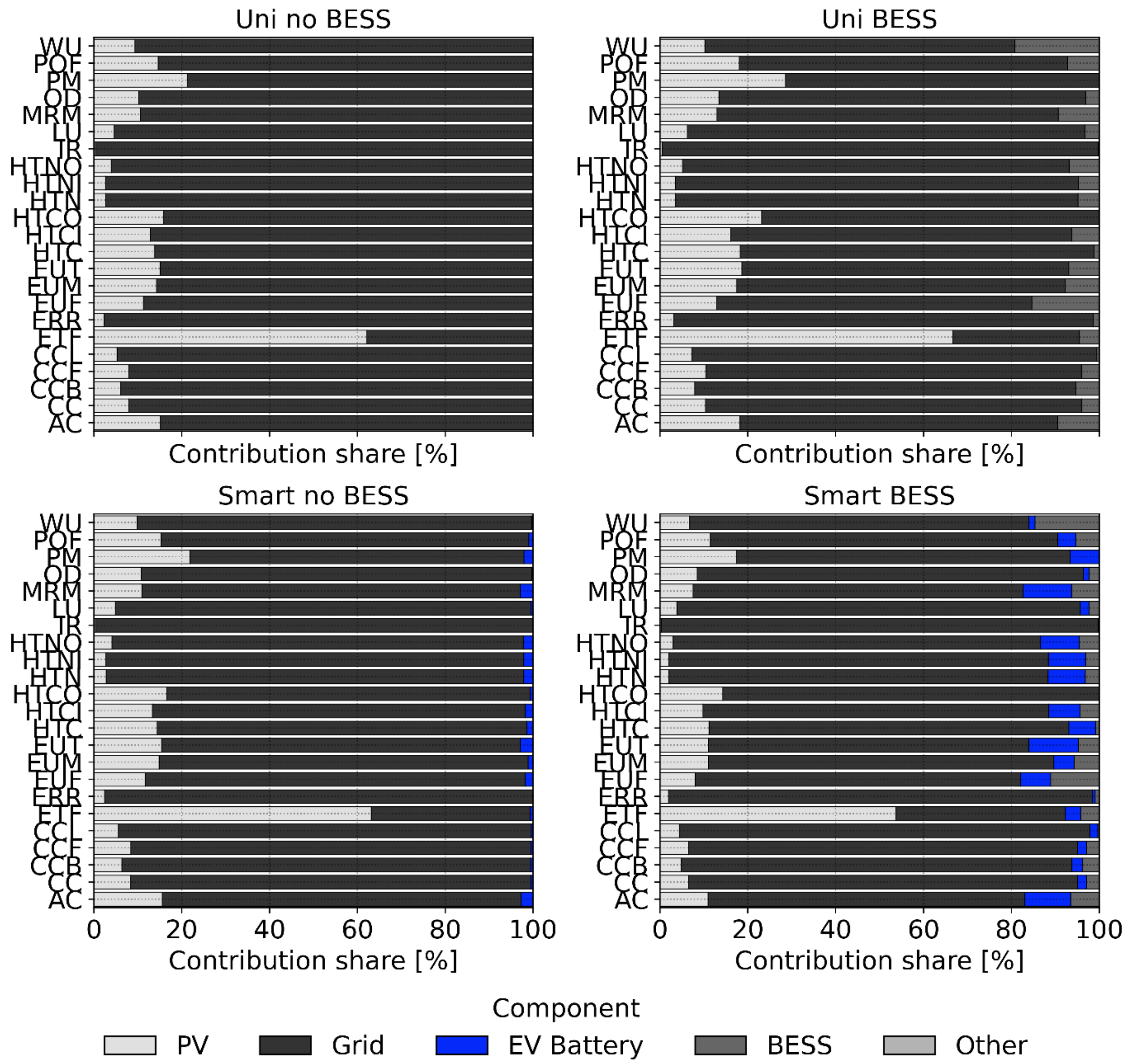

Figure 6: Contribution of each asset to all midpoint impact categories from EF v3.1 across all four system configurations of the micro-level use case in Belgium (PV = Photovoltaic; EV = Electric vehicle; BESS = Stationary battery electric storage; AC = Acidification; CC = Climate change; CCB = Climate change: biogenic; CCF = Climate change: fossil; CCL = Climate change: land use and land use change; ETF = Ecotoxicity: freshwater; ERR = Energy resources: non-renewable; EUF = Eutrophication: freshwater; EUM = Eutrophication: marine; EUT = Eutrophication: terrestrial; HTC = Human toxicity: carcinogenic; HTCI = Human toxicity: carcinogenic, inorganics; HTCO = Human toxicity: carcinogenic, organics; HTN = Human toxicity: non-carcinogenic; HTNO = Human toxicity: non-carcinogenic, organics; HTNI = Human toxicity: non-carcinogenic, inorganics; IR = Ionising radiation: human health; LU = Land use; MRM = Material resources: metals/minerals; OD = Ozone depletion; PM =

Particulate matter formation; POF = Photochemical oxidant formation: human health; WU = Water use).

When the mezzo-level use cases are evaluated across all EF v3.1 midpoint impact categories, the same performance trends observed in CC impacts hold. The *Uni - no BESS* configuration shows the highest impacts in most categories, while *Smart - BESS* yields the lowest burdens (Figure A24). In freshwater ecotoxicity, *Uni - no BESS* performs 7 % better than its BESS-equipped counterpart. Smart charging configurations also achieve similar reductions. For ionising radiation, both systems with BESS, regardless of charging strategy, exhibit comparably low impacts. In impact categories like freshwater ecotoxicity, human toxicity (carcinogenic, inorganics), and land use, both smart charging configurations show similarly low impacts. In general, *Uni - BESS* and *Smart - no BESS* yield comparable improvements relative to the baseline. Figure A24 confirms that *Smart - BESS* consistently achieves the greatest reductions, while *Uni - no BESS* performs worst.

Technology-specific contributions reveal reduced grid influence compared to the micro-level case (see Figure A25). In several categories, wind impacts exceed those from PV. For freshwater ecotoxicity, wind and PV combined account for 80 % of the impacts. For other categories, such as human toxicity, photochemical ozone formation, particulate matter, and eutrophication, wind and PV combined account over 50 % of total impacts. In contrast, battery storage (both stationary and mobile) has only minor influence across all categories.

4. Discussion

This research demonstrates that integrating smart charging and BESS can substantially reduce CC impacts in both micro- and mezzo-level energy systems. In the micro-level use case, combining smart charging with BESS lowers CC impacts from 165 to 66 gCO_2eq/kWh, representing a 60 % reduction. At the mezzo-level, the decrease is more modest, from 41 to 34 gCO_2eq/kWh (17 %). These results suggest that while flexibility strategies offer considerable environmental benefits in fossil-dependent systems, their relative advantage diminishes in systems with high shares of renewable electricity. In this context, the mezzo-level use case can be interpreted as a proxy for a future decarbonized energy is found to reduce GD and mitigate curtailment, particularly in the mezzo-level scenario.

For stakeholders, these findings imply clear environmental incentives to implement smart charging, especially for households in systems with limited renewable supply. In larger systems with high renewable penetration, as represented in the mezzo-level case, the primary advantage of smart charging (especially when combined with BESS) extends beyond CC impact mitigation. The ability to reduce GD and curtailment introduces operational and potentially financial benefits. These may include lower electricity purchase costs and reduced exposure to carbon taxation. However, the classification and monetization of these non-environmental benefits remain topics for future research.

Despite these strengths, the current modeling framework does not directly quantify the environmental effects of curtailed electricity. Because the functional unit is defined as generated electricity, curtailed energy is not reflected in the LCA itself. Nevertheless, curtailment is indirectly captured, as the DOF optimizes asset sizes with curtailed generation. Since curtailment typically affects wind and PV—technologies with relatively low specific CC impacts, its reduction can effectively displace grid electricity with higher emissions. To better capture such dynamics, this study implemented a temporally resolved electricity mix, offering a more accurate representation than the static ecoinvent average.

The allocation of EV battery production impacts is based on charged and discharged electricity. As this contribution accounts for less than 1 % of total CC impacts, alternative allocation methods (e.g., based on capacity fade or cycling intensity) are not explored. While such methods could offer greater precision, the minimal impact justifies the simplified approach. This also highlights the opportunity to use existing mobile storage (EVs) to support system flexibility with negligible environmental burden.

Some limitations arise from the study's scope. The micro-level analysis is based on a single user profile, while the mezzo-level reflects an aggregate of multiple users. Although the input data is user-dependent, exploring behavioral variability lies outside the scope of this study. Furthermore, discharged electricity is included in the perturbation analysis and is not identified as sensitive parameter. Additionally, the definition of flexibility is restricted to peak shaving. Other services, such as participation in ancillary or balancing markets, are not included and would require different system boundaries and objectives.

A notable issue emerged during the uncertainty assessment: negative CC impact values are observed in some Monte Carlo iterations. These results suggest net environmental benefits, which are implausible given the technologies modeled. The causes remain unclear, but may include scaling inconsistencies, incorrect uncertainty distributions, or flawed data in the background inventory. Furthermore, while background processes are subject to uncertainty analysis, the foreground system remained deterministic. Extending uncertainty analysis to foreground parameters could provide a more balanced assessment of model robustness.

Finally, results across other environmental impact categories revealed a shift in environmental burdens. While grid electricity remains the main contributor in most scenarios, the importance of wind and PV increases, especially in categories such as freshwater ecotoxicity, eutrophication, human toxicity, photochemical ozone formation, and particulate matter. These findings highlight the necessity of adopting a multi-impact approach to system design. Policymakers and technology developers should address not only CC impact mitigation but also the broader environmental footprint of renewable technologies. This underscores the need to optimize future energy systems across a broader set of environmental criteria, not CC impacts alone.

5. Conclusions

This paper investigated the environmental impacts of unidirectional and smart EV charging and BESS in micro- and mezzo-level electricity systems, using temporally refined LCA, Monte Carlo simulation, and sensitivity analysis.

In the micro-level use case, representing a system with limited renewable energy supply and high grid consumption, flexibility services offer great CC impacts reduction. Introducing smart charging or BESS leads to notable CC impact reductions, while combining both results in the most favorable outcome: a 60 % reduction from 165 to 66 CO_2eq/kWh. Grid electricity is found to be the dominant contributor to CC impacts, followed by PV, while BESS and allocation of EV battery production accounted for only a minor share. Monte Carlo simulations and discernibility analysis confirm, that only systems with smart charging and/or BESS result in more profound CC impacts improvements. Sensitivity results emphasize the importance of project lifetime and grid consumption, while other parameters have limited influence.

In contrast, the mezzo-level use case, depicting a potential future energy system with high shares of wind and PV installations, show consistently lower CC impacts across all configurations, with values ranging from 34 to 41 CO_2eq/kWh. Although differences between system designs are smaller, smart charging combined with BESS still outperformed other configurations in all assessments. While grid electricity remained the primary source of emissions, its relative contribution declined in favor of wind and PV. Moreover, smart charging with BESS is shown to reduce annual curtailment by a substantial amount (64,079.60 kWh/year) compared to the smart charging without BESS. Importantly, the discernibility analysis indicated that the CC impact differences between most configurations are not statistically robust, except for the smart charging with BESS system configurations. These insights highlight that flexibility strategies remain valuable, even in energy systems mainly supplied by RES.

Beyond CC impacts, additional EF v3.1 midpoint categories reveal a shift in environmental burdens from grid electricity toward renewable energy technologies, especially wind and PV—in the mezzo-level use case. For instance, in freshwater ecotoxicity, wind and PV together account for over 80\% of total impacts. These findings underscore the importance of improving the environmental impacts of renewable technologies, including resource efficiency and cleaner manufacturing, to avoid shifting the burden from operational emissions to upstream supply chains.

The results also demonstrate the value of combining LCA with high-resolution energy modeling. Using a temporally resolved electricity mix, rather than a static average, enabled a more accurate representation of system dynamics. However, limitations remain. The chosen functional unit (generated electricity) does not account for curtailed energy, and no environmental value is assigned to avoided curtailment. Future research could redefine the functional unit (e.g., consumed electricity) to better reflect system-level interactions.

Another key observation emerged from the uncertainty analysis. In several Monte Carlo iterations, negative CC impacts are obtained, suggesting net environmental benefits. Given the technologies involved, such outcomes are unrealistic and may point to data inconsistencies, flawed scaling assumptions, or distribution errors in the background inventory. Moreover, uncertainty is only applied to background datasets; all foreground processes are modeled deterministically. Incorporating uncertainty into the foreground system could yield more balanced estimates of overall model reliability.

From a modeling standpoint, this work also reveals areas for methodological improvement. Better and easier harmonization between the DOF and the LCA model is essential to ensure consistency in assumptions, data exchange, and boundary conditions. Additionally, refining the quantification of curtailed electricity and its environmental implications remains an important future task.

Looking ahead, this research encourages further exploration into the decarbonization trajectory of the Belgian electricity grid and the long-term environmental profiles of flexibility technologies under evolving scenarios. Expanding the analysis to include different user profiles, behavioral patterns, and flexibility markets could help bridge the gap between technical feasibility and real-world application.

In conclusion, the integration of smart charging and BESS offers clear environmental benefits, especially in today's fossil-fuel reliant energy systems, but also retains its relevance in future, renewables-based configurations. Its contribution to reducing emissions, GD, and curtailment, combined with minimal environmental impacts, makes it a promising strategy to help decarbonizing distributed energy systems. To fully unlock this potential, future energy planning must consider not only CC impacts, but a comprehensive spectrum of environmental indicators, supported by robust, uncertainty-aware modeling approaches.

6. References

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7. Appendix

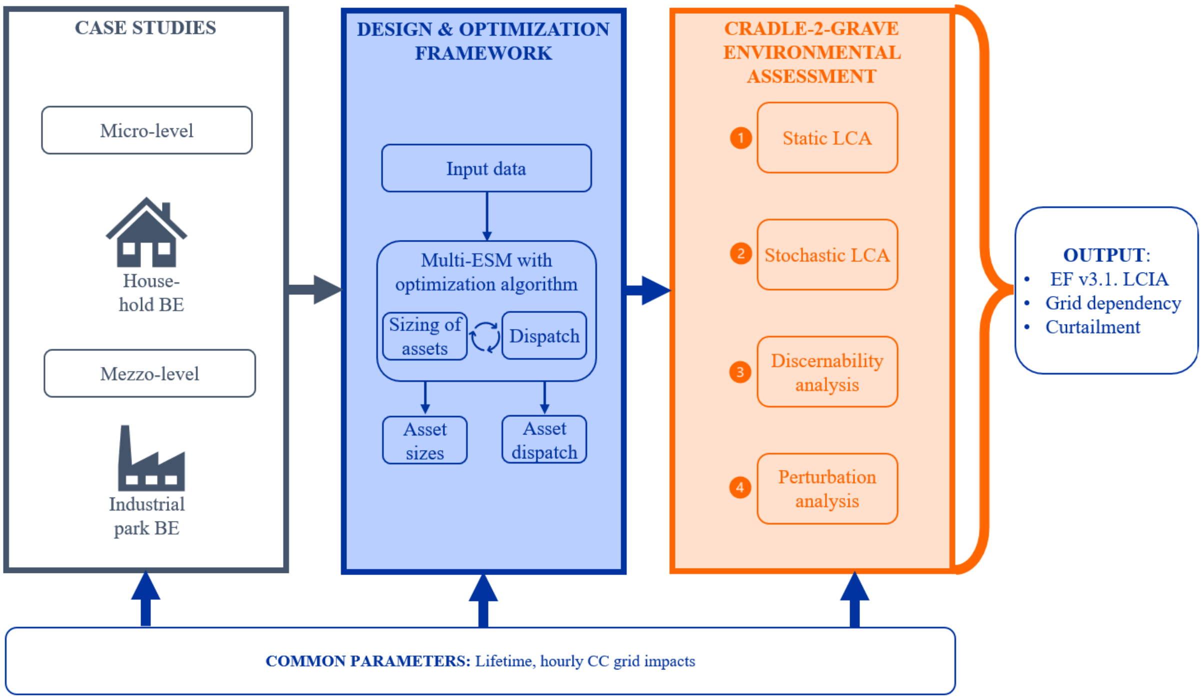

Figure A7: Research design to assess flexibility at different scales. It represents from left to right: the case studies (white boxes with gray frames), the applied design \& optimization framework including a rough high-level description (light blue background filling) and the conducted environmental assessment including post-LCA analysis (light orange background filling). (ESM = Energy system model; BE = Belgium; LCA = Life cycle assessment; CC = Climate change; EF v3.1 = Environmental Footprint version 3.1; LCIA = Life cycle impact assessment).

7.1. Other adjusted LCI data}

Due to a scope with limited amount of assets, instead of using LCI data available in commercial databases, the LCI of this study for the micro- and macro-level use case are modelled more precisely. Those assets are:

- **The Belgian electricity grid mix**: Therefore, data for the Belgian electricity grid mix, the PV installations and BESS are collected from literature. Reasons for choosing other LCI data instead of data from well-recognized databases such as for example ecoinvent are depending on the technology: for the Belgian grid electricity mix, only an average value is available in ecoinvent. Using the CC method of the EF v3.1 results in an average of 206 CO_2eq/kWh, whereas CC impact from the electricity map varies between 36 and 372 CO_2eq/kWh, making up an average of 170 gCO_2eq/kWh in 2023 [31]. Moreover, as the objective of this study is to understand trade-offs per hour over one year, a higher time resolution than annual average values is needed. For this reason, the 'dynamic LCA model' proposed by Naumann et al. (2024) is adjusted for Belgium. In this approach, the authors calculate hourly CC impact of the German electricity grid mix, taking into account imports and exports from neighbouring countries[32]. Additionally, their approach is normalized over five years to represent a generic year neglecting unique events such as the COVID time or the natural gas crises. The underlying data are also obtained from the Transparency Platform of the ENTSO-E. Three dataset per country (Belgium and its importing/exporting countries) are obtained: the hourly-resolved actual generation per production type, the installed capacity per production type in annual resolution and the cross-border physical flows in hourly resolution [33]. As a result, the hourly CC impact per hourly timestep for the Belgium electricity consumption mix is calculated.

- **PV installations**: Instead of using existing datasets from ecoinvent for PV installations, the LCI data for PV installations are extracted from a report of the International Energy Agency under the title 'Methodology Guidelines on Life Cycle Assessment of Photovoltaic' [34]. Supported by a yearly PV energy production of 2,996.39~kWh for a 3~kWp PV installation in Brussels, which is obtained from Photovoltaic Geographical Information System (PVGIS), the CC impact per kilowatt hour of produced electricity is determined [35]. The lifetime of the si-based PV installations is estimated to be 30~years [36]. Outdated data, e.g. efficiencies dating back to 2005 in the PV generated electricity datasets of the ecoinvent database or updated production locations is one main reason for remodelling the installations [37], [38]. Multi-Silicon PV installations with a capacity of 3~kWp are included, as this technology represents the dominating PV technology for small scale installations according to ecoinvent [37].
- **BESS**: Currently, only lead acid stationary batteries are available in ecoinvent, whereas all lithium-ion battery datasets are for mobile applications [37]. According to the International Energy Agency, the dominant technology for BESS 2022 remained lithium-ion battery. Due to the absence of lithium-ion BESS in ecoinvent, LCI data are used from Le Varlet et al. (2020) [39]. Furthermore, Le Varlet et al. (2020) identifies LFP as one of the most represented BESS technologies. Therefore, the mobile battery LCI modified by Le Varlet et al. (2020) of LFP battery are used in the micro-level use case. In the mezzo-level use case, one LFP and one NMC battery is selected as BESS, as those two chemistries are already installed at the Green Energy Park.

7.2. List of applied LCIA categories and sensitivity parameters

Table A5. Overview of the applied LCIA methods based on EF v3.1.

Abbreviation	EF v3.1 – midpoint
CCB	Climate change: biogenic
CCF	Climate change: fossil
CCL	Climate change: land use and land use change
ETF	Ecotoxicity: freshwater
ETFI	Ecotoxicity: freshwater, inorganics
ETFO	Ecotoxicity: freshwater, organics
ETT	Ecotoxicity: terrestrial
ETM	Ecotoxicity: marine
ERR	Energy resources: non-renewable
ERF	Energy resources: fossil
EUF	Eutrophication: freshwater
EUM	Eutrophication: marine
EUT	Eutrophication: terrestrial
HTC	Human Toxicity: Carcinogenic
HTCI	Human Toxicity: Carcinogenic, Inorganics
HTCO	Human Toxicity: Carcinogenic, Organics
HTN	Human Toxicity: Non-carcinogenic
HTNO	Human Toxicity: Non-carcinogenic, Organics
HTNI	Human Toxicity: Non-carcinogenic, Inorganics
OFH	Ozone formation, human health
IR	Ionising radiation: human health
LU	Land use
MRM	Material Resources: Metals/Minerals
MRF	Material Resources: Fossil
OD	Ozone Depletion
PM	Particulate Matter Formation
POF	Photochemical Ozone Formation: Human Health
WU	Water use
AC	Acidification

Table A6. Mapping of sensitivities (SEN) to parameter modifications at micro- and mezzo-level. Each parameter is perturbed by ± 10 % (PV = Photovoltaic; WT = Wind turbine; LFP =

Lithium-ion batteries with a cathode made of lithium iron phosphate; NMC = Lithium-ion batteries with a cathode made of lithium nickel manganese cobalt oxide; EV = Electric vehicle; BESS = Stationary battery electric storage).

Sensitivity	Micro-level parameter	Mezzo-level parameter
SEN_1&2	PV lifetime	PV lifetime
SEN_3&4	Lifetime BESS	WT lifetime
SEN_5&6	Project lifetime	Project lifetime
SEN_7&8	EV lifetime	Lifetime LFP
SEN_9&10	EV battery capacity	Lifetime NMC
SEN_11&12	EV battery weight	NMC density
SEN_13&14	Energy density	LFP density
SEN_15&16	PV capacity	PV capacity
SEN_17&18	BESS size	WT capacity
SEN_19&20	Grid consumption	LFP size
SEN_21&22	Charged electricity to EV	NMC size
SEN_23&24	Discharged electricity from EV	Grid consumption

7.3. Further analysis

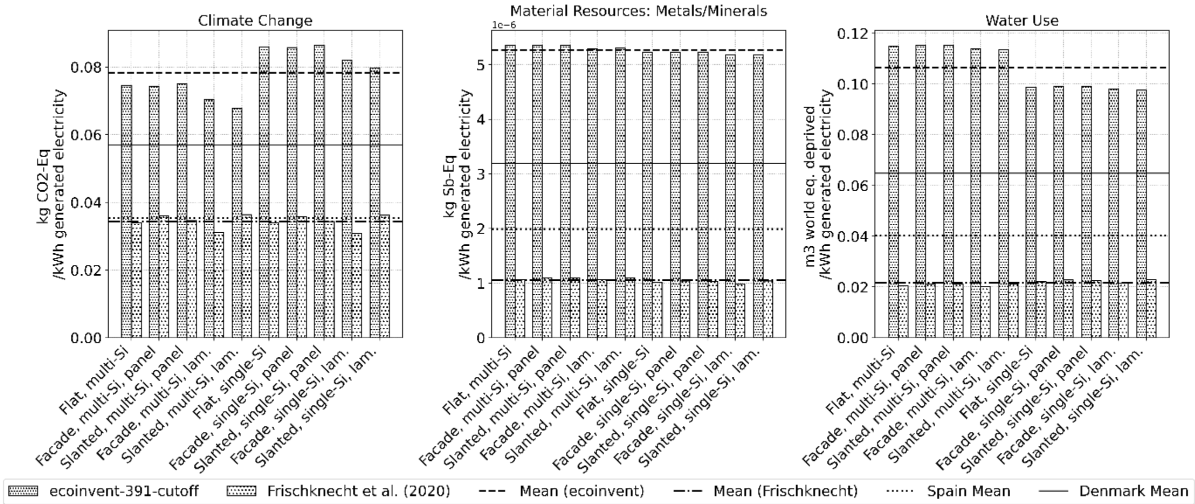

Figure A8: Comparison of 3 kWp PV installations modelled using LCI data from [40] and ecoinvent version 3.9.1, cut-off, in Belgium (bars), and reference values for Denmark and Spain (dotted lines; Source: [37], [40] and own calculation).

Figure A8 compares the CC impacts of 3~kWp PV installations in Belgium based on LCI data from Frischknecht et al. (2020) and from ecoinvent version 3.9.1 [37]. Using the Frischknecht dataset results in approximately 50 % lower CC impacts compared to the corresponding ecoinvent datasets (first subplot). Even larger reductions are observed for material resource depletion and water use. This trend is consistent across all PV technologies assessed. When accounting for electricity production in other countries, Belgium consistently shows lower CC impacts compared to Denmark and Spain. While the ecoinvent data indicates that single-Si panels generally have higher CC impacts than multi-Si panels, this distinction is not evident in the Frischknecht dataset. Furthermore, using Frischknecht's LCI data, building-integrated PV installations show lower CC impacts than roof-mounted systems. However, the overall variation between PV technologies is smaller in the Frischknecht dataset than in ecoinvent. For example, the CC impact of a 3 kWp flat-roof installation using multi-Si panels is 74 gCO_2eq/kWh according to ecoinvent, compared to only 35 gCO_2eq/kWh with the Frischknecht dataset.

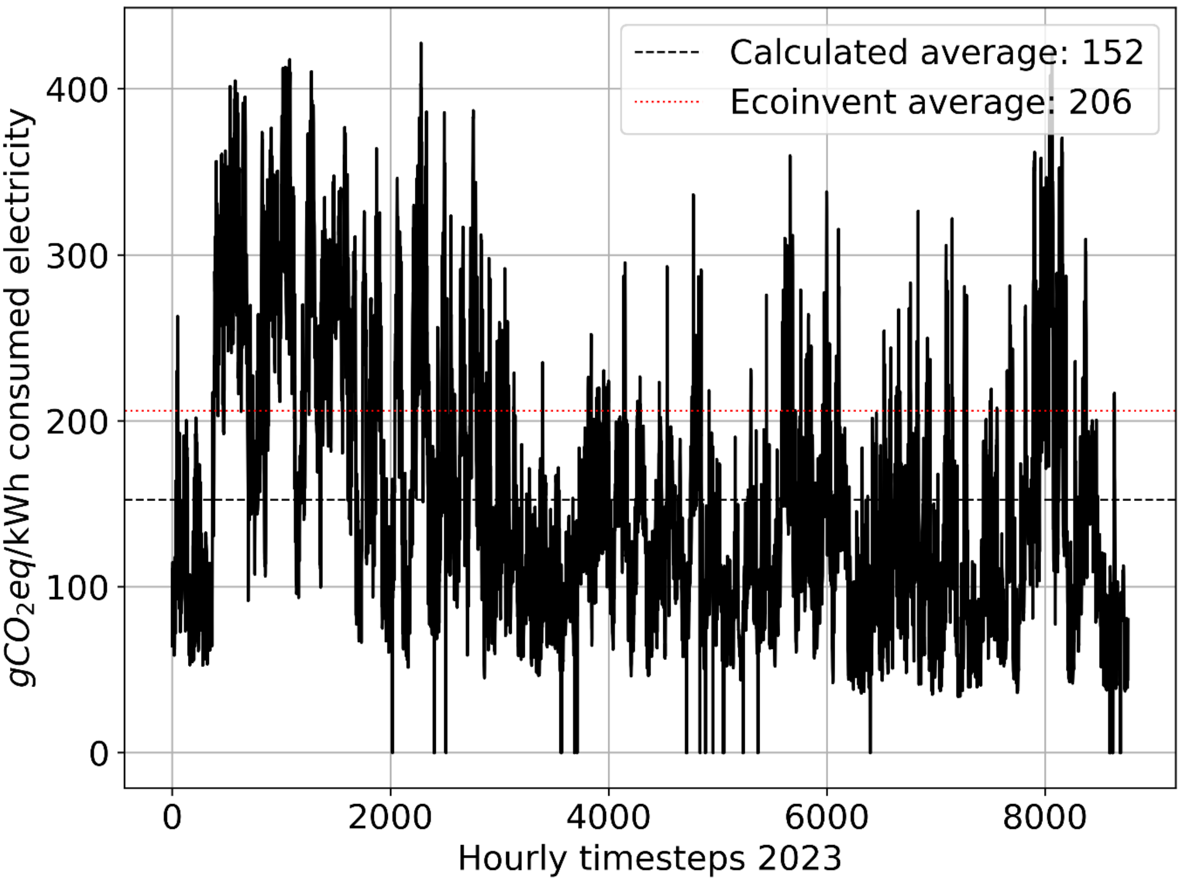

Figure A9: Hourly climate change impact of the Belgian electricity mix in 2023 (source: own calculation).

Figure A9 illustrates the hourly CC impact of the Belgian electricity mix in 2023, with an annual average of 152 gCO_2eq/kWh. The values range widely over the year, from a minimum of 0.02 to a maximum of 428 gCO_2eq/kWh. Notably, CC impacts are generally higher in the first quarter of the year, frequently exceeding 200 gCO_2eq/kWh, while the remainder of the year shows lower and more variable impacts. The primary contributors to elevated CC impacts are domestic electricity production from fossil gas and electricity imports from neighboring countries (see Figure A10). The average CC impact per kWh of imported electricity in 2023 of Germany, France, the Netherlands, Luxembourg and the United Kingdom is calculated as follows: 448, 57, 364, 91, and 64 gCO_2eq/kWh (see Figure A11). Given that 64\% of imports originate from France, 22~\% from Germany, and 14~\% from the Netherlands, the impacts of imported electricity is driven by the high CC impacts of the individual country mixes. For comparison, the CC impacts of the ecoinvent dataset ‘market for electricity, low voltage’ in Belgium (cut-off, version 3.9.1) is calculated to be 206 gCO_2eq/kWh. For the selected dataset a temporal coverage from 2014 to 2022 is reported [37].

7.4. Assessing Flexibility Solutions in Energy Systems

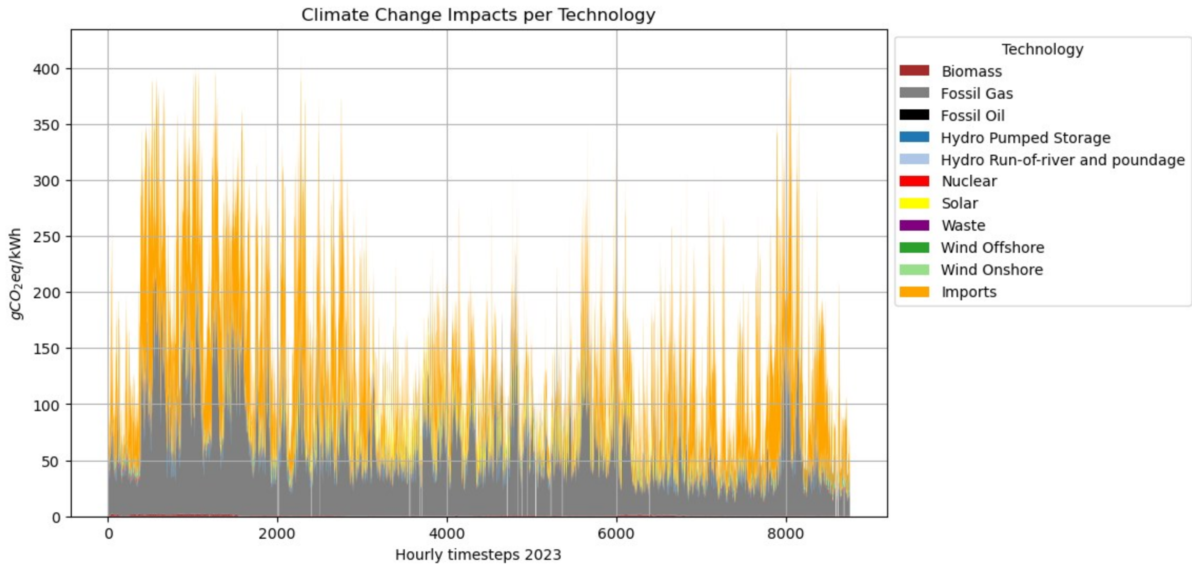

Figure A10: Contribution to hourly climate change impact of the Belgium electricity mix in 2023 (source: own calculation).

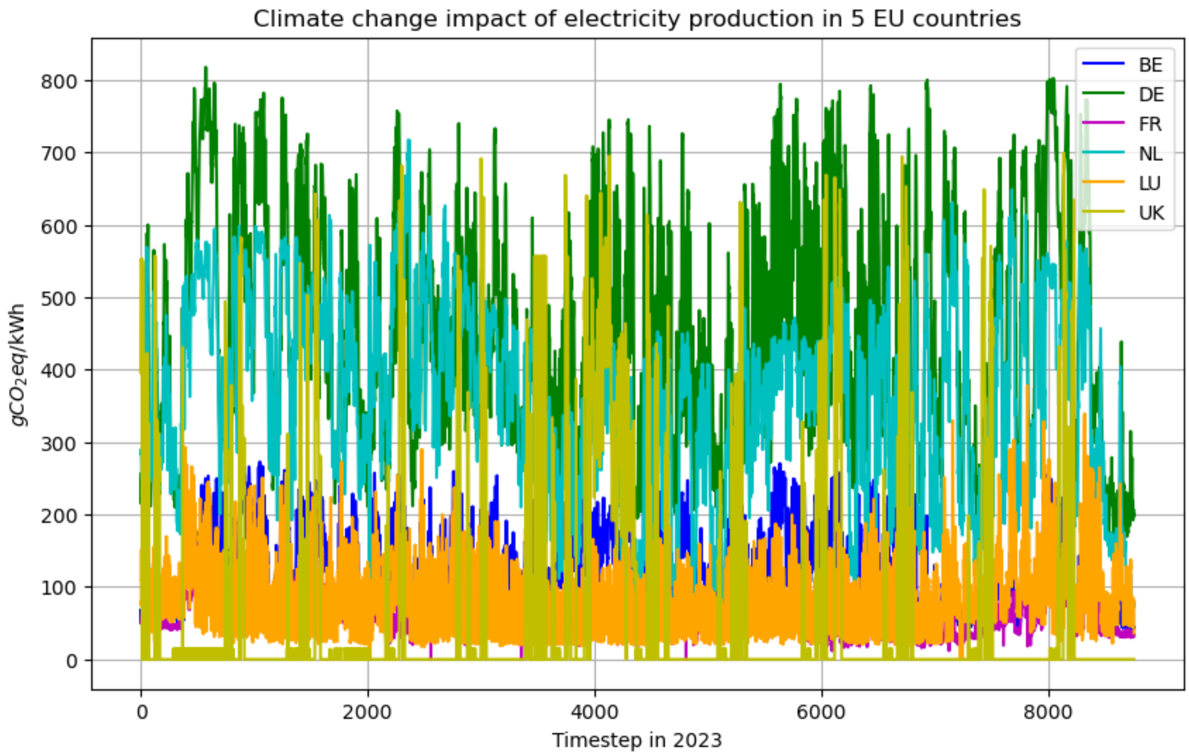

Figure A11: Hourly climate change impact of the Belgium electricity mix and the importing countries in 2023 (source: own calculation).

7.4.1. Micro-level results

Table A7. Energy production and consumption breakdown per charging service configuration at micro-level. Curtailment is not listed separately, but makes up 226.03 kWh/year in the Uni (no BESS) systems (BESS = Stationary battery electric storage; PV = Photovoltaic; EV = Electric vehicle).

Energy flows	**Uni – no BESS**	**Uni – BESS**	**Smart – no BESS**	**Smart – BESS**
PV production (kWh/year)	369.57	4,309.23	2,282.08	5,238.08
Grid consumption (kWh/year)	6,732.24	4,388.18	6,097.53	3,617.36
Grid injection (kWh/year)	-158.26	-1,491.89	-1,568.33	-1,868.82
BESS - discharge (kWh/year)	0.00	2,395.92	0.00	2,655.44
EV - discharge (kWh/year)	0.00	0.00	33.41	167.12
Total production (kWh)	**6,943.55**	**9,601.44**	**6,844.69**	**9,809.18**
GEP consumption (kWh/year)	-3,897.72	-3,897.72	-3,897.72	-3,897.72
EV - charge (kWh/year)	-3,045.83	-3,048.96	-2,946.98	-2,969.14
BESS - charge (kWh/year)	0.00	-2,654.76	0.00	-2,942.31
Total consumption (kWh)	**-6,943.55**	**-9,601.44**	**-6,844.69**	**-9,809.18**

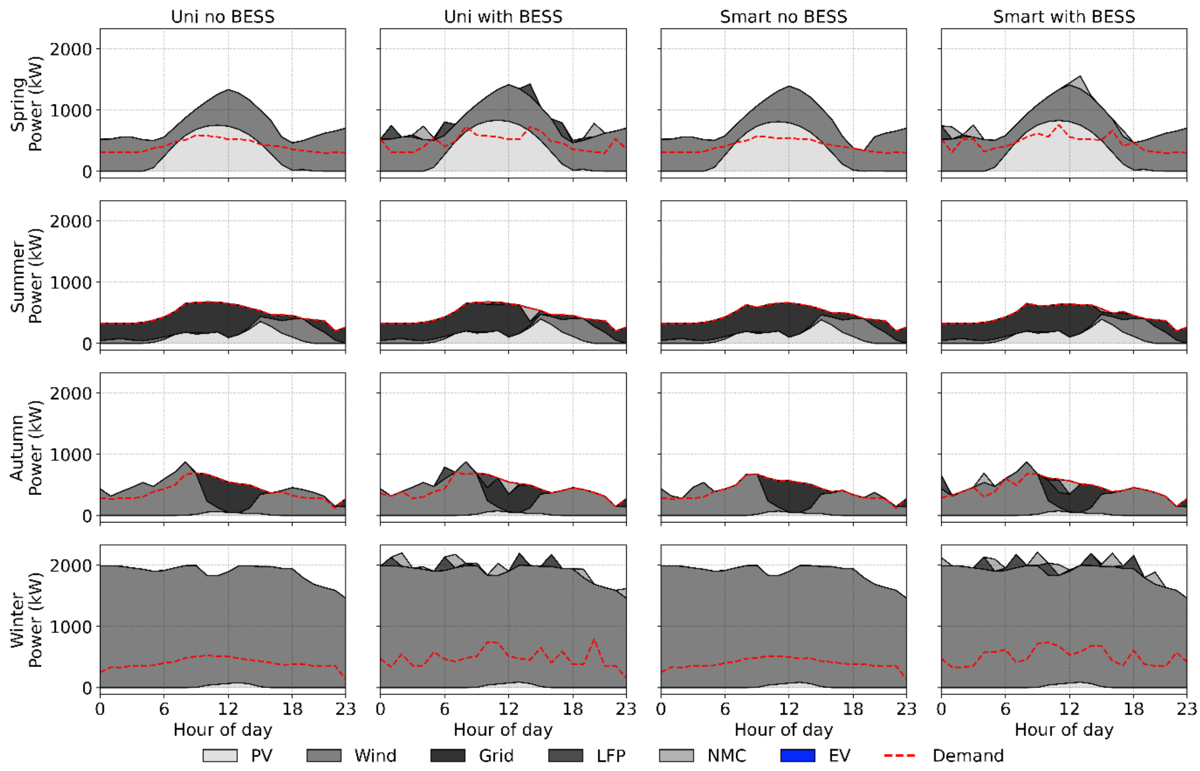

Figure A12: Hourly electricity supply and demand of a household used in the micro-level use case for four representative days in spring (2023-03-20), summer (2023-07-17), autumn (2023-10-09), and winter (2023-12-15) (BESS = Stationary battery electric storage; PV = Photovoltaic; EV = Electric vehicle).

Table A8. Descriptive statistics of climate change impact results (gCO_2eq/kWh) from 10,000 Monte Carlo iterations per system configuration (BESS = Stationary battery electric storage; SD = Standard deviation).

Statistic	**Uni – no BESS**	**Uni – BESS**	**Smart – no BESS**	**Smart – BESS**
Count	10,000.00	10,000.00	10,000.00	10,000.00
Mean	230.67	132.88	179.01	148.98
SD	40.14	24.67	31.34	26.37
Min	-1,687.66	-1,085.72	-1,325.25	-1,136.81
25th percentile	221.35	127.77	171.83	143.15
Median (50\%)	229.35	132.17	178.02	148.16
75th percentile	238.68	137.21	185.16	154.02
Max	3,392.82	2,074.22	2,647.67	2,204.87

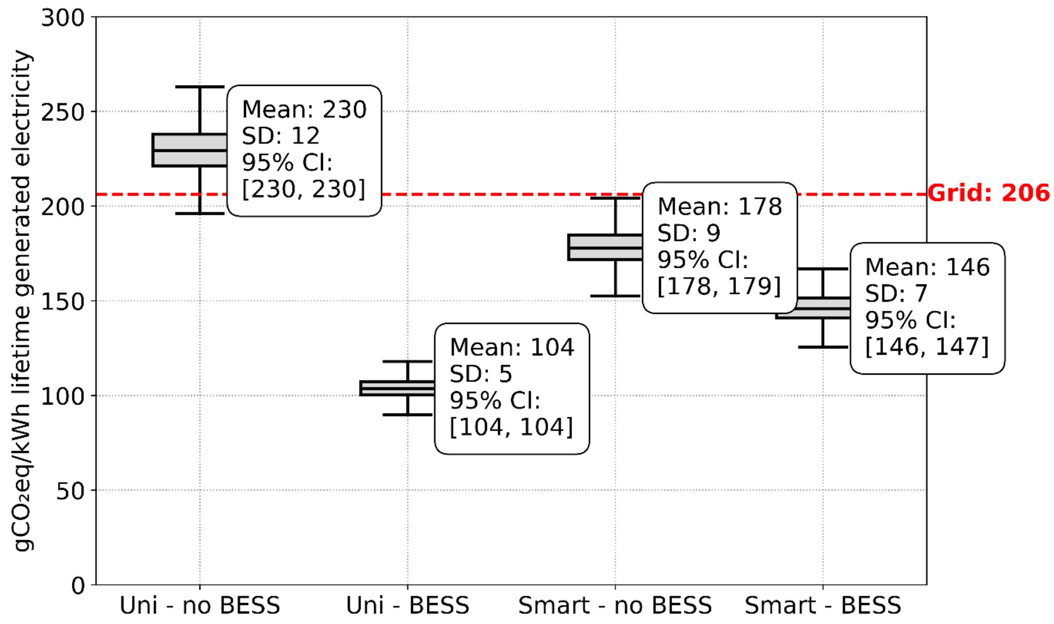

Figure A13: Results of a Monte Carlo simulation for a micro-level electricity system in Belgium (n = 10,000). Extreme outliers were removed using the interquartile range method to improve statistical robustness (BESS = Stationary battery electric storage; SD = Standard deviation; CI = Confidence interval).

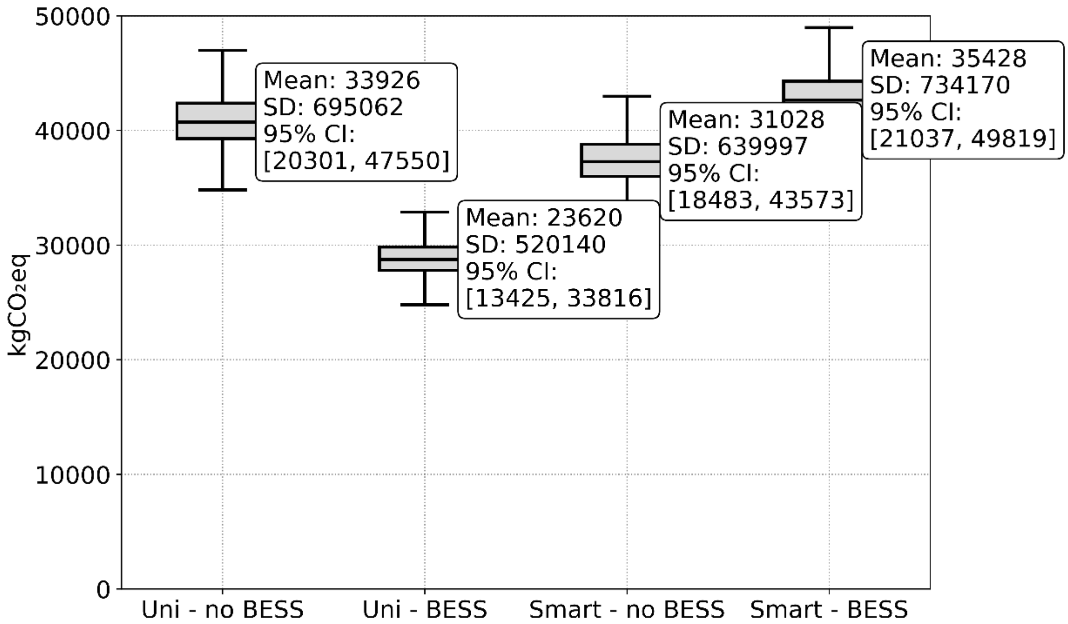

Figure A14: Unnormalized results of a Monte Carlo simulation for a micro-level electricity system in Belgium (n = 10,000). Extreme outliers were removed using the interquartile range method to improve statistical robustness (BESS = Stationary battery electric storage; SD = Standard deviation; CI = Confidence interval).

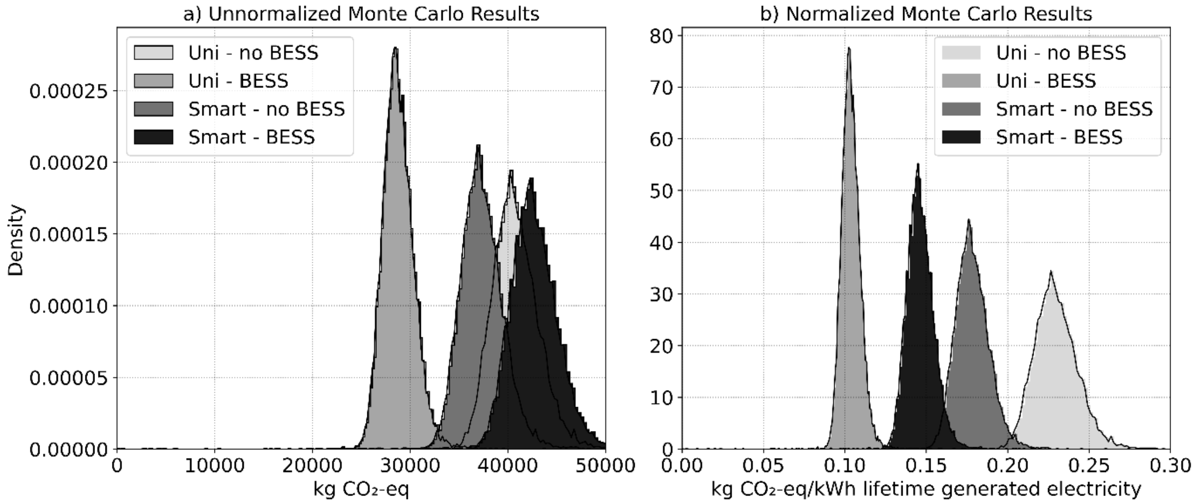

Figure A15: Comparison of normalized (per kWh) and unnormalized (total) distributions of climate change impact for four flexibility configurations in a micro-level electricity system in Belgium. Results are based on 10,000 Monte Carlo simulations.

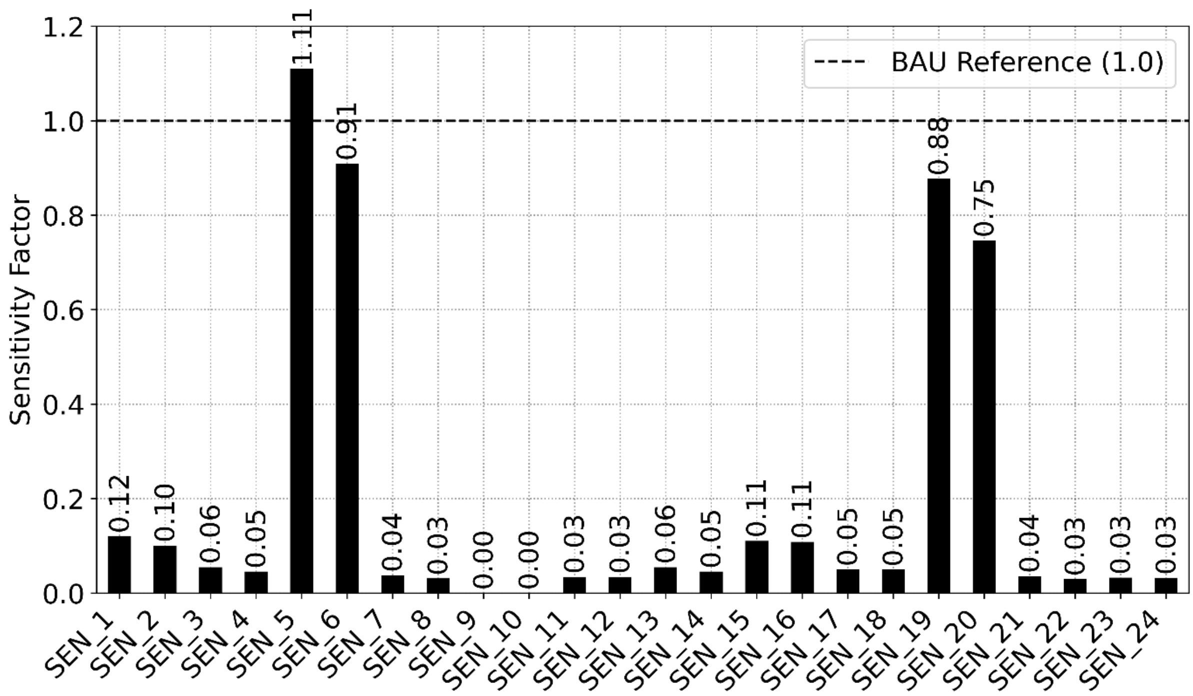

Figure A16: Results of the perturbation analysis for the LCA model of a micro-level electricity system in Belgium (BAU = smart_BESS; SEN_1&2: PV lifetime; SEN_3&4: Lifetime BESS; SEN_5&6: Project lifetime; SEN_7&8: EV lifetime; SEN_9&10: EV battery capacity; SEN_11&12: EV battery weight; SEN_13&14: Energy density; SEN_15&16: PV capacity; SEN_17&18: BESS size; SEN_19&20: Grid consumption; SEN_21&21: Charged electricity to EV; SEN_23&24: Discharged electricity from EV).

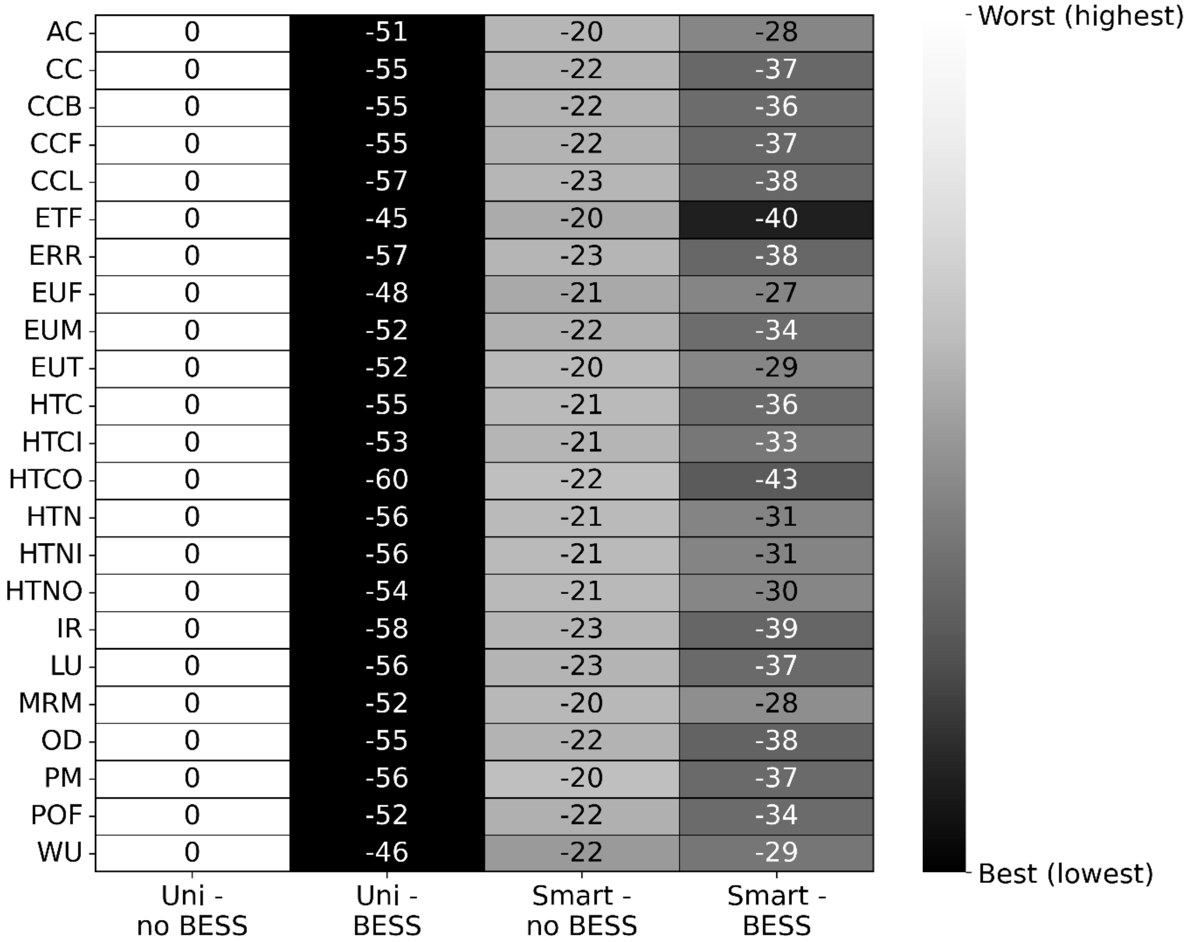

Figure A17: Results of all midpoint impact categories from EF v3.1 for the LCA model of a micro-level energy system with different charging strategies in Belgium (AC = Acidification; CC = Climate change; CCB = Climate change: biogenic; CCF = Climate change: fossil; CCL = Climate change: land use and land use change; ETF = Ecotoxicity: freshwater; ERR = Energy resources: non-renewable; EUF = Eutrophication: freshwater; EUM = Eutrophication: marine; EUT = Eutrophication: terrestrial; HTC = Human toxicity: carcinogenic; HTCI = Human toxicity: carcinogenic, inorganics; HTCO = Human toxicity: carcinogenic, organics; HTN = Human toxicity: non-carcinogenic; HTNO = Human toxicity: non-carcinogenic, organics; HTNI = Human toxicity: non-carcinogenic, inorganics; IR = Ionising radiation: human health; LU = Land use; MRM = Material resources: metals/minerals; OD = Ozone depletion; PM = Particulate matter formation; POF = Photochemical oxidant formation: human health; WU = Water use).

7.4.2. Mezzo-level results

Table A9. Energy production and consumption breakdown of the mezzo-level use case per charging service configuration. Curtailment is not listed separately, but makes up 66,855.95 kWh/year and 2,776.34 kWh/year in the Smart (no BESS) and Smart (BESS) systems (BESS = Stationary battery electric storage; PV = Photovoltaic; LFP = Lithium-ion batteries with a cathode made of lithium iron phosphate; NMC = Lithium-ion batteries with a cathod made of lithium nickel manganese cobalt oxide; EV = Electric vehicle).}

Energy flows	**Uni – no BESS**	**Uni – BESS**	**Smart – no BESS**	**Smart – BESS**
PV production (kWh/year)	989,578.22	1,096,685.64	1,058,856.33	1,089,947.92
Wind production (kWh/year)	4,768,926.52	4,768,926.52	4,708,656.89	4,766,348.77
Grid consumption (kWh/year)	798,663.11	671,981.44	770,789.79	669,280.56
Grid injection (kWh/year)	-3,050,849.90	-2,992,425.74	-3,031,985.06	-2,978,956.25
LFP discharge (kWh/year)	0.00	179,778.68	0.00	190,852.12
NMC discharge (kWh/year)	0.00	179,832.11	0.00	182,209.38
EV - discharge (kWh/year)	0.00	0.00	12,237.45	16,524.09
Total production (kWh)	**3,506,317.95**	**3,904,778.65**	**3,518,555.40**	**3,936,206.59**
GEP consumption (kWh/year)	-3,407,026.47	-3,407,026.47	-3,407,026.47	-3,407,026.47
EV - charge (kWh/year)	-99,291.48	-99,291.48	-111,528.93	-115,815.57
LFP charge (kWh/year)	0.00	-199,200.75	0.00	-211,470.49
NMC charge (kWh/year)	0.00	-199,259.96	0.00	-201,894.05
Total consumption (kWh)	**-3,506,317.95**	**-3,904,778.00**	**-3,518,555.40**	**-3,936,206.58**

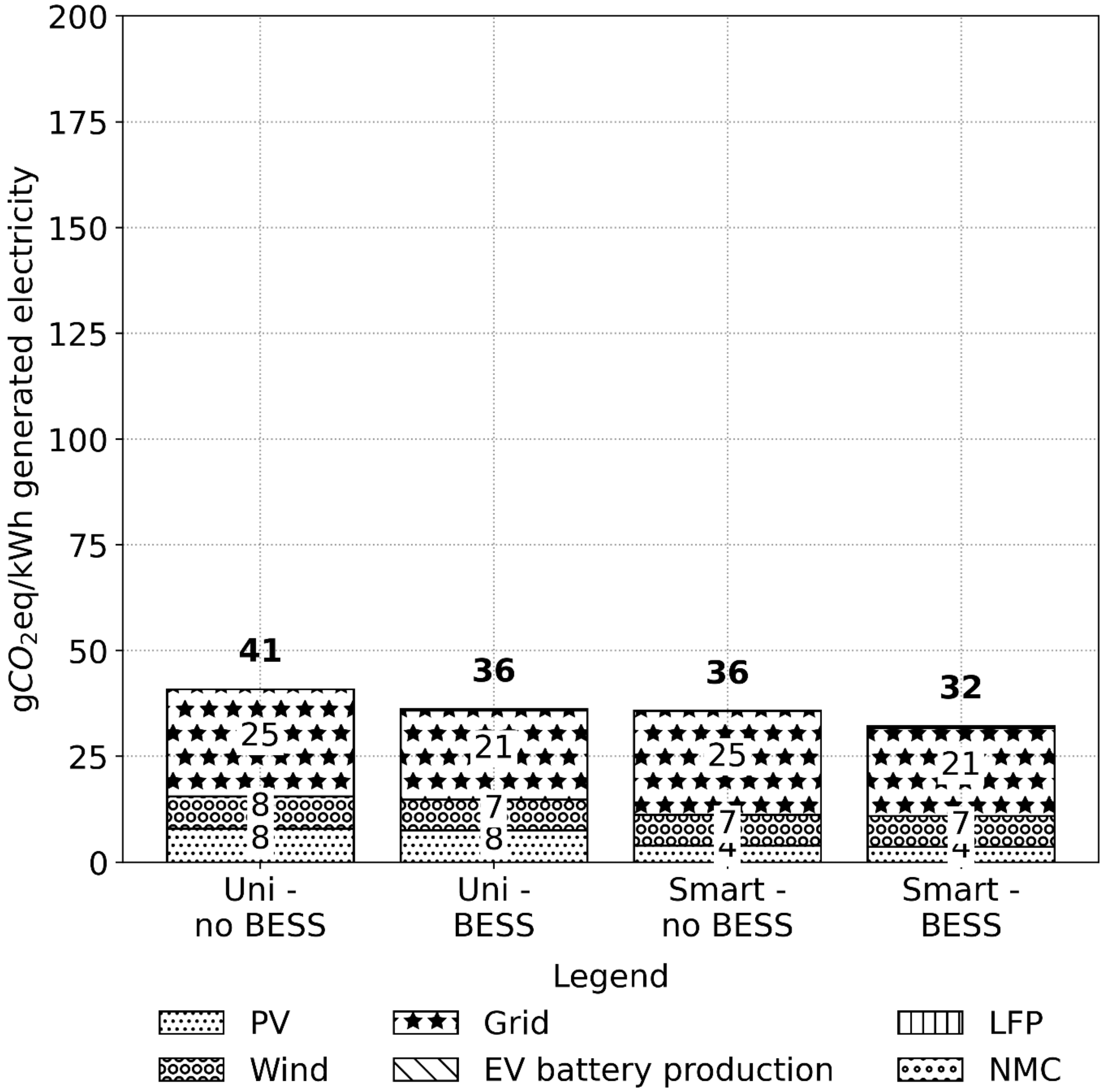

Figure A18: Contribution to climate change impact of assets at a mezzo-level electricity system in Belgium (PV = photovoltaic installations; EV = allocated impact of manufacturing a battery for an electric vehicle; LFP = Lithium-ion batteries with a cathode made of lithium iron phosphate; NMC = Lithium-ion batteries with a cathode made of lithium nickel manganese cobalt oxide).

Table A10. Descriptive statistics of climate change impact results (in gCO_2eq/kWh) based on 10 million Monte Carlo iterations for each flexibility configuration at the mezzo-level (BESS = Stationary battery electric storage; SD = Standard deviation).

Statistic	Uni – no BESS	Uni – BESS	Smart – no BESS	Smart – BESS
Count	10,000.00	10,000.00	10,000.00	10,000.00
Mean	44.87	40.02	39.55	34.70
SD	14.17	13.47	13.55	12.75
Min	-246.48	-238.59	-236.71	-226.23
25th percentile	43.23	38.58	38.02	33.36
Median (50\%)	44.64	39.82	39.32	34.50
75th percentile	46.18	41.15	40.75	35.75
Max	1,269.60	1,204.78	1,214.93	1,141.91

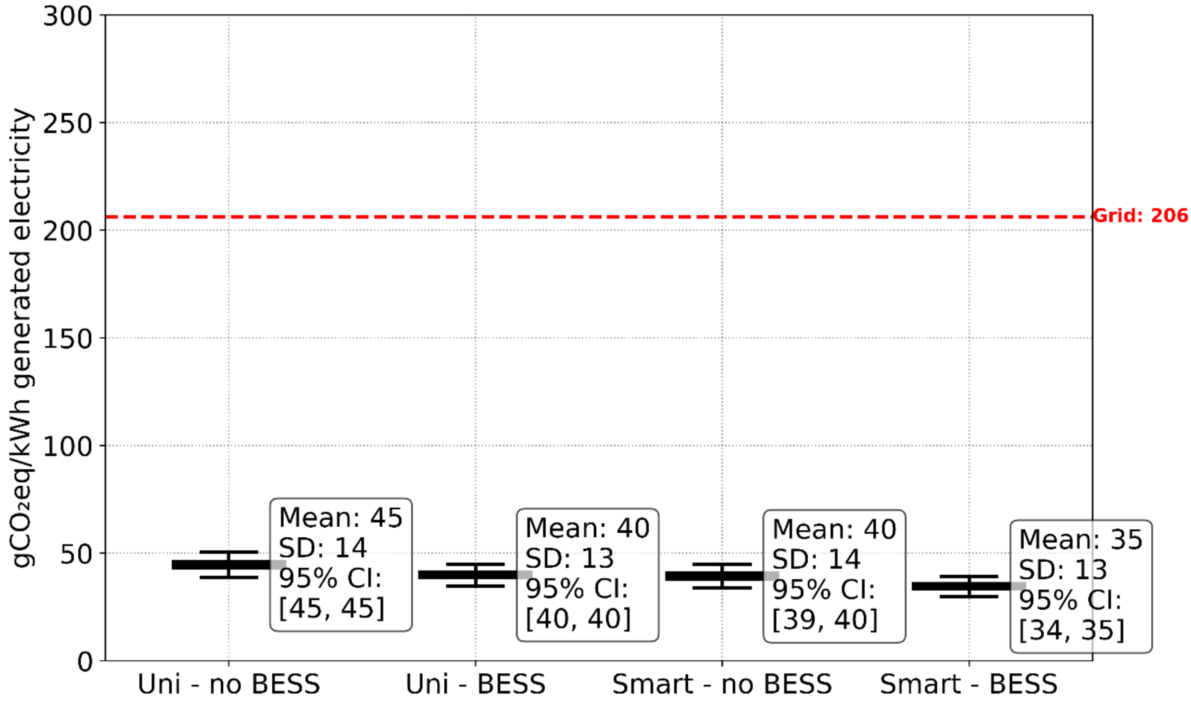

Figure A19: Results of a Monte Carlo simulation for a mezzo-level electricity system in Belgium (n = 10,000; BESS = Stationary battery electric storage; SD = Standard deviation; CI = Confidence interval).

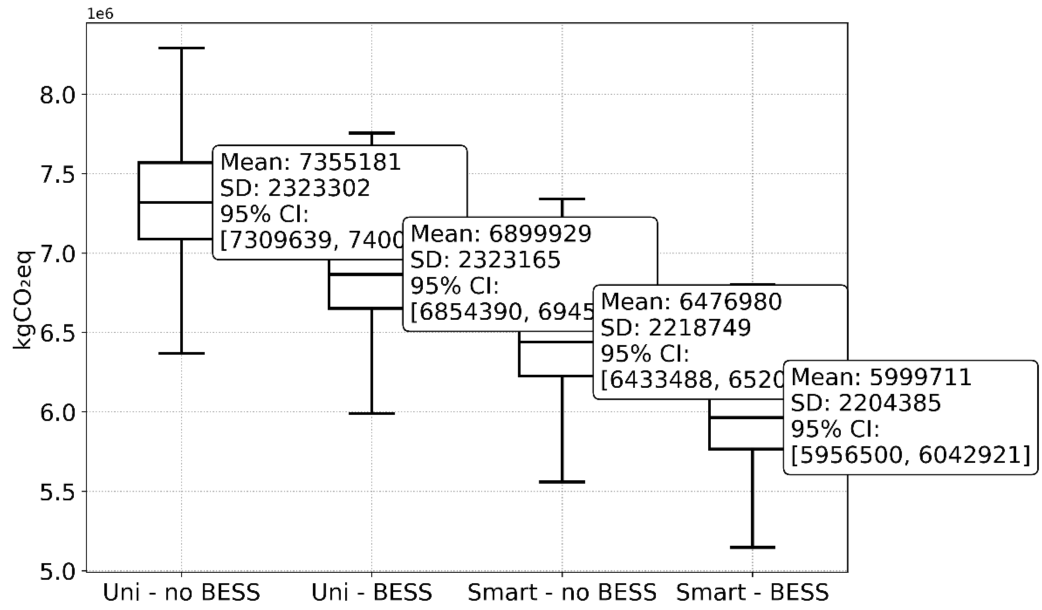

Figure A20: Unnormalized results of a Monte Carlo simulation for a mezzo-level electricity system in Belgium (n = 10,000; BESS = Stationary battery electric storage; SD = Standard deviation; CI = Confidence interval).

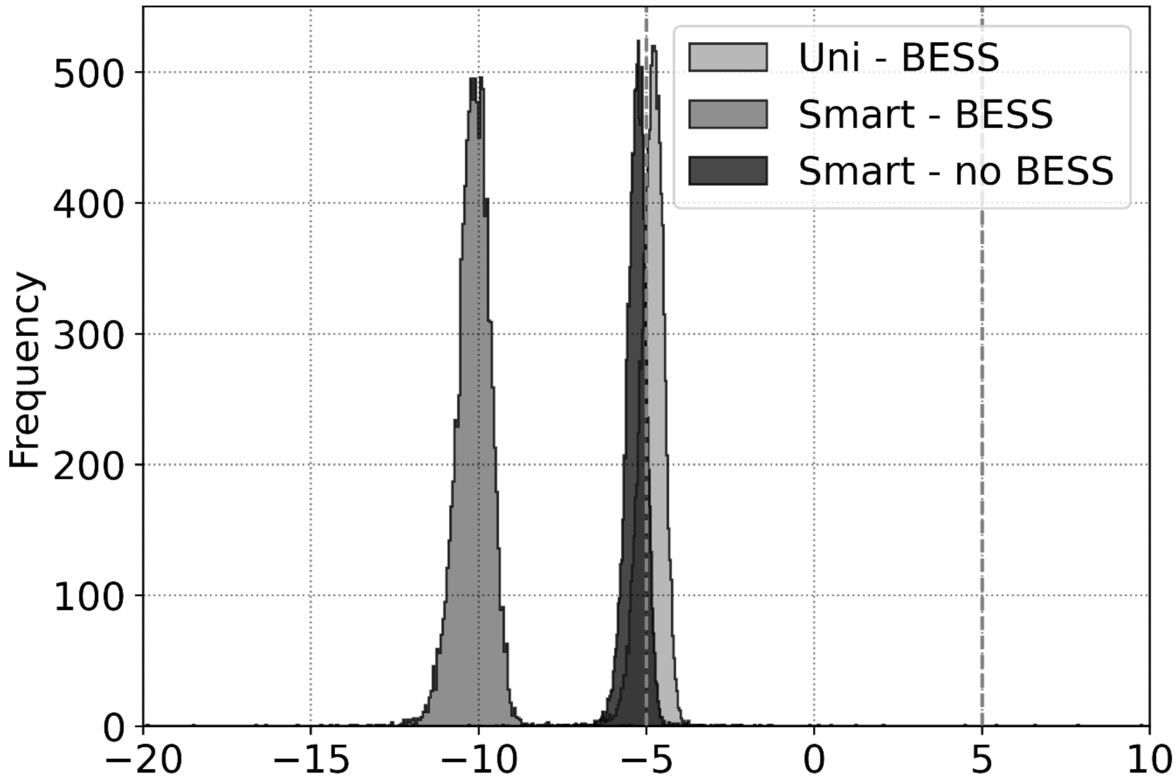

Figure A21: Distribution of differences in climate change impact (gCO_2eq/kWh) between the baseline (Uni – no BESS) and alternative system configurations. Results are based on 10,000

Monte Carlo iterations. Vertical dashed lines indicate a ±50 gCO_2eq/kWh threshold for discernibility.

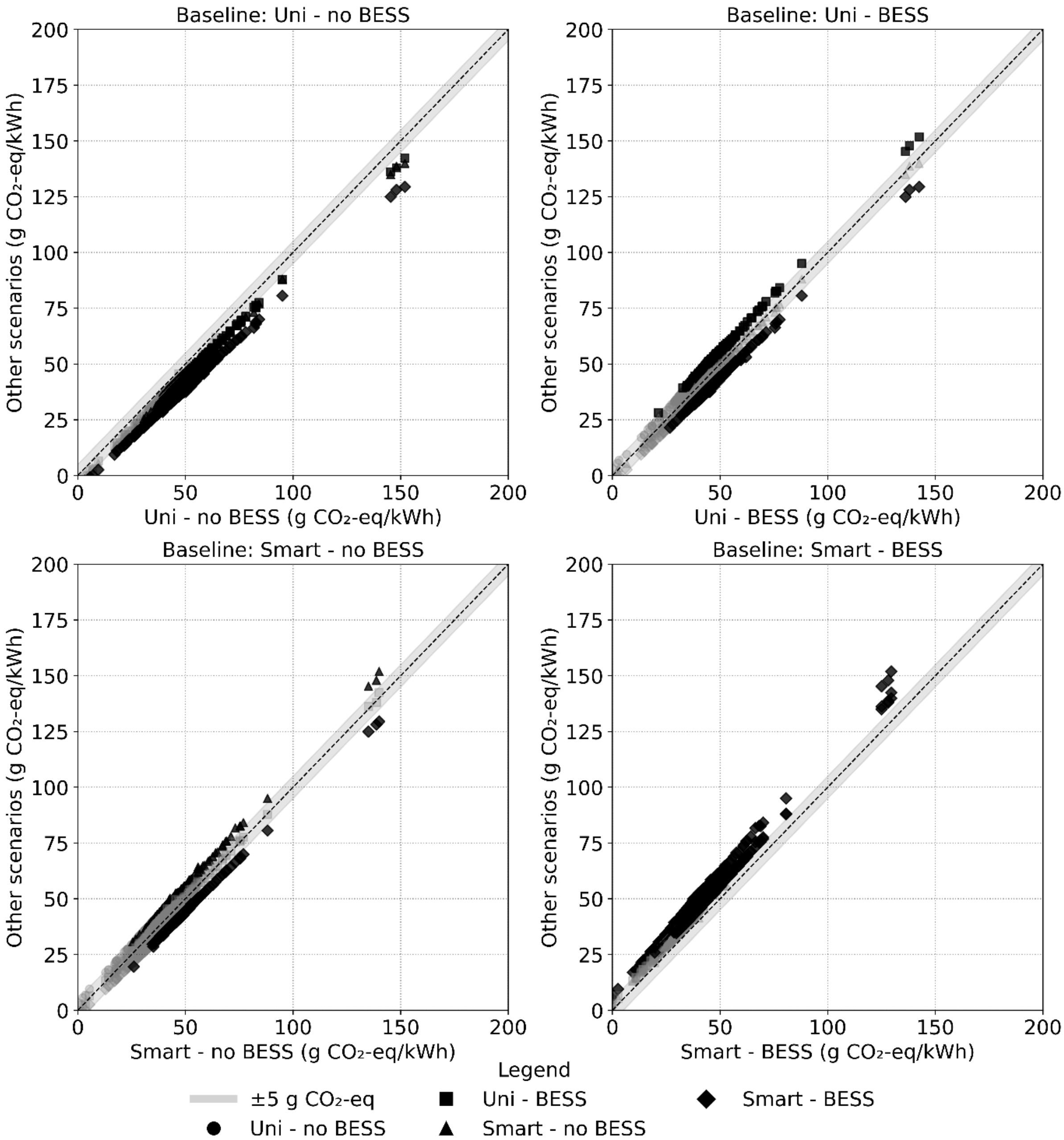

Figure A22: Results of the discernibility analysis for climate change impacts (EF v3.1, midpoint, CC) comparing three energy systems with different charging strategies against the default configuration (uni-directional charging without BESS). Each dot represents the outcome of a single Monte Carlo run (n = 10,000). Points falling within the grey zone indicate statistically similar results (±5 gCO_2eq/kWh); points above or below indicate which scenario is environmentally preferable.

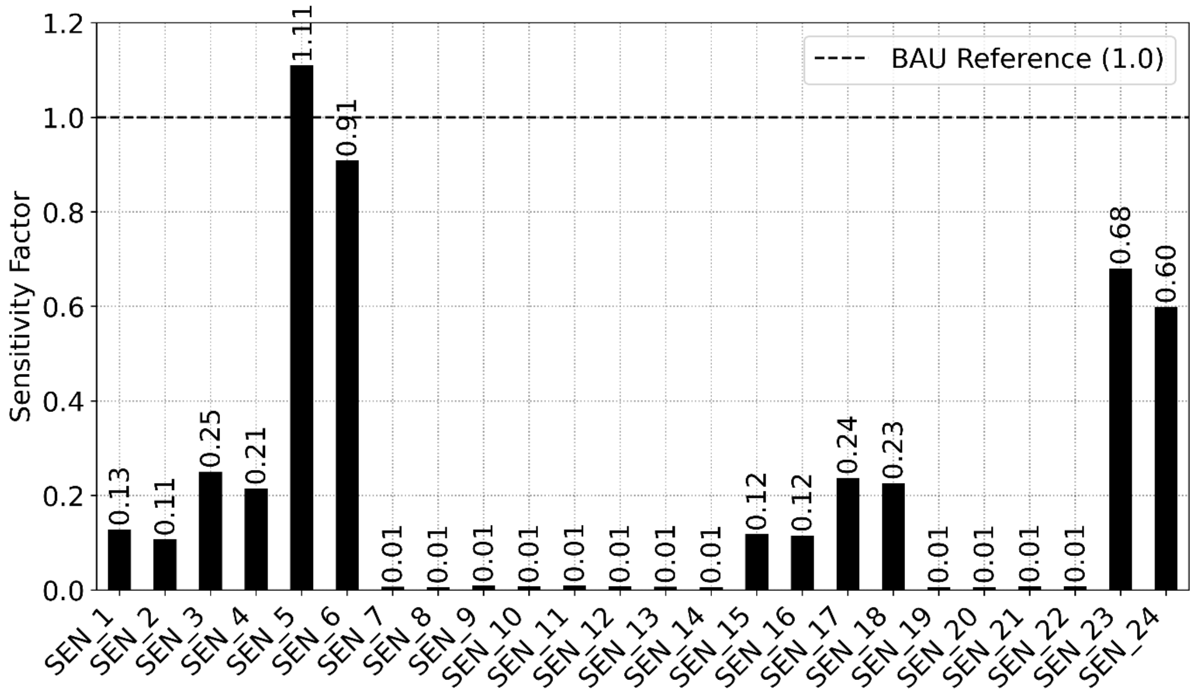

Figure A23: Results of the perturbation analysis for the LCA model of a mezzo-level electricity system in Belgium (SEN_1&2: PV lifetime; SEN_3&4: Wind turbine lifetime; SEN_5&6: Project lifetime; SEN_7&8: LFP lifetime; SEN_9&10: NMC lifetime; SEN_11&12: NMC density; SEN_13&14: LFP density; SEN_15&16: PV capacity; SEN_17&18: Wind turbine capacity; SEN_19&20: LFP size; SEN_21&22: NMC size; SEN_23&24: Grid consumption).

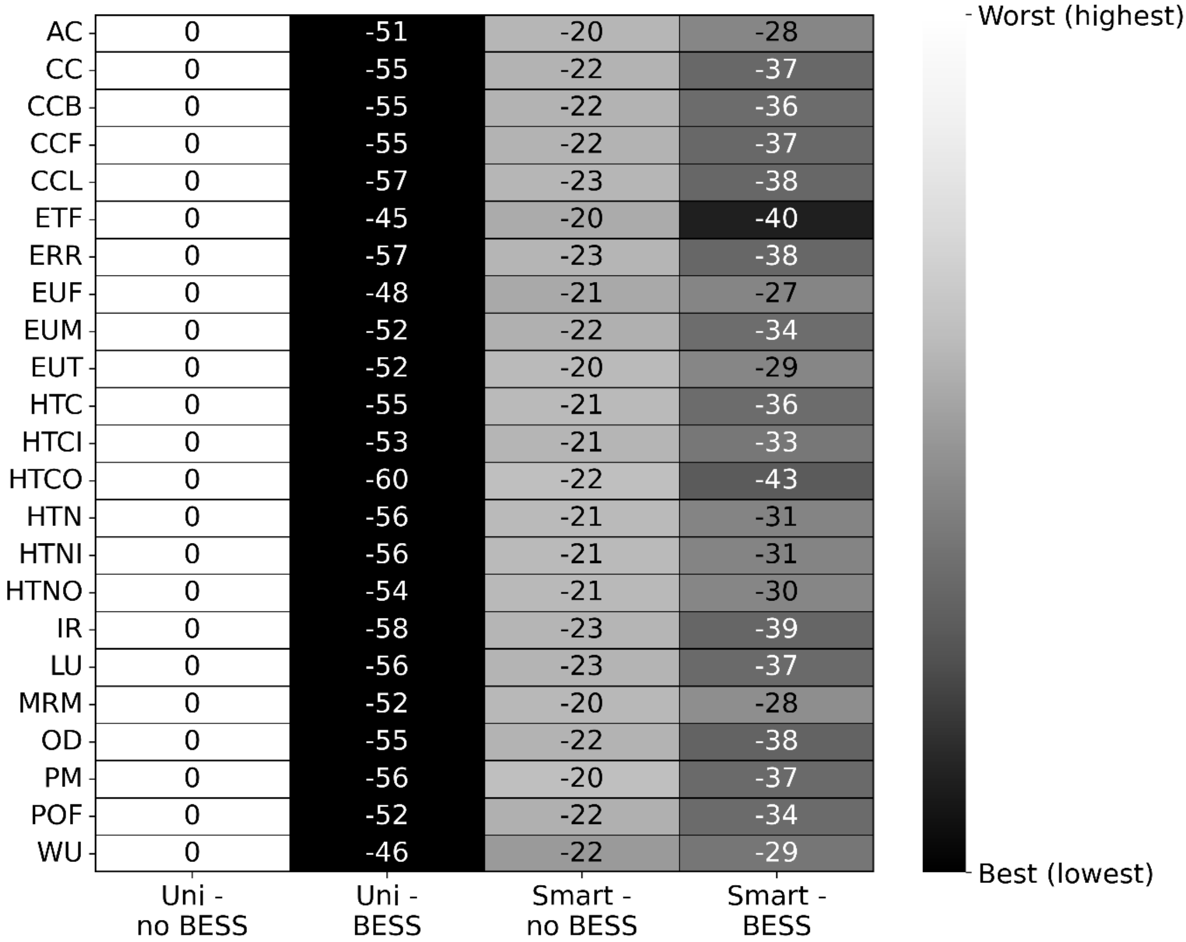

Figure A24: Results of all midpoint impact categories from E.F. version 3.1. for the LCA model of a mezzo-level energy system with different charging strategies in Belgium (BESS = Stationary battery electric storage; CC = Climate change; CCB = Climate change: biogenic; CCF = Climate change: fossil; CCL = Climate change: land use and land use change; ETF = Ecotoxicity: freshwater; ERR = Energy resources: non-renewable; EUF = Eutrophication: freshwater; EUM = Eutrophication: marine; EUT = Eutrophication: terrestrial; HTC = Human Toxicity: Carcinogenic; HTCI = Human Toxicity: Carcinogenic, Inorganics; HTCO = Human Toxicity: Carcinogenic, Organics; HTN = Human Toxicity: Non-carcinogenic; HTNO = Human Toxicity: Non-carcinogenic, Organics; HTNI = Human Toxicity: Non-carcinogenic, Inorganics; IR = Ionising radiation: human health; LU = Land use; MRM = Material Resources: Metals/Minerals; OD = Ozone Depletion; PM = Particulate Matter Formation; POF = Photochemical Ozone Formation: Human Health; WU = Water use).}

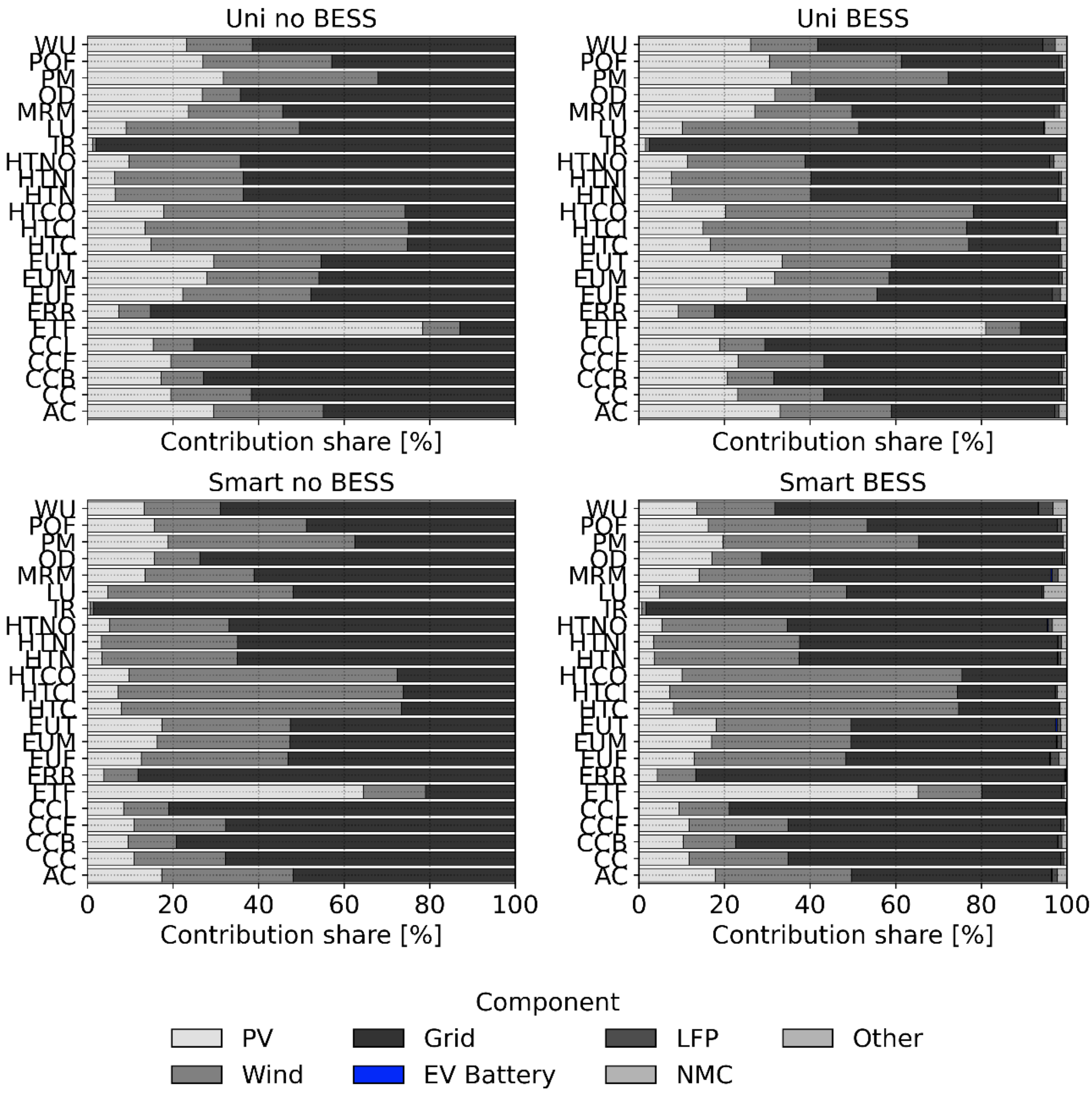

Figure A25: Contribution analysis of all midpoint impact categories from EF v3.1 for the LCA model of a mezzo-level energy system with different charging strategies in Belgium (BESS = Stationary battery electric storage; LFP = Lithium-ion batteries with a cathode made of lithium iron phosphate; NMC = Lithium-ion batteries with a cathod made of lithium nickel manganese cobalt oxide; EV = Electric vehicle; AC = Acidification; CC = Climate change; CCB = Climate change: biogenic; CCF = Climate change: fossil; CCL = Climate change: land use and land use change; ETF = Ecotoxicity: freshwater; ERR = Energy resources: non-renewable; EUF = Eutrophication: freshwater; EUM = Eutrophication: marine; EUT = Eutrophication: terrestrial; HTC = Human toxicity: carcinogenic; HTCI = Human toxicity: carcinogenic, inorganics; HTCO = Human toxicity: carcinogenic, organics; HTN = Human toxicity: non-carcinogenic; HTNO = Human toxicity: non-carcinogenic, organics; HTNI = Human toxicity: non-carcinogenic, inorganics; IR = Ionising radiation: human health; LU =

Land use; MRM = Material resources: metals/minerals; OD = Ozone depletion; PM = Particulate matter formation; POF = Photochemical oxidant formation: human health; WU = Water use).