When CO_2 Accounting changes the Optimum: Implications for Energy Systems with Energy Storage and Electricity Export

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Abstract:

In the context of the energy transition, greenhouse gas (GHG) emissions especially carbon dioxide (CO_2) emissions have become a key metric for designing and assessing energy systems. However, accounting for the demand-side emissions of grid-connected multi-energy-systems is particularly challenging, if emission export is considered. This complexity increases further when integrating energy storage, which shifts both energy and associated emissions over time. Several CO_2 accounting approaches have been proposed but their impact on the operation of storage, system design, and the resulting emissions has not been systematically evaluated. This study investigates the impact of different CO_2 accounting approaches for emission export on the energy system of a real-world example of a small industrial site. The findings contribute to a better understanding of the advantages, limitations, and implications of the respective CO_2 accounting approaches for energy system optimization and thereby supports creating an effective regulatory framework.

Keywords:

Carbon Accounting, CO_2 Emission Export, Energy Storage, Multi-Energy-System

1. Introduction

Climate change mitigation requires a rapid and sustained reduction of greenhouse gas (GHG) emissions across all sectors of human activity. In response, the European Union has committed to climate neutrality by 2050, with an intermediate goal of reducing net GHG emissions by at least 55 % by 2030 compared to 1990 levels, as established in the European Climate Law and the “Fit for 55” legislative package [1]. Many countries have adopted similarly ambitious goals, aiming for climate neutrality and introducing legally binding sectoral emission budgets for electricity, buildings, and industrial sectors [2].

To minimize their GHG emissions and to comply with future emission targets, industry in Europe is aiming to decarbonize their energy supply. First measures often include the installation of renewable energy sources (RES), such as photovoltaics (PV), and energy storage systems like batteries to synchronize supply and demand. In addition, companies are exploring suitable technologies to decarbonize their heat supply, which remains largely dependent on fossil fuels. Therefore, heat pumps and renewable energy carriers like renewable hydrogen and its derivatives are gaining importance [3].

The resulting multi-energy systems and microgrids can be regarded as key enablers of this energy transition [4,5]. Evaluating microgrids alongside district or national scale energy systems and transitions is a central objective of the growing field of energy system optimization [6]. In this context, environmental indicators, particularly carbon emissions, are becoming increasingly important alongside economic metrics as drivers of sustainable system design. In this work, carbon emissions refer to CO_2 emissions and are used as a proxy for GHG emissions.

Accounting for the demand-side carbon emissions of such systems can be challenging, particularly when energy storage is involved [5]. Energy storage mixes and shifts energy and its associated carbon emissions over time. If energy export is allowed and local energy storage is either used for energy arbitrage or as intermediate storage for fossil and renewable energy, assessing exported emissions becomes more complex. As grid electricity prices are becoming more volatile, energy arbitrage gains in economic appeal, especially for seasonal storage with high capacities, few annual storage cycles and consequently high storage costs.

Several approaches have been proposed in recent years to account for carbon emissions. Despite these methodological developments, no consensus has yet been reached on an appropriate accounting approach for multi-energy systems and microgrids, particularly regarding emission export [7–9].

Effects of different carbon export accounting methods on system design, storage operation, and resulting carbon emissions have not yet been systematically evaluated. Our work addresses this gap by analyzing and comparing carbon accounting approaches for exported energy suitable for system design and operational decision-making in integrated multi-energy systems. The study aims to advance the discussion and provide insights into their implications for dispatch strategies, system configuration and most importantly for decarbonization outcomes.

2. Carbon accounting

Carbon accounting involves quantifying carbon emissions that cross the system boundaries. Scope 1 (direct) carbon emissions arise from sources within the system boundary, such as fossil fuel combustion or process-related emissions. While emissions from standard fuel combustion can be estimated relatively easily, other direct sources may require more detailed measurement or modeling. Scope 2, on the other hand, accounts for carbon emissions associated with externally supplied energy, such as electricity imported from the grid. In this case, imported electricity must be assigned a carbon intensity (or burden). With the increasing share of renewable energy in national and local grids, and the resulting fluctuations in generation mix, conventional annual average emission factors (AEF) are becoming increasingly inadequate for accurately capturing Scope 2 emissions of local consumers and time-resolved emission factors have been developed [8,9].

2.1. Carbon intensity of imported energy

Two main approaches are commonly used to resolve grid emissions over time. The first method, the **Grid Mix Emission Factor (XEF)**, assigns each energy source connected to the grid a specific carbon intensity. The temporal carbon intensity of the grid (e.g., hourly) is then calculated as a weighted average, based on the respective contributions of each source [7].

A more recent method, the **Marginal Emission Factor (MEF)**, considers the merit order of the power plants in the grid. The MEF reflects the carbon intensity of the power plant(s) most likely to start up or shut down in response to changes in consumer demand. It thus quantifies the emissions caused or avoided by variations in electricity consumption, providing a more accurate assessment of the impact of different operational strategies. There are different methods for the determination of the MEF. In-detail explanations can be found in [7,8].

2.2. Carbon intensity of exported energy

The carbon intensity of energy exported out of systems *without* storage can be calculated similarly to the Grid Mix Emission Factor as the weighted average of the generation types and their associated carbon intensities [10]. Intermediate storage of burdened energy causes a mixing of energies with different carbon intensities, complicating the assessment of exported emissions.

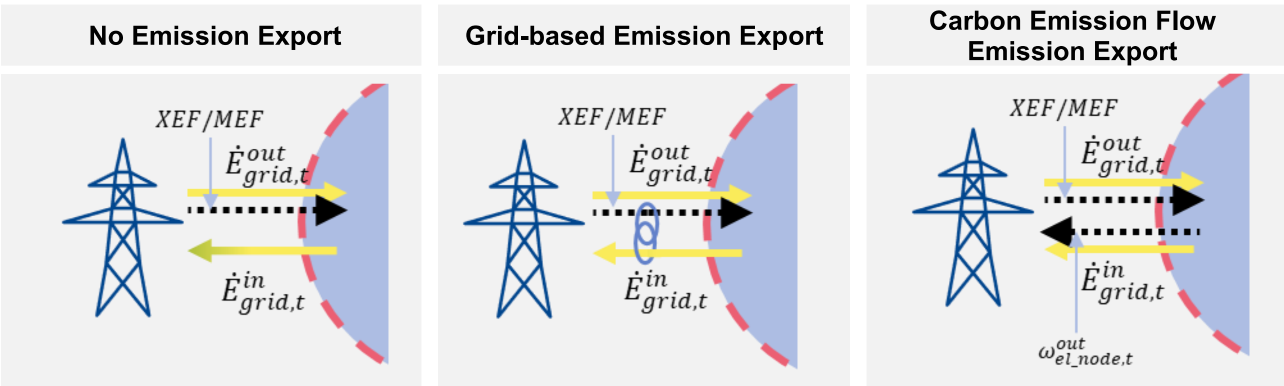

Figure 1. *Graphical depiction of the three discussed emission export approaches. Emissions entering the system boundary can always be accounted for with the imported energy* $\dot{E}_{out}^{Grid}$ *and a grid emission factor (XEF or MEF) while the carbon emission intensity of the exported energy* $\dot{E}_{in}^{Grid}$ *depends on the chosen approach.*

A simple assumption to handle this complexity is that all carbon emissions remain within the system. Under this assumption, all exported energy is therefore carbon-free, regardless of origin. We will refer to this approach as **No Emission Export (No-EE)**. The system's total CO2 emissions can be calculated multiplying the imported energy with the chosen grid emission factor $f_{g,t}^{\mathrm{em}}$ (XEF or MEF):

$$\sum_{g\in Grids}\left(\sum_{t\in T}\dot{E}^{out}_{g,t}\cdot f^{\mathrm{em}}_{g,t}\right)=\text{Total CO}_2\text{ Emissions} \quad (1)$$

(See Appendix for further details on the model and its parametrization.)

This approach is sometimes implicitly applied and represents a worst-case scenario for the evaluated system/microgrid [5,11]. Chen et al. [10] label this approach the “Carbon-Free Generator” model, highlighting the possibility to act as carbon-free energy supplier when the system is operated under this assumption.

Alongside the development of the Marginal Emission Factor, another approach has emerged that bases emissions of exported energy on grid emissions. Here, the grid emission factor f^{Grid}_{t} (XEF or MEF) is used for both imported and exported energy [7,12]:

$$\sum_{g\in Grids}\left(\sum_{t\in T}\dot{E}^{out}_{g,t}\cdot f^{\mathrm{em}}_{g,t}-\sum_{t\in T}\dot{E}^{in}_{g,t}\cdot f^{\mathrm{em}}_{g,t}\right)=\text{Total CO}_2\text{ Emissions} \quad (2)$$

The main purpose of this **Grid-based Emission Export (Grid-based-EE)** approach is to evaluate operational performance of renewable energy sources from an emission perspective. Since the exported energy of renewable energy sources like PV displaces grid electricity with a certain carbon intensity while not running on fossil fuels, the Grid-based EE accounting method can result in negative emissions for the systems. In this context, more negative emission values indicate a higher displacement of carbon-intensive grid electricity, particularly when export occurs during periods of high grid carbon intensity. The drawback of the Grid-based-EE approach is that it does not reflect the microgrid’s actual produced and exported emissions. From an outside perspective, the microgrid acts as an energy provider with the same emission intensity as the current grid mix, if the XEF is applied.

A third approach developed in recent years are the so-called **Carbon Emission Flows (CEF)** or Carbon Aware Power Flows. The fundamental idea of this approach is to introduce virtual emission flows analogous to energy flows. The introduction of these flows allows explicit tracking of emissions and their temporal shifts throughout energy systems, as well as accurate accounting of emission export. Several studies have advanced this methodology, introducing different implementation nuances [8,10,13–18].

The Carbon Emission Flows CEF_i can be determined as product of the energy flows $\dot{E}$ and their associated carbon intensity ω:

$$CEF_{i,t} \;=\; \omega_{i,t}\cdot\dot{E}_{i,t} \quad (3)$$

The carbon emission balance for a converter unit or a node (bus) U can be written as

$$\sum_{in\,\epsilon\,\mathrm{A_u}} CEF_{in,t} \;=\; \sum_{out\,\epsilon\,\mathrm{O_u}} \mathrm{CEF}_{out,t} \quad (4)$$

The carbon intensity $\omega_{i,t}$ is always specific to the source of the energy flow $\dot{E}_{i,t}$, which means incoming carbon flows’ intensity $\omega_{\mathrm{in},t}$ is specific to their source $\mathrm{in}\,\epsilon\,\mathrm{A_u}$ (the unit or node (bus) they originate from), while the carbon intensity of the outgoing flows is specific to the unit or node *u* itself (and not to the unit or node $\mathrm{out}\,\epsilon\,\mathrm{O_u}$they connect to):

$$\sum_{in\,\epsilon\,\mathrm{A_u}} \omega_{in,t}\cdot\dot{E}_{in,t} \;=\; \omega_{u,t}\cdot\sum_{out\,\epsilon\,\mathrm{O_u}}\dot{E}_{out,t} \quad (5)$$

With this formulation, the unit or node specific carbon intensity is calculated as average carbon intensity for all outgoing energy flows. This is commonly referred to as “proportional sharing principle” [10,16,18]. It implies a perfect mixture of the carbon emission flows at every converter unit or node.

For energy storage, the carbon intensity of the discharge flow, which corresponds to the storage carbon intensity ω_{es} can be described as follows.

$$\omega_{es,t+1}=\lambda_{es,t}\cdot\omega_{es,t}+\left(1-\lambda_{es,t}\right)\cdot\omega_{in,t}$$
$$\text{with}\quad \lambda_{es,t}\coloneqq\frac{\eta^{\mathrm{sdc}}_{es}E_{es,t}}{\eta^{\mathrm{sdc}}_{es}E_{es,t}+\Delta t\cdot\eta^{\mathrm{ch}}_{es}\dot{E}^{\mathrm{in}}_{es,t}} \quad (6)$$

with $\eta^{\mathrm{sdc}}_{es}$and η^{ch}_{es}as self-discharge and charge efficiency, E_{es} as energy storage level, $\dot{E}^{\mathrm{in}}_{es}$ as charge flow and Δt as time step duration. This formulation for the carbon intensity of energy storages was developed by Chen et al. [10]. In the following, only the characteristics of this equation are discussed, for the derivation it is referred to Chen et al. [10].

A key feature of this CEF implementation is the explicit consideration of storage self-discharge as well as charging and discharging losses in the emission balance. As a result, the storage carbon intensity remains constant as long as the storage is not charged or empty ($\lambda_{es,t} = 1$). For an initially empty storage charged with burdened energy, the storage carbon intensity equals the carbon intensity of the charging flow $w_{in,t}$(with $\lambda_{es,t} = 0$). When a storage that already contains emissions is charged again, the resulting carbon intensity is given by a convex combination of the previous storage carbon intensity and that of the incoming flow. Chen et al. [10] also propose implementing a minimum storage level to ensure that Eq. (6 is well-defined and to avoid numerical issues caused by the undefined weight of an empty storage.

Eq. 6 further shows that the storage carbon intensity depends on the storage level. While some approaches exist to integrate seasonal storage with temporally aggregated energy system models (e.g., [11,19]), storage levels themselves cannot be temporally aggregated. Consequently, Carbon Emission Flow calculations for systems with seasonal storage require full temporal resolution, entailing a significant computational burden.

Additionally, since both energy flows or storage levels and carbon intensities are variables, the resulting model becomes at least a (mixed-integer) quadratically constrained program. This explains why system design optimization with CEFs for energy systems that include seasonal storage is computationally very challenging.

However, once an optimization without CEFs has been completed, the resulting model variables can be fixed and treated as parameters. The model can then be extended with the CEF equations and solved in a post-processing step to determine carbon emission intensities. Using Eq. (5 for converters and nodes, together with Eq. 6 for storages, all carbon intensities can be determined. In addition, carbon emission flows and storage-related emissions can be derived. The system's total CO2 emissions can then be calculated with

$$\sum_{g\in Grids}\left(\sum_{t\in T}\dot{E}^{\mathrm{out}}_{g,t}\cdot f^{\mathrm{em}}_{g,t} - \sum_{t\in T}\dot{E}^{\mathrm{in}}_{g,t}\cdot \omega^{\mathrm{out}}_{el\_node,t}\right) = \text{Total CO}_2\text{ Emissions} \tag{7}$$

For further details on carbon accounting as well as associated challenges, we refer to Chen et al. [8].

3. Electricity contracts, grid fees and virtual storage

To increase the economic viability of energy storages in local energy systems, we allow energy arbitrage with the power grid in our case study, assuming participation in the day-ahead-market for electricity import as well as export. In Germany, fixed feed-in tariffs for PV energy will be discontinued in 2026 [20]. PV electricity will presumably be sold through direct marketing and flexible electricity contracts are already available. Thus, this scenario can be considered realistic, even for a rather small company.

We add a fixed amount of 0.06 €/kWh to the day-ahead-market prices for imported energy to account for grid fees. In Germany, energy storage (only) connected the power grid can be exempted from grid fees, avoiding double accounting and thereby increasing the economic viability of storage installations [21]. Currently, this exemption is not possible for energy storage which is not solely connected to the power grid but rather integrated into a local energy system (multi-use storage). Exempting multi-use storages from grid fees would exclude internally consumed energy from grid fees. Defining a practical approach for balancing such systems is a current topic of discussion [21,22].

To utilize this incentive in integrated systems, we propose introducing a virtual energy storage for each energy storage type within the local energy system that allows energy to be exported again. For our case study, this includes battery and hydrogen storage system while heat storage is excluded, since we do not consider any heat-to-power conversion. In general, the virtual storage is applicable und useful for any type of power-X-power energy storage. The virtual storage level E_{virt_es} can be defined analogous to the energy storage level as

$$E_{virt\_es,t+1} = E_{virt\_es,t}\cdot\left(\eta^{\mathrm{sdc}}_{es}\right)^{\Delta t} + \Delta t\left(\eta^{\mathrm{ch}}_{es}\cdot\dot{E}^{\mathrm{in}}_{virt\_es,t} - \frac{1}{\eta^{\mathrm{dc}}_{es}}\cdot\dot{E}^{\mathrm{out}}_{virt\_es,t}\right) \tag{8}$$

With η^{sdc}_{es}, η^{ch}_{es} and η^{dc}_{es}as self-discharge, charge and discharge efficiencies of the corresponding real energy storage and $\dot{E}^{\mathrm{in}}_{virt\_es}$ and $\dot{E}^{\mathrm{out}}_{virt\_es}$ as virtual (dis)charge flows.

The virtual storage level is constrained by the corresponding real energy storage level, while the virtual charging and discharging flows are constrained by the associated energy flows:

$$E_{virt\_es,t} <= E_{es,t},\quad \dot{E}^{\mathrm{in}}_{virt\_es,t} <= \dot{E}^{\mathrm{in}}_{es,t},\quad \dot{E}^{\mathrm{out}}_{virt\_es,t} <= \dot{E}^{\mathrm{out}}_{es,t} \tag{9,10,11}$$

To ensure that the virtual storage represents only the energy for arbitrage, the sum over all virtual (dis)charge flows for all virtual storages C is constrained by the grid import $\dot{E}^{\mathrm{out}}_{grid}$ and export $\dot{E}^{\mathrm{in}}_{grid}$.

$$\textstyle\sum_{n\epsilon C}\dot{E}^{\mathrm{in}}_{n,t} <= \dot{E}^{\mathrm{out}}_{grid,t},\quad \sum_{n\epsilon C}\dot{E}^{\mathrm{out}}_{n,t} <= \dot{E}^{\mathrm{in}}_{grid,t} \tag{12, 13}$$

This formulation restricts charging of the virtual storage to periods in which the associated physical energy storage is charged and energy is simultaneously imported from the grid. Likewise virtual discharge is only possible up to the amount of energy discharged from the physical energy storage and simultaneously exported to the grid. If a conversion of the energy carrier takes place between grid import/export and storage (dis)charging, as it is the case for a hydrogen system, the corresponding efficiencies are taken into account.

The amount of **virtual energy discharged** and exported can be used as a measure of energy that is only stored temporarily for **energy arbitrage** and may therefore be exempt from grid fees. We discourage using imported virtual energy for this purpose, as some storage technologies, such as hydrogen systems, exhibit significant losses along the conversion and storage cycle. In contrast to exported virtual energy, imported virtual energy includes these losses. Exempting imported virtual energy from grid fees would therefore also exclude cycle losses. However, these losses represent internal consumption rather than energy used for arbitrage and excluding them would be inconsistent with the intended purpose of the incentive.

It should be noted that the utilization of virtual storage to cut grid fees for integrated energy storage if used for energy arbitrage is only a theoretical consideration as of now and is not (yet) embedded in any legal framework.

4. Case study

As an exemplary investigation, this work focuses on a small-scale industrial site. Apart from the gas and power grid connections, we assume a greenfield scenario for the installation of the energy system. The system can be built from various units as illustrated in Figure 2.

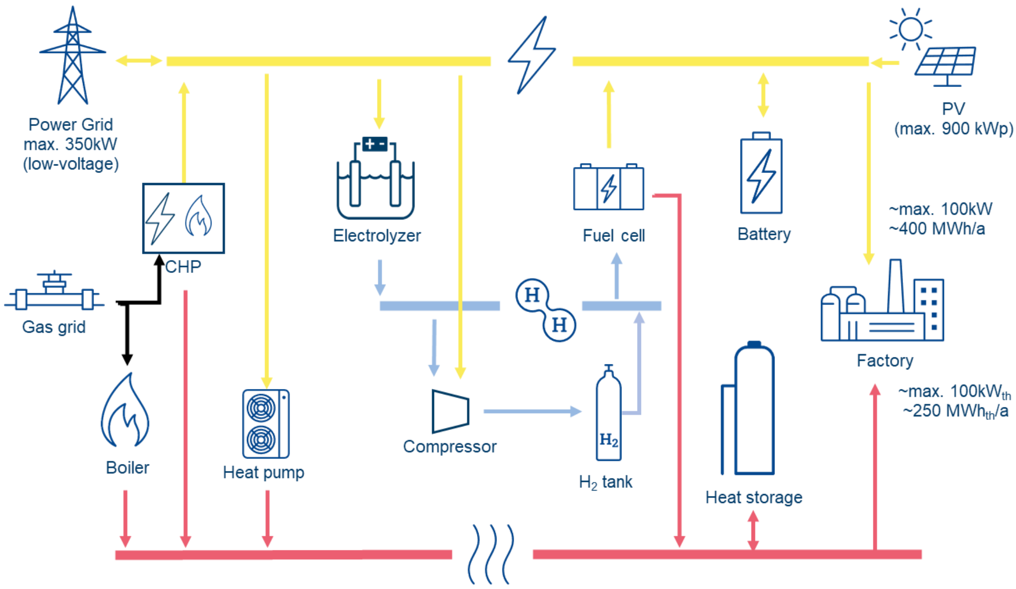

Figure 2. *Structure of the investigated energy system with connections to the electricity and natural gas grid, hourly resolved power and heat demands, PV as renewable energy source, boiler, CHP, heat pump, electrolyzer, fuel cell and compressor as converters and heat storage, battery and hydrogen tank as energy storages.*

Fossil-based units include a Combined Heat and Power unit (CHP) and a gas boiler. Other options for heat supply are a low temperature heat pump or the use of waste heat from the fuel cell. A hydrogen system consisting of a Proton Exchange Membrane (PEM) electrolyzer, a compressor, a 200 bar compressed hydrogen storage tank and a PEM fuel cell can be used for energy storage. Additionally, a battery for electricity storage or a water tank for low temperature heat storage can be installed. Other types of energy storage, e.g. hydraulic, compressed air etc., are not included due to the scope of this study being a small industrial site. For renewable energy sources, only photovoltaic panel (PV) up to a maximum of 900 kWp are considered, due to the site's space limitations. The generation is based on 2023 weather data from a location in the west of Germany [23]. Wind power is not included due to higher installation requirements. The grid connection for electricity is restricted to 350 kW. Electricity and gas grid connections are assumed to be available without additional costs. The hourly time series for electricity and heat demand are characterized by working hours from 6 a.m. to 10 p.m. on weekdays and strong seasonal heat demand fluctuations, since heat is only used for building and water heating. All time series, i.e. for electricity and heat demand, PV generation, electricity day-ahead-market as well as grid emission factors are based on the year 2023 to ensure accurate interactions. We use the Grid Mix Emission Factor (in hourly resolution) for the German grid mix, as provided by the "Green Grid Compass" [24].

The energy system is implemented as mixed integer linear program (MILP) in Pyomo [25,26] and solved with Gurobi [27]. The implementation of equation and constraints is adapted from similar works, e.g. [6,19,28,29]. The considered economic lifetime is 20 years, while the optimization was performed for one year in hourly time steps. See Appendix for further details on model constraints and parameters.

5. Results

In the following, we analyze the impact of carbon emission constraints on system design, operation, and associated costs by comparing the No Emission Export (No-EE) and Grid-based Emission Export (Grid-based-EE) approaches. For this investigation, we use the Grid Mix Emission Factor as carbon emission intensity for the power grid and restrict the permitted carbon emissions of our system while optimizing the total annual costs. Optimization using the Carbon-Emission-Flow Emission Export (CEF-EE) was not feasible due to its high computational costs. Instead, we conduct a post-calculation of the Carbon Emission Flows and make a final comparison of the emission results on the optimized systems for all three approaches.

As **conventional reference system**, only the boiler, CHP and heat storage are allowed, without any emission restriction. The resulting system design consists of a 117 kW_{th} boiler with a 263 kWH_{th} water tank, yielding direct CO_2 emissions of 52 t_{CO2}/a form natural gas combustion and emissions imported via electricity of 120 t_{CO2}/a. Since no internal power generation or electricity storage is installed, no burdened electricity is exported, so all accounting approaches render the same result for this reference system. This conventional reference system corresponds to 100% CO_2 emissions with total system emissions of 172 t_{CO2}/a.

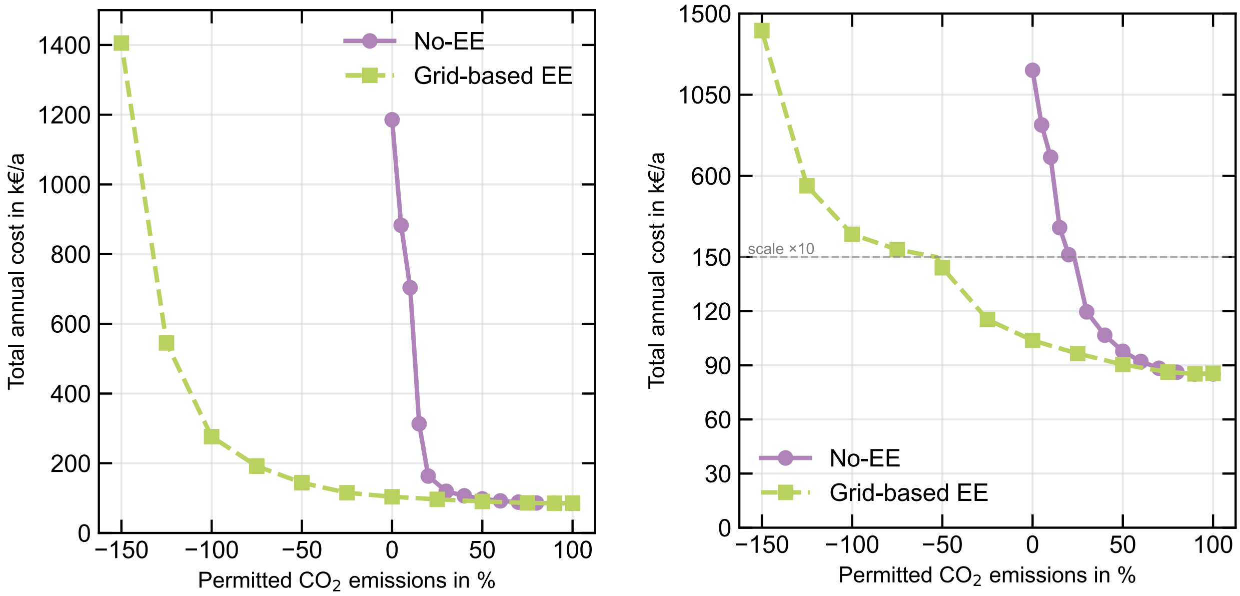

Figure 3. *Total annual costs for energy systems optimized under the No-EE and the Grid-based-EE, plotted against the imposed CO_2 restriction. Right plot includes a break in the y-axis at 150 k€/a to improve the visibility of the results. Lines are included to improve visual guidance.*

It can be observed that, for both approaches, substantial CO_2 reductions are achievable without an excessive increase in total annual cost. For the No-EE approach, carbon emissions can be reduced to 30% while keeping total annual costs below 120 k€/a. Under the Grid-based-EE approach, apparent CO_2 reductions of around 120% relative to the reference system increase the costs by one third. These apparent CO_2 reductions result from the accounting method, in which exported (PV) electricity is credited using the grid emission factor, leading to negative emission balances in the accounting sense, rather than representing physical negative emissions. The underlying system dynamics are examined in the following section, focusing on energy imports, exports, and local renewable energy generation.

A key driver of CO_2 emission reduction is the expansion and utilization of local PV generation, which strongly influences energy imports and exports (**Figure 4**). For the No-EE approach (left), a system restricted to the same CO_2 emissions as the conventional reference system (100 %) mainly uses imported electricity and natural gas but already has a small local renewable energy generation (PV), indicating that PV installation offers an economic benefit. As CO_2 constraints tighten, PV capacity is extended up to the area-limited maximum of 900 kWp, which is reached at around 20 % CO_2 emissions. Electricity export from excess PV generation initially increases but decreases beyond this point, as energy is increasingly required internally to further reduce energy imports. Energy arbitrage here is insignificant as indicated by the virtual discharge.

Similar trends can be detected for the Grid-based-EE approach (right), with two main differences. The first difference is that the maximum PV capacity is reached at around -25 % CO_2 emissions, since low (or negative) emission values are more easily achieved if exported electricity is associated with the grid emissions rather than its actual emissions. Second, instead of a further decrease in energy imports at stricter CO_2 constraints, electricity and even gas imports rise again, as electricity is imported during periods of low grid emissions and exported during periods of high grid emissions, also indicated by the increasing levels of virtual discharge. This emission arbitrage intensifies as CO_2 constraints tighten, requiring increasingly high local storage capacities, as discussed in the next section.

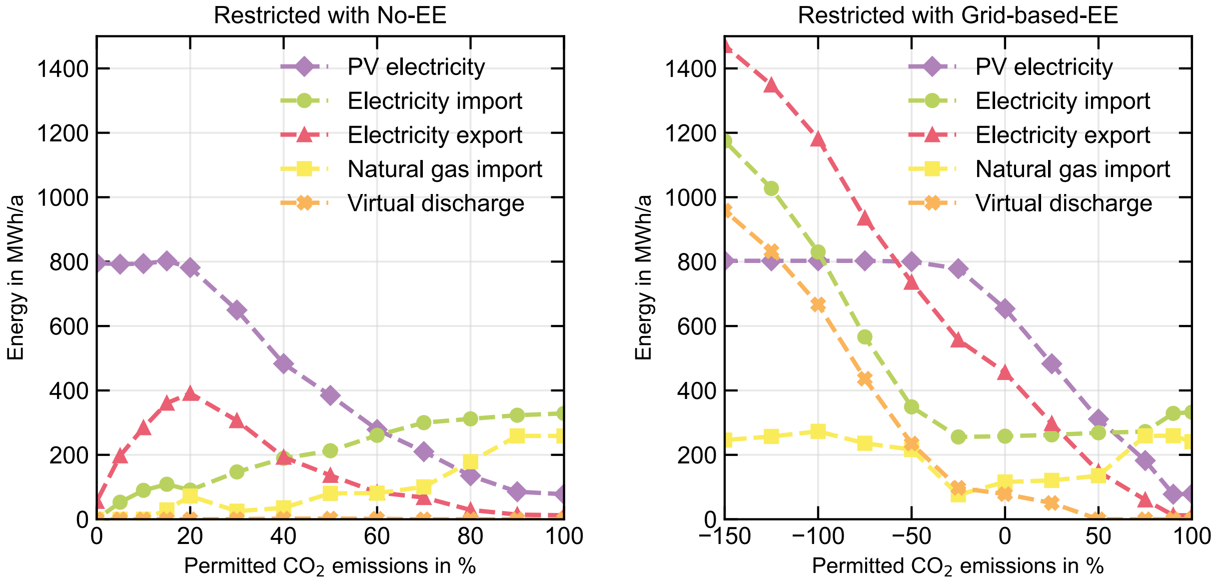

***Figure 4**. Total annual energy imports, export, local RES generation and virtual discharge for energy systems optimized under the No-EE (left) and under the Grid-based-EE approach (right), plotted against the imposed CO_2 restriction. Lines are included to improve visual guidance.*

Taking a closer look at cost distribution (**Figure 5**), several trends can be observed. Under the No-EE approach, substantial CO_2 reductions can be achieved with minor impact on the total annual costs. At low CO_2 constraints – i.e., when the system exhibits high CO_2 emissions – total costs are dominated by variable OPEX, with smaller contributions from the CAPEX associated with a small PV system and a gas boiler. Installing a small PV is cost efficient, as the reference CO_2 emissions restriction could be achieved with the reference system even without PV.

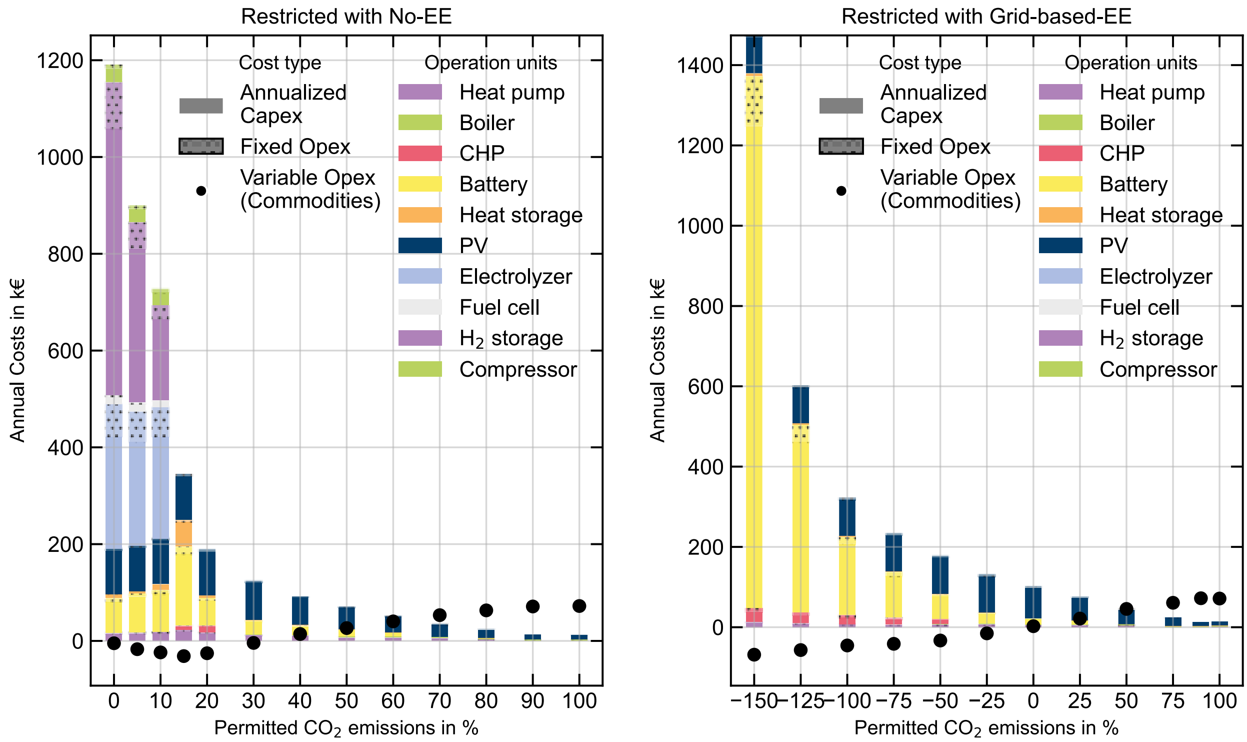

Figure 5. *Annual Costs distribution for energy systems optimized under the No-EE (left) and under the Grid-based-EE approach (right), plotted at the imposed CO_2 restriction. The costs consist of capital expenditure (CAPEX) distribution across different operation units and their associated fixed operational expenditure (OPEX) as well as the variable OPEX for gas and electricity.*

As CO_2 constraints tighten and system emissions decrease, PV capacity is expanded up to the site's maximum available area, while expenditures on imported energy decline. Battery storage also increases in size, reaching its maximum capacity at around 10-15% CO_2 emissions relative to the reference system. At this CO_2 emissions level, commodity expenditures drop below zero, indicating trade profits from low energy imports and high energy exports due to excess PV generation.

Under stricter CO_2 constraint (10%, 5%, or 0%), the system is complemented by a hydrogen storage system consisting of an electrolyzer, a fuel cell, a compressor, and a hydrogen storage, partially replacing the battery. This inclusion of a hydrogen storage system shows that for a nearly autarkic energy systems, a hydrogen storage system can be economically more favorable than a large battery system. Variable OPEX approaches zero at low CO_2 emission levels, because energy cannot be imported without also importing the associated carbon emissions, while internally generated (PV) electricity cannot be exported in large quantities, as it is required to sustain the local energy system.

The Grid-Based Emission Export approach shows different characteristics. Here, under low CO_2 constraints and high system CO_2 emissions, high variable OPEX costs are also observed due to the commodities electricity and gas.

As CO_2 constraints tighten, battery expansion is initially less pronounced than in the No-EE approach. A stronger expansion of battery capacity only occurs at negative system CO_2 emissions (in the accounting sense). Even under very strict CO_2 constraints, no hydrogen storage system is implemented. Energy storage in the Grid-based-EE system is not used solely for balancing local supply and demand (daily or seasonal). While storage still shifts energy from periods of high local production to times with demand-supply mismatch, it is also extensively used for emission arbitrage: electricity is imported when grid emissions are low and exported at times of high grid emissions. This dual use of storage allows the system to reduce its apparent CO_2 emissions by taking advantage of temporal variations in grid carbon intensity. For this energy and emission arbitrage, high cycle efficiencies are beneficial, favoring a battery system over a hydrogen storage system.

As CO_2 emission constraints become stricter, variable OPEX decreases due to lower costs for gas and electricity. However, this reduction does not compensate for the additional expenditures associated with increased storage capacities (s. Figure 3). Consequently, the observed increase in energy arbitrage is not motivated by economic incentives, but rather by the goal of reducing system CO_2 emissions, emphasizing that the choice of carbon accounting method directly influences the system design and operating strategies. The implications of these operational strategies for the resulting system CO_2 emissions across different accounting approaches are analyzed in the following section.

Figure 6 shows the CO_2 system emissions for all three introduced accounting approaches. As expected, the CO_2 emissions calculated with the respective accounting approaches used for restriction closely match the imposed CO_2 emission limit. Only for very high permissible emissions, i.e. 100 %, we can see that the optimized system design and operation for both approaches reach emission values lower than the reference conventional system, which is the benchmark at 100 % CO_2 emission with 172 t/a. That is due to the already mentioned optimized system design including a PV. This lowers not only the total annual costs of the system in comparison to the benchmark but also the CO_2 emissions regardless of accounting approach.

For the optimizations restricted with the No-EE approach (**Figure 6** left), the system emissions are significantly lower when evaluated using the Grid-based-EE approach. A minimum occurs at around 15-20 % permissible CO_2 system emissions, coinciding with maximum electricity export from excess PV generation. Under the Grid-based-EE approach, these exports are associated with grid emission factors, resulting in apparent negative emissions (i.e. accounting credits due to displaced grid electricity). If the system emissions are evaluated with the CEF-EE approach, however, they are almost identical to the No-EE approach, because there is no local generation of burdened electricity (e.g. by a CHP) or energy arbitrage. Electricity is only exported in case of excess PV electricity generation, which is emission-free.

Optimizations restricted according to the Grid-based-EE approach on the other hand show different accounting results (**Figure 6** right). Again, the accounting approaches No-EE and CEF-EE deliver similar results, but only down to a restriction of system emission to around -25 %. At lower CO_2 restrictions, the system starts to exploit emission arbitrage by importing and exporting grid electricity during periods of low grid emissions and exporting it during periods of high grid emissions. But while the Grid-based-EE approach assigns high (grid) emission values to the reexported electricity, the same reexport of energy carries no emissions back out of the system for the No-EE approach. Under the CEF-EE approach, exported electricity carries a carbon burden that reflects its origin and possibly a mixing with renewable energy, and is therefore never higher than the emissions associated with its import. As a result, emission arbitrage does not lead to emission reductions under the CEF-EE or the No-EE approaches, in contrast to Grid-based-EE approach.

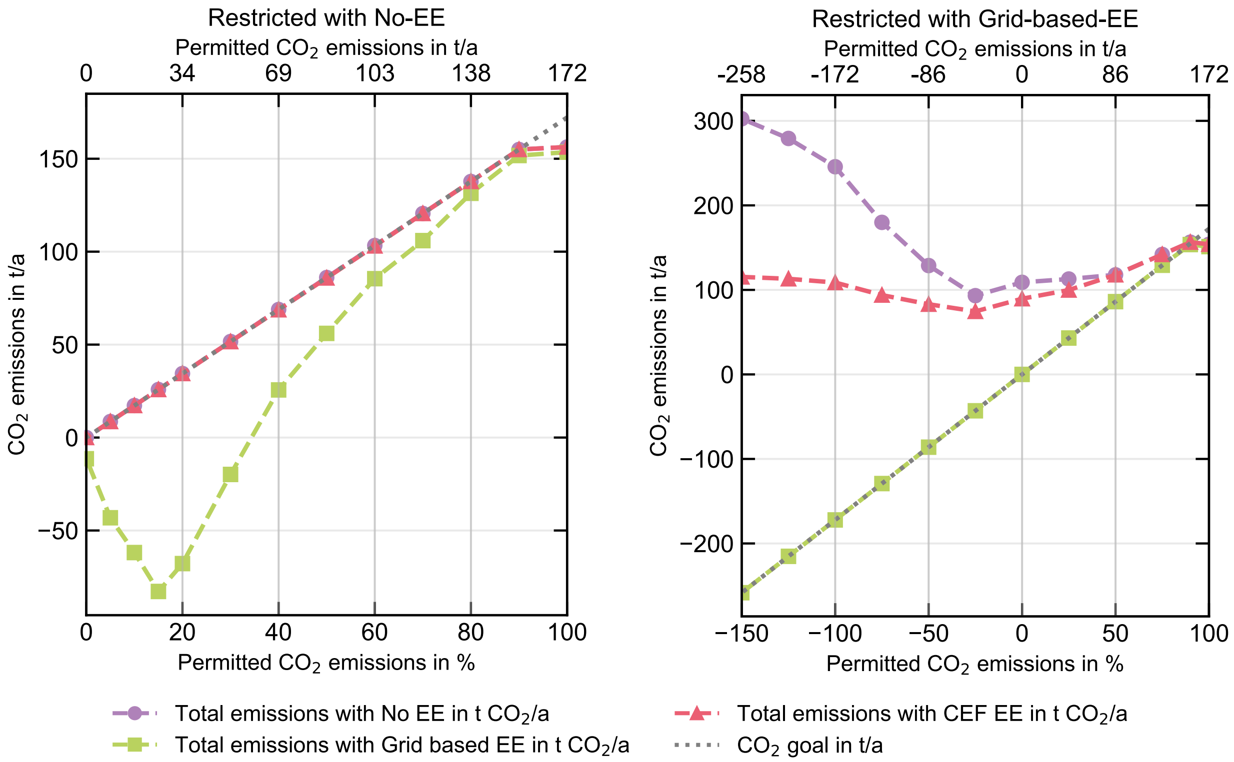

Figure 6. *Total annual system emissions according to the three approaches No-EE, Grid-based-EE and CEF-EE for energy systems optimized under the No-EE (left) and under the Grid-based-EE approach (right), plotted against the imposed* CO_2 *restriction. Lines are included to improve visual guidance.*

Consequently, a strong divergence between the accounting approaches is observed at low emission constraints and high levels of energy arbitrage. The No-EE approach represents an upper bound (worst-case) for system emissions, while the Grid-based-EE approach represents a lower bound. The CEF-EE approach provides the physically most consistent representation of actual system emissions. Overall, the results underline that the selected carbon accounting approach critically determines the interpretation of system emission performance and the perceived effectiveness of emission reduction strategies.

6. Conclusion

In this work, we investigated the impact of different carbon emission accounting approaches on energy system design and operation for a real-world example of a small industrial site. Using a conventional energy system as reference, we imposed CO_2 emission constraints under either the No Emission Export (No-EE) or the Grid-Based Emission Export (Grid-based-EE). In addition, the resulting system emission are evaluated using all three accounting approaches, including the Carbon-Emission-Flow Emission Export (CEF-EE) approach.

The results show that substantial CO_2 emission reductions can be achieved with only moderate increases in total annual costs for both the No-EE and Grid-Based EE approaches. While the No-EE approach enables emission reductions of up to approximately 70% without excessive cost increases, the Grid-Based EE approach allows for apparent negative emission levels at moderate cost increase due to the attribution (crediting) of grid emission factors to exported electricity.

The underlying system behavior differs between the two approaches. Under the No-EE restriction, emission reductions are mainly achieved through structural changes in the energy system, namely the expansion of local renewable generation (PV), reduced energy imports, and increased deployment of storage technologies. At very low emission levels, when PV-generated electricity is seasonally shifted to cover demand, hydrogen-based storage becomes economically favorable.

In contrast, the Grid-based-EE approach promotes operational strategies such as temporal shifting of electricity imports and exports, leading to pronounced emission arbitrage. This increases energy flows and storage utilization without necessarily reflecting physical emission reductions. In this context, a battery storage system is favored over the hydrogen storage system due to its higher round-trip-efficiency, which is advantageous for arbitrage-driven operation. While this system behavior may reduce system-related grid emissions by shifting electricity from periods of high- to low-carbon periods, it does not directly correspond to physical emission reductions at the system level.

The comparison of accounting methods further reveals significant differences in the assessment of system emissions. While No-EE and CEF-EE approaches yield similar and physically consistent results, the Grid-based-EE approach can substantially underestimate physical emissions under strict constraints due to its treatment of exported electricity. Consequently, Grid-based-EE and No-EE can be interpreted as a lower and upper bounds of possible emission outcomes, whereas the CEF-EE approach provides the most physically consistent representation of actual system emissions.

The findings underline that the choice of emission accounting methodology has a decisive impact not only on evaluated emission levels but also on the system design and operational strategies. In particular, results based on the Grid-Based EE approach, which enables emission arbitrage, should be interpreted with caution when assessing actual system emissions, especially in systems with energy storage or direct emissions. The occurrence of apparent negative emissions under the Grid-based EE approach is a methodological artefact arising from accounting credits rather than a physical reduction of emissions. However, it can still provide valuable insights into potential benefits for grid operation.

Overall, the study demonstrates that substantial emission reductions are achievable in industrial energy systems, but that their assessment strongly depends on the chosen emission accounting approach. Further work could extend this analysis by applying marginal emission factors instead of grid mix emission factors and by developing optimization procedures directly based on carbon emission flows or suitable approximations.

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Appendix A

The key model constraints and parameters are presented below.

The objective function of the model defines the total annual cost (TAC) as follows:

$$\mathrm{TAC} = \sum_{k \in K} \left(\mathrm{Capex}_k^{\mathrm{annual}} + \mathrm{Opex}_k^{\mathrm{fixed}} \right) + \mathrm{Opex}^{\mathrm{var}}$$

with $$\mathrm{Capex}_k^{\mathrm{annual}} = \left(c_k^{\mathrm{b}} \cdot b_k^{\mathrm{inst}} + c_k^{\mathrm{m}} \cdot C_k \right) \left(f_k^{\mathrm{inst}} + f_k^{r} \cdot \gamma_k^{\mathrm{r}} \right) \cdot f^{\mathrm{ic}} \cdot \gamma^{\mathrm{a}}$$

$$\mathrm{Opex}_k^{\mathrm{fixed}} = \left(c_k^{\mathrm{b}} \cdot b_k^{\mathrm{inst}} + c_k^{\mathrm{m}} \cdot C_k \right) \cdot f_k^{\mathrm{op}}$$

$$\text{Opex}^{\text{var}} = \sum_{g \epsilon Grid} \sum_{t \epsilon T} \left(\dot{E}_{g,t}^{\text{out}} \cdot \left(f_{g,t}^{c} + f_{g}^{\text{fees}} \right) - \dot{E}_{g,t}^{\text{in}} \cdot f_{g,t}^{c} \right) - \sum_{n \epsilon virt\_es} \sum_{t \epsilon T} \dot{E}_{n,t}^{\text{in}} \cdot f_{n}^{\text{fees}}$$

and $\gamma^{a} = \frac{irr(1+irr)^{L}}{(1+irr)^{L}-1}$, $\quad \gamma_{k}^{r} = \sum_{n=1}^{Y} (1+irr)^{-\Delta t^{r} \cdot n}$, $\quad Y = \left\lceil \frac{L-1}{\Delta t^{r}} \right\rceil$, $\quad b_{k}^{\text{inst}} M_{k} \geq C_{k}$

Energy storages are defined with the following equations:

$$E_{es,t+1} = E_{es,t} \cdot {\eta_{es}^{\text{sdc}}}^{\Delta t} + \Delta t \left(\eta_{es}^{ch} \cdot \dot{E}_{es,t}^{\text{in}} - \frac{1}{\eta_{es}^{\text{dc}}} \cdot \dot{E}_{es,t}^{\text{out}} \right)$$

$$E_{es,t=\text{T}+1} = E_{es,t=1}, \qquad E_{es,t} \leq C_{es}$$

Converters generally conform to the following constraints:

$$\dot{E}_{Conv}^{\text{out}} = \dot{E}_{Conv}^{\text{in}} \cdot \eta^{1\text{st}}, \qquad \dot{E}_{Conv}^{\text{ref}} \leq C_{Conv}$$

The maximum capacity is restricted for the referenced commodity. Moreover, depending on type, there is possibly a secondary input/output relation between the respective commodities. Minimal part load is implemented with the bigM-formulation.

Project/economic lifetime is assumed as 20 years, with an internal rate of return of 0.08 and indirect costs of 30% ($f^{ic} = 1.3$).

Table A1. Cost and performance parameters of utilized units in the energy system model.

Converter units	c^b, €	c^m, €/kW	f^{inst}	f^{op}	Δt^r, a	f^r	partload^{min}	η^{1st}	η^{2nd}	Sources
Compressor	150000	3500 (el.)	1.3	0.05			0.2	1	27	[30,31]
PEM electrolyzer	1000000	1000 (el.)	1.3	0.06	8	0.3	0.2	0.6		[32,33]
PEM fuel cell	10000	1000 (el.)	1.3	0.05	6	0.3	0.2	0.4	0.5	[34,35]
Boiler	1000	100 (therm.)	1.5	0.03			0.2	0.9		*
CHP	10000	1000 (el.)	1.5	0.08			0.2	0.35	0.5	*
Heat Pump	2000	610 (therm.)	1.5	0.05	15	1	0.1	3		[36]
Storage units	c^b, €	c^m, €/kWh	f^{inst}	f^{op}	Δt^r, a	f^r	η^{sdc}	η^{ch}	η^{dc}	Sources
Battery	2000	130	1.5	0.03	8	0.8	0.99993	0.95	0.95	[34,37]
Heat Storage	1500	4	1.5	0.02			0.99917	0.9	0.9	*
H_2 Storage	0	15	1.3	0.03			0	1	1	[30]
RES units	c^b, €	c^m, €/kWp	f^{inst}	f^{op}	Δt^r, a	f^r	C^{max}	Sources		
PV	1000	500	1.5	0.01	20	0.9	900	[34]		

*independent research

Nomenclature

b^{inst}	installation binary
C	capacity, kW(h)
c^b	base cost, €
c^m	capacity-dependent costs, €/kW(h)
CEF	carbon emission flow, kg/h
E	energy, kWh
$\dot{E}$	energy flow, kW
f^c	commodity price, €/kWh
f^{em}	emission factor, kg/kWh
f^{ic}	indirect cost factor
f^{inst}	installation factor
f^{fees}	grid fees, €/kWh
f^{op}	fixed opex as fraction of uninstalled costs
f^r	replacement costs as fraction
K	component
irr	internal rate of return
L	project/economic lifetime, a
M	bigM value, kW(h)
t	time step
Δt	time step duration, h
Δt^r	replacement period, a
TAC	total annual cost, €/a
Y	component replacements

Greek symbols

γ^a	capital recovery factor/annuity factor
γ^r	single payment present value factor
η	efficiency
λ	weight for storage emission intensity
ω	carbon intensity, kg/kWh

Subscripts and superscripts

Conv	converter
ch	charge
dc	discharge
es	energy storage units
Grids	grid units
in, out	in- and outgoing
min	minimal
max	maximal
op	operation
ref	reference
sdc	self-discharge
u	unit or node
var	variable
virt_es	virtual energy storage

References

[1] European Union. European Climate Law; 2021.
[2] Federal Climate Action Act of 12 December 2019 (Federal Law Gazette I, p. 2513), as last amended by Article 1 of the Act of 15 July 2024 (Federal Law Gazette I No. 235).
[3] Peschel A. Industrial Perspective on Hydrogen Purification, Compression, Storage, and Distribution. Fuel Cells 2020;20(4):385–93. https://doi.org/10.1002/fuce.201900235.
[4] Mancò G, Tesio U, Guelpa E, Verda V. A review on multi energy systems modelling and optimization. Applied Thermal Engineering 2024;236:121871. https://doi.org/10.1016/j.applthermaleng.2023.121871.
[5] Terlouw T, Gabrielli P, AlSkaif T, Bauer C, McKenna R, Mazzotti M. Optimal economic and environmental design of multi-energy systems. Applied Energy 2023;347:121374. https://doi.org/10.1016/j.apenergy.2023.121374.
[6] Hoffmann M, Schyska BU, Bartels J, Pelser T, Behrens J, Wetzel M et al. A review of mixed-integer linear formulations for framework-based energy system models. Advances in Applied Energy 2024;16:100190. https://doi.org/10.1016/j.adapen.2024.100190.
[7] Baumgärtner N, Delorme R, Hennen M, Bardow A. Design of low-carbon utility systems: Exploiting time-dependent grid emissions for climate-friendly demand-side management. Applied Energy 2019;247:755–65. https://doi.org/10.1016/j.apenergy.2019.04.029.
[8] Chen X, Chao H, Shi W, Li N. Towards carbon-free electricity: A flow-based framework for power grid carbon accounting and decarbonization. Energy Conversion and Economics 2024;5(6):396–418. https://doi.org/10.1049/enc2.12134.
[9] Miller GJ, Novan K, Jenn A. Hourly accounting of carbon emissions from electricity consumption. Environ. Res. Lett. 2022;17(4):44073. https://doi.org/10.1088/1748-9326/ac6147.
[10] Chen X, Sun A, Shi W, Li N. Carbon-Aware Optimal Power Flow. IEEE Trans. Power Syst. 2025;40(4):3090–104. https://doi.org/10.1109/TPWRS.2024.3514516.
[11] Gabrielli P, Gazzani M, Martelli E, Mazzotti M. Optimal design of multi-energy systems with seasonal storage. Applied Energy 2018;219:408–24. https://doi.org/10.1016/j.apenergy.2017.07.142.
[12] Gabrielli P, Fürer F, Mavromatidis G, Mazzotti M. Robust and optimal design of multi-energy systems with seasonal storage through uncertainty analysis. Applied Energy 2019;238:1192–210. https://doi.org/10.1016/j.apenergy.2019.01.064.
[13] Gu C, Liu Y, Wang J, Li Q, Wu L. Carbon-Oriented Planning of Distributed Generation and Energy Storage Assets in Power Distribution Network With Hydrogen-Based Microgrids. IEEE Trans. Sustain. Energy 2023;14(2):790–802. https://doi.org/10.1109/TSTE.2022.3225314.
[14] Wang Y, Qiu J, Tao Y. Optimal Power Scheduling Using Data-Driven Carbon Emission Flow Modelling for Carbon Intensity Control. IEEE Trans. Power Syst. 2022;37(4):2894–905. https://doi.org/10.1109/TPWRS.2021.3126701.
[15] Parlikar A, Tepe B, Möller M, Hesse H, Jossen A. Quantifying the carbon footprint of energy storage applications with an energy system simulation framework — Energy System Network. Energy Conversion and Management 2024;304:118208. https://doi.org/10.1016/j.enconman.2024.118208.
[16] Kang C, Zhou T, Chen Q, Wang J, Sun Y, Xia Q et al. Carbon Emission Flow From Generation to Demand: A Network-Based Model. IEEE Trans. Smart Grid 2015;6(5):2386–94. https://doi.org/10.1109/TSG.2015.2388695.
[17] Liu N, Yan J, Tan L, Li X, Chen Y, Zhang K. A low-carbon trading strategy of multi-microgrid system considering electricity-hydrogen-carbon coupling characteristics. Energy 2025;327:136420. https://doi.org/10.1016/j.energy.2025.136420.
[18] Gu Y, Li J, Xing X, Cai Z, Deng G, Sun T et al. Carbon Emission Flow Calculation of Power Systems Considering Energy Storage Equipment. In: 2023 8th Asia Conference on Power and Electrical Engineering (ACPEE). IEEE; 2023, p. 1268–1272.
[19] Kotzur L, Markewitz P, Robinius M, Stolten D. Time series aggregation for energy system design: Modeling seasonal storage. Applied Energy 2018;213:123–35. https://doi.org/10.1016/j.apenergy.2018.01.023.
[20] Gieße A. Solarförderung: Bund will fixe Einspeisevergütung abschaffen 2025, 5 December 2025; Available from: https://www.adac.de/news/fixe-einspeiseverguetung-pv-anlagen-vor-dem-aus/.
[21] Bundesnetzagentur. Speichernetzentgelte: Orientierungspunkte der BNetzA: Festlegungsverfahren AgNes (GBK-25-01-1#3); Available from: https://bundesnetzagentur.de/DE/Beschlusskammern/GBK/GBK_Termine/Downloads/2026/01_2026/30.01./Orientierungspunkte_Speichernetzentgelte.pdf?__blob=publicationFile&v=3.
[22] Bundesnetzagentur. Entwurf des Tenors für die Festlegung zur Marktintegration von Speichern und Ladepunkten (MiSpeL); Available from: https://www.bundesnetzagentur.de/DE/Fachthemen/ElektrizitaetundGas/ErneuerbareEnergien/EEG_Aufsicht/MiSpeL/DL/Tenor.pdf?__blob=publicationFile&v=2.
[23] Huld T, Müller R, Gambardella A. A new solar radiation database for estimating PV performance in Europe and Africa. Solar Energy 2012;86(6):1803–15. https://doi.org/10.1016/j.solener.2012.03.006.
[24] 50Hertz Transmission GmbH. Green Grid Compass; Available from: https://www.greengrid-compass.eu/.
[25] Hart WE, Watson J-P, Woodruff DL. Pyomo: modeling and solving mathematical programs in Python. Math. Prog. Comp. 2011;3(3):219–60. https://doi.org/10.1007/s12532-011-0026-8.
[26] Michael L. Bynum Gabriel A. Hackebeil William E. Hart Carl D. Laird Bethany L. Nicholson John D. Siirola Jean-Paul Watson David L. Woodruff. Pyomo — Optimization Modeling in Python. 3rd ed. Springer; 2021.
[27] Gurobi Optimization LLC. Gurobi Optimizer Reference Manual; Available from: https://www.gurobi.com.

[28] Wang Y, Bornemann L, Reinert C, Aßen Nvd. A Power-to-Gas energy system: modeling and operational optimization for seasonal energy supply and storage. In: Kokossis AC, Georgiadis MC, Pistikopoulos E, editors. 33rd European Symposium on Computer Aided Process Engineering. Elsevier; 2023, p. 2867–2872.
[29] Kotzur L, Nolting L, Hoffmann M, Groß T, Smolenko A, Priesmann J et al. A modeler's guide to handle complexity in energy systems optimization. Advances in Applied Energy 2021;4:100063. https://doi.org/10.1016/j.adapen.2021.100063.
[30] Tractebel and Hinicio. STUDY ON EARLY BUSINESS CASES FOR H2 IN ENERGY STORAGE AND MORE BROADLY POWER TO H2 APPLICATIONS; Available from: https://hsweb.hs.uni-hamburg.de/projects/star-formation/hydrogen/P2H_Full_Study_FCHJU.pdf.
[31] Amgad E, Krishna R, Sajag P, Sheir T, Zilong F. Hydrogen Delivery Scenario Analysis Model (HDSAM). Argonne National Laboratory; 2025.
[32] Hemauer J, Rehfeldt S, Klein H, Peschel A. Performance and cost modelling taking into account the uncertainties and sensitivities of current and next-generation PEM water electrolysis technology. International Journal of Hydrogen Energy 2023;48(66):25619–34. https://doi.org/10.1016/j.ijhydene.2023.03.050.
[33] European Hydrogen Observatory. Datasets; Available from: https://observatory.clean-hydrogen.europa.eu/tools-reports/datasets.
[34] IEA. World Energy Outlook 2024; Available from: https://www.iea.org/reports/world-energy-outlook-2024.
[35] Ciglotti V, Genovese M. STATIONARY FUEL CELL APPLICATIONS: CURRENT AND FUTURE TECHNOLOGIES - COSTS, PERFORMANCES, AND POTENTIAL; Available from: https://ieafuelcell.com/wp-content/uploads/2024/11/uptake-international-standards-deployment-stationary.pdf.
[36] IEA. World Energy Outlook 2021; Available from: https://www.iea.org/reports/world-energy-outlook-2021.
[37] Stephan A, Hettesheimer T, Neef C, Schmaltz T, Stephan M, Link S et al. Alternative Battery Technologies Roadmap 2030+. Fraunhofer-Gesellschaft; 2023.