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Research Paper

Dynamic life cycle assessment of European electricity generation based on a retrospective approach

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ABSTRACT

The composition of electricity varies significantly throughout the year. As a result, the environmental impact of the electricity mix is also highly variable. However, most LCA studies assume a static annual average electricity mix and neglect these fluctuations. Therefore, this study examines the time-varying environmental impacts of electricity generation in Germany, France, Italy, Spain, and Poland using a dynamic life cycle assessment. It shows that the impacts of environmental categories vary considerably depending on when the electricity is generated, resulting from the different energy generation patterns throughout the day and year. In particular, the integration of renewable energy sources such as photovoltaic systems and wind turbines leads to significant fluctuations of environmental impacts. To determine the magnitude of the variation, coefficients of variation are calculated for each environmental impact category for a representative year. High coefficients of variation of more than 20% can be observed for several environmental impact categories. In addition, both a production-based and a consumption-based approach were used for the dynamic life cycle assessment. Comparing these two approaches shows significant differences in impact category results, for example, for Italy, with an average of 15%. These differences highlight the importance of including cross-border electricity flows in assessing the environmental profile of electricity. Overall, the results of the study emphasize the need to implement dynamic electricity mix models in life cycle assessments, especially for systems with time-varying electricity consumption. The provided Excel spreadsheet files with hourly time profiles of environmental impacts for the countries studied facilitate the adoption of the developed models by other practitioners and provide a valuable tool for assessing environmental impacts.

Nomenclature.

Abbreviations	
AP	Acidification
CV	Coefficient of variation
DE	Germany
EF	Environmental footprint
ENTSO-E	European Network of Transmission System Operators for Electricity
ES	Spain
EU	European Union
EU_f	Eutrophication, freshwater
EU_m	Eutrophication, marine
EU_t	Eutrophication, terrestrial
FR	France
GWP	Global warming
HT_c	Human toxicity, cancer
HT_nc	Human toxicity, non-cancer
IR	Ionising radiation
IT	Italy
LCA	Life cycle assessment
LU	Land use
ODP	Ozone depletion
PL	Poland
PM	Particulate matter
POCP	Photochemical ozone formation
PV	Photovoltaic
RU_fo	Resource use, energy carriers
RU_m	Resource use, minerals and metals
TPY	Typical meteorological year
WU	Water use
Symbols	
C	Installed capacity

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$\underline{\boldsymbol{C}}$	Consumption-based electricity generation matrices
E	Exports
$\underline{\boldsymbol{EI}}$	Environmental impacts matrices
I	Imports
L	Transformation and self-consumption losses
$\underline{\boldsymbol{LCA}}$	LCA matrices
P	Electricity production time series
$\underline{\boldsymbol{P}}$	Production-based electricity generation matrices
$\underline{\widehat{\boldsymbol{P}}}$	Production-based electricity generation matrices of trading partners
Indices	
g	Electricity transmission and distribution grid
i	Hour
j	Electricity production type
$\widehat{j}$	Electricity production type of trading countries
lv	Electricity generation at low voltage level
n	Environmental impacts categories
t	Trading countries
y	Year

1. Introduction

The power industry, which includes power and heat generation plants, is responsible for almost 40 % of global greenhouse gas emissions [1]. In addition to global warming caused by greenhouse gas emissions, electricity generation significantly contributes to other environmental impacts. These have been examined in many life cycle assessment (LCA) studies. In their review article, Barros et al. compared the results of 47 studies that carried out an LCA of electricity generation [2]. Jordaan et al. even identified 251 articles published between 2009 and 2018 that deal with the environmental impact of electricity generation, either for individual generation types or at grid level [3].

Often, electricity consumption is the most significant influencing factor on the environmental impact of a product system. This applies particularly to electricity-powered systems. For the life cycle impacts of heat pumps, Greening et al. found that the operation of heat pumps, mainly the electricity required, is the primary source of pollution in most environmental impact categories, accounting for an average of 84 % [4]. This finding is confirmed by Naumann et al.'s study on the environmental impact of an air-to-water heat pump in Germany [5]. Similar conclusions are reached by Famiglietti et al. [6]. In addition to heat pumps, the LCA of electric cars also depends heavily on the composition of the electricity mix. Bauer et al. found that the greenhouse gas emissions of an electric car per kilometer driven can be reduced by about half by 2030 compared to 2012, as the greenhouse gas intensity of the European electricity mix is expected to decrease [7]. Similar conclusions were reached by Nordelöf et al. [8]. Cox et al. also investigated the environmental impacts of different passenger cars under different energy scenarios [9]. They found that the benefits of electrifying cars are mainly related to the decarbonization of the electricity sector. The composition of the electricity mix has an even more significant influence on the environmental impact of hydrogen production by water electrolysis. For example, Bareiß et al. found that, considering the German electricity mix of 2017, 96 % of greenhouse gas emissions are attributable to electricity generation [10]. Schropp et al. came to similar conclusions in their study of polymer electrolyte membrane water electrolysis [11]. An evaluation of the environmental and material criticality of anion exchange membrane electrolysis was performed in [12]. This study also identified electricity consumption as the most influential factor.

All the LCA studies mentioned above take a dynamic approach by looking at future impacts using electricity scenarios. However, in all scenarios, they assume a constant electricity mix in the grid on an annual average. Therefore, they neglect that the composition of electricity is subject to strong fluctuations over a year. Fluctuations in the composition of electricity mean that the environmental impact of electricity generation varies greatly. This particularly impacts the LCA of systems whose operation is not evenly distributed throughout the year. Using average electricity data over the year will lead to an over- or underestimation of the environmental impact of these products.

1.1. Literature review

As there are more and more products whose environmental impact is dominated by electricity, the number of studies discussing different approaches to consider electricity generation patterns increases. In their review paper from 2022 on dynamic LCA, Cornago et al. identified a total of 39 publications that designed the life cycle inventory of electricity consumption or the electricity technology mix dynamically, which is a very small number compared to the studies that use an annual average electricity mix [13].

Some studies analyzed the time-varying environmental impacts of electricity generation in general. While Tranberg et al. developed dynamic emission factors for 27 European countries [14], other studies focused on analyzing individual countries. For example, Messagie et al. developed time-resolved emission factors for Belgium [15], Vuarnoz et al. for Switzerland [16], and Kono et al. for the German electricity grid [17]. All these studies used hourly electricity market data to determine hourly carbon emission factors. As such, they do not consider environmental impact categories other than global warming potential (GWP).

Methods for short-term forecasting of time-varying environmental impacts of electricity generation were also presented. While Leerbeck et al. [18] and Bodke et al. [19] forecasted the short-term CO_2 emissions of the electricity grid in their studies, Portolani et al. [20] described a methodology that can be used to forecast several dynamic LCA impact indicators of electricity generation.

Other studies aimed to analyze electricity-consuming systems using a dynamic electricity model. For example, some studies use dynamic electricity mix modeling for LCAs of battery electric vehicles. In their study, Mehlig et al. determined the retrospective emissions associated with charging electric cars in the UK [21]. They used both average and marginal emission factors. Rupp et al. [22] determined greenhouse gas emissions from electric buses in Germany using quarter-hourly electricity CO_2 intensities, and Rangaraju et al. [23] examined the environmental impact of electric cars in Belgium. In addition to battery electric vehicles, LCA studies with dynamic electricity mix modeling have also been conducted in the building sector. For instance, Roux et al. [24] and Collinge et al. [25] used dynamic electricity data to assess the environmental impact of a building. The studies compared the dynamic results with an annual average electricity mix and found large deviations in individual impact categories. Naumann et al. applied a dynamic electricity mix to investigate the environmental performance of a hybrid solar-hydrogen energy system [26]. Although these studies considered a time-resolved electricity mix, they all followed a retrospective approach. Therefore, the electricity models are based on empirical data from previous years. In contrast, Frapin et al. took a prospective approach in their study [27]. They, therefore, considered both short and long-term variations in electricity generation to assess the environmental impact of buildings. A method for incorporating a prospective approach using hourly time steps was also presented by Roux et al. for an LCA of a single-family house in France [28].

In addition to determining environmental impacts, some studies use time-varying electricity mix modeling to identify environmentally optimized system operations. Fattler [29] and Zacharopoulos et al. [30] applied this to identify environmentally optimized charging strategies for electric vehicles. Both studies followed a prospective approach and, thus, considered hourly variations of future electricity scenarios. On the other hand, Terlouw et al. [31] presented an approach for the optimal design of residential energy systems, considering time-varying electricity generation.

In most studies, GWP is considered as the only impact category. In their review, Cornago et al. found that two-thirds of the identified studies that use the dynamic environmental impact as an optimization analysis only consider reducing greenhouse gas emissions [13]. This, however, risks burden shifting, i.e., reducing the environmental impact of one category while increasing the impact of another [32].

1.2 Research gap and objectives

As the analysis of previous studies shows, using time-varying electricity mixes in LCA studies is still rare despite its significant impact on environmental performances. Therefore, this study aims to develop a model to determine European electricity generation's time-varying environmental impacts. To this end, a dynamic life cycle assessment of electricity generation in the five largest electricity consumers in the European Union (EU) is carried out: Germany (DE), France (FR), Italy (IT), Spain (ES), and Poland (PL), which consume two-thirds of the total EU electricity [33]. Two approaches are used to calculate the environmental impact of electricity consumption in these countries. While the production-based approach considers domestic electricity production, the consumption-based model considers the composition of electricity consumption, i.e., excluding exports and including imports [14]. The LCA results obtained from the two approaches are compared and differences are identified.

To the authors' knowledge, no study provides dynamic environmental profiles of electricity generation that are ready for use. Therefore, another aim of the study is to provide the developed temporal profiles of the environmental impacts of electricity generation so that other LCA practitioners can use them without modeling effort and background knowledge of electricity markets. In this way, the dissemination of dynamic LCAs will be promoted. Although it is possible to develop environmental profiles of European electricity generation using the Python package published by Lédée et al. [34], this requires a certain amount of programming expertise. In addition, the tool only allows environmental profiles to be produced based on individual years. Therefore, if these electricity profiles are used in LCA studies, weather variations and other events may affect results disproportionally. In contrast, the model developed in this study compensates for such year-specific fluctuations and thus analyzes the environmental impact of electricity generation in an average year. In addition, the individual dynamic environmental profiles of electricity generation for 2018 to 2022 are provided to increase transparency.

2. Materials and methods

This section presents the methodology used to develop the temporal profiles of electricity generation's environmental impacts in five countries: Germany, France, Italy, Spain, and Poland. First, section 2.1 presents the framework of the environmental assessment. Section 2.2 addresses the required electricity data basis and describes how the generated electricity time series are linked to LCA datasets.

Within the LCA methodology, two general approaches can be distinguished. The attributional approach relies on average data that includes all relevant energy and material inputs throughout the life cycle of a product to examine the direct physical flows involved [35]. In contrast, the consequential approach considers how the relevant physical flows adapt in response to shifts in demand for the product under analysis. Thus, consequential models consider only unrestricted, marginal suppliers capable of adjusting their output in response to increased demand [36]. The choice of approach depends strongly on the application and the research question [37].

In this study, the profiles of environmental impacts of electricity production are developed using the attributional approach, which results in temporally resolved, retrospective, average impact factors. Therefore, the developed impact profiles can only be used in ex-post LCA analyses. However, depending on the research question, it may be necessary to apply the consequential approach. The difference between a dynamic attributional electricity mix and a dynamic marginal electricity mix was investigated by Roux et al. using a life cycle assessment for the electric heating of a single-family house in France [38]. Frapin et al. also investigated the difference between long-term and short-term temporal variations in electricity generation for both methodologies [27].

In contrast to the dynamic attributional electricity factors developed in this study, Hawkes [39] presented a methodology for developing dynamic consequential electricity factors for the UK grid, and Braeuer et al. [40] provided dynamic marginal greenhouse gas factors for the German power system. The choice of using average or marginal emission factors depends on the objective of the study.

2.1. Life cycle assessment methodology

The LCA methodology is used to determine the environmental impact of electricity generation in Germany, France, Italy, Spain, and Poland. LCA is a standardized method used to assess the environmental impact of a product system over its entire life cycle, from the cradle to the grave [41,42]. The product systems cover the following system components:

- the power plants used to generate electricity
- the energy carriers used during the operation of the electricity generators, including extraction, processing, distribution, incineration, and disposal of the resulting waste
- the transmission and distribution grid

The functional unit is the supply of 1 kWh of electricity at a low voltage level in the five analyzed countries. The temporal scope refers to the installed power capacities in 2022. To model the background system, the allocation and cut-off by classification system model of the ecoinvent v3.9.1 database is used [36]. This system model classifies intermediate exchanges into allocatable products, recyclable materials, and waste products. While allocatable products are assessed according to the allocation methods implemented in the system model, recyclable materials are removed from the product system in the End-of-Life phase. The treatment of waste products is entirely attributed to the waste producer [36].

For the impact assessment, the Environmental Footprint (EF) 3.1 method is used to calculate the environmental profiles [43]. The following impact categories were included in the study: acidification (AP), climate change (GWP), ecotoxicity – freshwater (ET), energy resources – non-renewable (RU_fo), eutrophication – freshwater (EU_f), eutrophication – marine (EU_m), eutrophication – terrestrial (EU_t), human toxicity – carcinogenic (HT_c), human toxicity – non-carcinogenic (HT_nc), ionizing radiation (IR), land use (LU), material resources – metals/minerals (RU_m), ozone depletion (ODP), particulate matter formation (PM), photochemical oxidant formation (POCP), and water use (WU). Furthermore, the dynamic profiles provided contain data on the subcategories climate change – biogenic, climate change – fossil, climate change – land use and land use change, ecotoxicity – freshwater inorganics, ecotoxicity – freshwater organics, human toxicity – carcinogenic inorganics, human toxicity – carcinogenic organics, human toxicity – non-carcinogenic inorganics, and human toxicity – non-carcinogenic organics.

2.2. Dynamic electricity emissions model

Within the framework of the study, two different concepts to model the dynamic power generation structures were followed for all countries investigated: a production-based approach and a consumption-based approach. The nomenclature was adopted from Tranberg et al. [14]. While the production-based model considers all local electricity producers within the country's borders, the consumption-based approach additionally includes all imports and exports. The consumption-based model thus considers all electricity flows in the European interconnected grid. However, this is accompanied by a considerably higher simulation effort.

Fig. 1 illustrates the methodology of the developed dynamic models. First, time series for both the production- and consumption-based electricity models are generated using publicly available electricity data. The profiles are then linked to an LCA database. This allows the generation of temporal profiles of the environmental impacts of the respective electricity mixes. The following two sections describe the development of the dynamic models in detail. All models were generated with Python 3.11.4.

2.2.1. Data for electricity generation

The Transparency Platform of the European Network of Transmission System Operators for Electricity (ENTSO-E) is the data basis for the developed dynamic models [44]. This online platform publishes detailed information on electricity generation, consumption, and transmission for all EU Member States. This data is then further processed in the dynamic LCA model. The following datasets of the ENTSO-E Transparency Platform are used in the developed models:

- Hourly-resolved actual generation per production type
- Installed capacity per production type in annual resolution
- Cross-border physical flows in hourly resolution

In both the production-based and consumption-based approaches, electricity production time series P are first calculated for each production type j for each hour i according to Eq. (1). Therefore, for each production type j, the utilization rate for each hour i is calculated by dividing the electricity production $P_{i,j,y}$ by the installed capacity $C_{j,y}$ in the year y. Subsequently, the 5-year averages of the hourly utilization rates for 2018 to 2022 are calculated. These are then multiplied by the installed capacity of each technology $C_{2022,j}$ in 2022. A matrix $\underline{\boldsymbol{P}} \in \mathbb{R}^{i,j}$ with j columns and 8,760 rows displays the generated time series.

Using utilization rates averaged over five years adjusts for annual weather variations. It also reduces the influence of year-specific events such as the COVID-19 pandemic or the war in Ukraine, which had and still have a significant impact on the European power generation. Therefore, it is possible to analyze electricity generation in an average

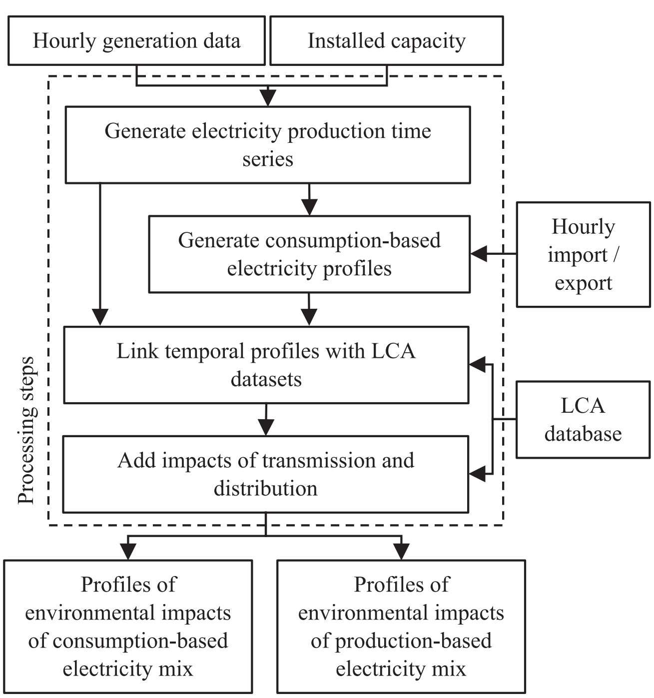

Fig. 1. Schematic overview of the required data and the processing steps to develop the dynamic profiles.

year. This approach also mitigates the impact of data gaps in the ENTSO-E database. However, using utilization rates of all generators averaged over five years does not represent a typical meteorological year (TPY) as used in dynamic building simulations [45]. Such TPYs include temperature peaks, for example, and thus adequately represent the climatic variations of a year. However, the dynamic LCA models developed in this study are based on empirical ENTSO-E electricity market data. The development of electricity models based on TPYs is, therefore, beyond the scope of this study. As it may be necessary for some studies to include temperature peaks, the environmental profiles of the electricity mix for each year are also presented without averaging utilization rates for the years 2018 to 2022.

$$P_{i,j} = C_{2022,j} \cdot \sum_{y=2018}^{2022} \frac{1}{5} \cdot \frac{P_{i,j,y}}{C_{j,y}} \tag{1}$$

Finally, in the production-based model, the environmental impacts are calculated using the generated electricity production matrix $\underline{\boldsymbol{P}}$. The procedure is explained in Section 2.2.2. Table 1 shows the relative annual electricity production structure for all countries considered. For this purpose, the electricity production for the whole year is summed up for each production type and divided by the total electricity production.

For the consumption-based models, the country-specific electricity production time series $P_{i,j}$ generated according to Equation 1 are modified by imports I and exports E occurring with trading countries t. These imports and exports are averaged over five years (Eqs. (2) and (3)).

$$E_{i,t} = \sum_{y=2018}^{2022} \frac{1}{5} \cdot E_{i,t,y} \tag{2}$$

$$I_{i,t} = \sum_{y=2018}^{2022} \frac{1}{5} \cdot I_{i,t,y} \tag{3}$$

$$\overline{P}_{i,j} = P_{i,j} - \left(\frac{P_{i,j}}{\sum_i P_{i,j}} \cdot \sum_t E_{i,t} \right) \tag{4}$$

The sum of all exports is then subtracted proportionally from all electricity producers (Equation 4). In contrast, imports are added as additional columns to the production-based electricity matrix $\overline{\underline{\boldsymbol{P}}}$. These additional columns are, in turn, linked to the country-specific production-based generation matrices of the trading partners $\widehat{\underline{\boldsymbol{P}}} = \in \mathbb{R}^{i,\hat{j}}$, where $\hat{j}$ represents the electricity production technologies of the trading countries. This results in the consumption-based electricity generation matrix $\underline{\boldsymbol{C}}$ (Equation 5).

Table 1
Average production-based electricity mix composition.

Energy source	DE [%]	ES [%]	FR [%]	IT [%]	PL [%]
Biomass	9.0	1.6	0.5	2.2	1.0
Fossil brown coal	20.6	0.0	0.0	0.0	24.4
Fossil coal-derived gas	0.0	0.0	0.0	2.5	0.4
Fossil gas	10.3	28.3	7.1	49.9	10.2
Fossil hard coal	9.8	3.2	0.4	9.2	44.1
Fossil oil	0.7	0.7	0.3	0.6	1.2
Geothermal	0.1	0.0	0.0	2.4	0.0
Hydro pumped storage	2.1	0.0	1.3	1.3	0.5
Hydro run-of-river and poundage	2.8	3.4	8.7	13.2	0.7
Hydro water reservoir	0.3	7.9	3.2	2.6	0.2
Nuclear	6.7	20.8	66.7	0.0	0.0
Photovoltaic	9.9	10.3	3.5	7.4	5.2
Waste	1.3	1.0	0.3	0.1	0.0
Wind offshore	5.7	0.0	0.0	0.0	0.0
Wind onshore	20.8	22.9	8.0	8.6	12.0

$$\underline{\boldsymbol{C}} = \left(\overline{\underline{\boldsymbol{P}}}\middle|\widehat{\underline{\boldsymbol{P}}}\right) \in \mathbb{R}^{i,j+\hat{j}} \tag{5}$$

Accordingly, production-based matrices must be established for all countries with which electricity is exchanged. As a result, a total of 21 production-based electricity matrices are calculated. Fig. 2 shows the flows of electricity imports for the five countries considered. For example, Spain imports electricity from both France and Portugal. As 10 different energy sources are used to generate electricity in Spain, the production-based electricity matrix consists of 10 columns: biomass, fossil gas, fossil hard coal, fossil oil, hydro run-of-river and poundage, hydro water reservoir, nuclear, photovoltaic, waste, and wind onshore. In contrast, the consumption-based electricity matrix has 29 columns: 10 for Spanish, 11 for French, and 8 for Portuguese electricity generation. The resulting consumption-based electricity generation matrices $\underline{\mathbf{C}}$ are then linked to the LCA model to determine the environmental impacts for each time step (see Section 2.2.2).

The ENTSO-E Transparency Platform is a comprehensive source of European electricity market data. However, the platform also has some shortcomings, as already reported by Hirth et al. in their study on the data quality of the platform [46]. Therefore, several adjustments were necessary, which are listed below:

- Occasionally, values are missing in the data series of ENTSO-E. These data gaps were closed by adopting the values occurring directly before. The subsequent value was transferred if a data gap was at the beginning of a year.
- For some countries, values are not available for all five years. For example, data is only provided up to 2020 for the United Kingdom. In such cases, only the available years were included in the calculation.
- For Switzerland, no values are provided for the installed capacity of wind turbines and photovoltaic (PV) systems. These were added manually from [47–49].
- Although data are available for power exchanges between Italy and Malta and between Poland and Ukraine, hourly-resolved power generation time series are missing for Malta and Ukraine. Therefore, these two countries are excluded from the model.

Fig. 2. Electricity trading partners of the five countries analyzed. The arrows indicate the electricity imports. Luxembourg is not shown on the map for the sake of overview.

Furthermore, it should be noted that power generation data listed under the production type "other" were divided among all fossil power generation units used in the respective country under consideration. For example, in Spain's case, the hourly power generation data and the installed capacity were allocated proportionally to fossil gas, hard coal, and oil. This allows for allocating appropriate LCA datasets for each electricity generation type (Section 2.2.2) for calculating the environmental impacts. The electricity generation of the production type "other renewable" was excluded from the model.

2.2.2. Life cycle assessment of electricity generation

The electricity generation time series created in Section 2.2.1 are linked to fitting datasets of the allocation and cut-off by classification system model of the LCA database ecoinvent v3.9.1 [36]. Therefore, a matrix multiplication of the production or consumption-based electricity generation matrices $\underline{\mathbf{P}}$ or $\underline{\mathbf{C}}$ with $\underline{\boldsymbol{LCA}} \in \mathbb{R}^{j,n}$ matrices is used to derive the environmental impact matrices $\underline{\boldsymbol{EI}} \in \mathbb{R}^{i,n}$ (Equations 6 and 7). The $\underline{\boldsymbol{LCA}}$ matrices consist of *j* rows representing the different types of electricity generation and 25 columns corresponding to the 25 environmental impact categories of the EF. 3.1 method.

$$\underline{\boldsymbol{EI}} = \underline{\boldsymbol{P}} \cdot \underline{\boldsymbol{LCA}} \tag{6}$$

$$\underline{\boldsymbol{EI}} = \underline{\boldsymbol{C}} \cdot \underline{\boldsymbol{LCA}} \tag{7}$$

Table 2 uses the example of Spain to show which datasets are used for which production types. The ecoinvent market datasets of the respective country's electricity mix were used to select suitable datasets. For the generation type waste, the Swiss dataset was selected for all countries since the country-specific datasets do not contain values for electricity

Table 2
ecoinvent datasets used to model the electricity supply with corresponding shares of energy conversion technologies.

Energy source	ecoinvent dataset	Share [%]
Biomass	heat and power co-generation, biogas, gas engine – ES	11
	heat and power co-generation, wood chips, 6667 kW, state-of-the-art 2014 – ES	89
Fossil gas	electricity production, natural gas, combined cycle power plan – ES	97
	electricity production, natural gas, conventional power plant – ES	3
Fossil hard coal	electricity production, hard coal – ES	100
Fossil oil	electricity production, oil – ES	100
Hydro run-of-river	electricity production, hydro, run-of-river – ES	100
Hydro water reservoir	electricity production, hydro, reservoir, non-alpine region – ES	100
Nuclear	electricity production, nuclear, boiling water reactor – ES	20
	electricity production, nuclear, pressure water reactor – ES	80
Solar	electricity production, photovoltaic, 3kWp slanted-roof installation, multi-Si, panel, mounted – ES	33
	electricity production, photovoltaic, 3kWp slanted-roof installation, single-Si, panel, mounted – ES	27
	electricity production, photovoltaic, 570kWp open ground installation, multi-Si – ES	40
Waste	electricity, from municipal waste incineration to generic market for – CH	100
Wind onshore	electricity production, wind, <1MW turbine, onshore – ES	35
	electricity production, wind, >3MW turbine, onshore – ES	1
	electricity production, wind, 1–3 MW turbine, onshore – ES	64

generation by waste. The shares of the datasets for the production types, which are additionally listed in Table 2, are chosen to represent the ratios in the ecoinvent market dataset for the respective electricity mix. For all other countries, the selected datasets are listed with the corresponding shares in a supplementary file.

Since the functional unit refers to electricity supply at the low-voltage level, the environmental impacts of electricity transmission and distribution are also considered. Therefore, to calculate the environmental impacts of electricity generation at low voltage level $\underline{\boldsymbol{EI}_{lv}} \in \mathbb{R}^{i,n}$, the $\underline{\boldsymbol{EI}}$ matrices are multiplied by the occurring transformation and self-consumption losses L (Equation 8). In addition, the environmental impacts of the electricity transmission and distribution grid $\underline{\boldsymbol{EI}_{g}} \in \mathbb{R}^{i,n}$ are added. Both the datasets for the transmission and distribution grid infrastructure and the transformation and self-consumption losses are based on the ecoinvent market dataset for the respective electricity mix. Using the $\underline{\boldsymbol{EI}_{lv}}$ matrices, it is possible to determine the environmental impacts of electricity generation for each hour of the year for the countries analyzed. The developed $\underline{\boldsymbol{EI}_{lv}}$ matrices are provided as supplementary Excel files for both consumption- and production-based approaches. In addition, $\underline{\boldsymbol{EI}_{lv}}$ matrices for 2018 to 2022 are presented without averaging utilization rates.

$$\underline{\boldsymbol{EI}_{lv}} = \underline{\boldsymbol{EI}} \cdot L + \underline{\boldsymbol{EI}_{g}} \quad (8)$$

3. Results and discussion

Section 3.1 first shows how the environmental impact of electricity generation changes over a year. This highlights the need to implement dynamic electricity models in LCA studies. The different results of consumption-based and production-based electricity modeling are shown in Section 3.2.

3.1. Change in the environmental impact of electricity generation over time

Fig. 3 shows the composition of electricity generation in Germany in the developed model as a function of time. The data for France, Italy, Spain, and Poland are provided as supplementary material. As can be seen, the electricity production varies both on a daily and monthly basis. Some energy sources, such as biomass, lignite, and nuclear power, generate constant electricity and serve as base-load power plants. In contrast, other energy sources are subject to strong temporal fluctuations. PV and wind power plants are particularly noteworthy here. While PV plants mainly generate electricity in summer, wind power plants are particularly productive in winter.

These different compositions of electricity, which depends on the time of day and season, lead to a variation in the environmental impact of electricity over the year. This is particularly reflected in Fig. 4, which shows the time series for GWP and RU_m of the consumption-based electricity mix for Germany. The orange horizontal line indicates the mean value of the respective impact category. It highlights that the results in both impact categories are subject to strong fluctuations.

For the GWP, variations can be observed throughout the year. The higher the share of renewable electricity generators in the total electricity generation, the lower the GWP of the electricity mix. As can be seen in Table 1, more than 35 % of electricity in Germany is generated by PV plants and wind turbines. However, these two types of generation are subject to fluctuations in electricity generation due to weather conditions, season, and location. Therefore, at a point in time with a high share of renewable electricity generation, the minimum GWP value of 0.248 kg CO_2-eq/kWh is reached. In contrast, the maximum value at a time when renewable electricity generation is low is 0.680 kg CO_2-eq/kWh.

Solar power generation is accompanied by high metal and mineral consumption, which is represented by the impact category RU_m. Since PV power generation mainly takes place in summer in Germany, the RU_m values associated with electricity production in summer are many times higher than in winter. In addition, extreme fluctuations can be observed during the day since the impacts drop sharply when there is no PV power generation at night.

The extent of variation in environmental impacts can be determined for each impact category using the coefficient of variation (CV). This is the quotient of the standard deviation σ and the mean value μ (Equation 7) and is, therefore, a measure of the average deviation of the data points from the mean value. The larger the value, the greater the variation in emissions. In addition to the CVs for each impact category, Table 3 lists the mean values of the LCA results per kWh of electricity and the minimum and maximum values.

$$CV = \frac{\sigma}{\mu} \quad (7)$$

The high CV values of 16 % and 18 % confirm the fluctuations of GWP

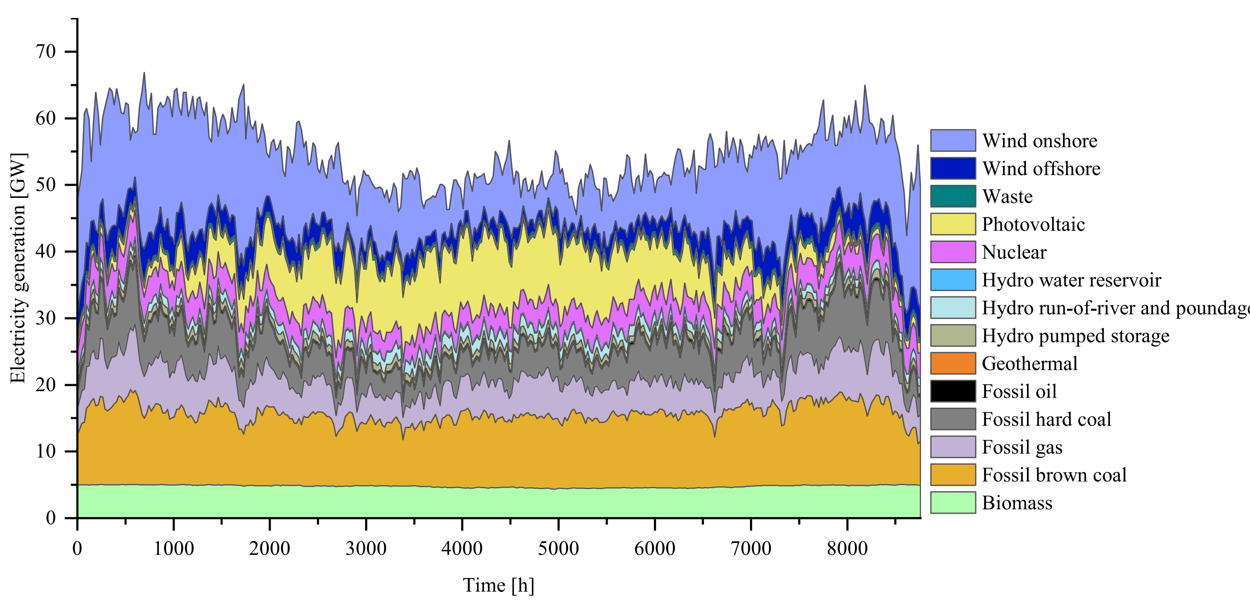

Fig. 3. Hourly composition of the electricity generation profile in Germany for one year.

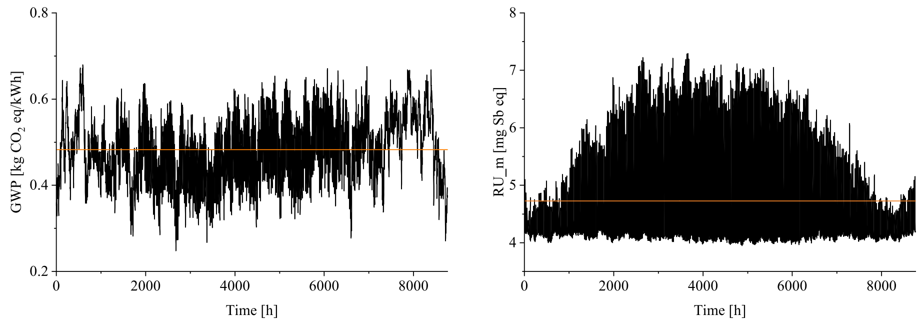

Fig. 4. Time series of GWP and RU_m for German electricity generation using the consumption-based approach.

Table 3
LCA results of the consumption-based German power generation with mean, minimum, and maximum values, as well as the coefficient of variation (CV) of each impact category.

Impact category	Unit	Mean value	Minimum value (deviation from mean value in %)	Maximum value (deviation from mean value in %)	CV [%]
AP	mol H + -eq	1.39E-03	9.64E-04 (70 %)	1.72E-03 (125 %)	9
GWP	kg CO_2-eq	4.83E-01	2.48E-01 (51 %)	6.80E-01 (141 %)	16
ET	CTUe	1.95E-00	1.29E-00 (66 %)	2.40E-00 (123 %)	9
RU_fo	MJ	6.47E-00	3.41E-00 (53 %)	8.87E-00 (137 %)	16
EU_f	kg P-eq	7.04E-04	3.30E-04 (47 %)	1.00E-03 (143 %)	17
EU_m	kg N-eq	3.58E-04	2.11E-04 (59 %)	4.84E-04 (135 %)	14
EU_t	mol N-eq	2.81E-03	1.87E-03 (67 %)	3.67E-03 (131 %)	11
HT_c	CTUh	1.82E-10	1.61E-10 (89 %)	1.99E-10 (110 %)	3
HT_nc	CTUh	7.58E-09	5.93E-09 (78 %)	9.05E-09 (119 %)	7
IR	kBq U235-eq	6.81E-02	3.87E-02 (57 %)	1.30E-01 (191 %)	24
LU	dimensionless	1.52E-00	1.12E-00 (74 %)	2.30E-00 (151 %)	17
RU_m	kg Sb-eq	4.69E-06	3.96E-06 (84 %)	7.19E-06 (153 %)	18
ODP	kg CFC-11-eq	4.98E-09	2.76E-09 (55 %)	7.49E-09 (150 %)	18
PM	disease incidence	6.61E-09	5.47E-09 (83 %)	8.02E-09 (121 %)	8
POCP	kg NMVOC-eq	7.76E-04	5.03E-04 (65 %)	1.04E-03 (134 %)	11
WU	m^3 world eq deprived	1.01E-01	4.80E-02 (48 %)	1.86E-01 (184 %)	22

and RU_m for German electricity generation observed in Fig. 4, respectively. Besides GWP and RU_m, high CVs above 15 % are observed for six further impact categories: RU_fo, EU_f, IR, LU, ODP, and WU. Like GWP, RU_fo directly depends on the share of renewable power generation, which results in a high CV. As can be seen in Fig. 3, hard coal-fired power plants in Germany are used as more flexible medium-load power plants. Leachate from hard coal mines releases large amounts of phosphorus into groundwater, leading to freshwater eutrophication. Therefore, the fluctuations in the EU_f results are mainly due to the fluctuating use of hard coal-fired power plants. Since domestic nuclear power plants are base-load plants with constant operation, the high CV value for IR results from imports from France, where around two-thirds of electricity generation is based on nuclear power. These imports, in turn, are subject to strong temporal fluctuations. The main factors influencing the impact category LU are electricity generation from biomass and ground-mounted PV plants. Biomass power plants are used as base load power plants in Germany and are only subject to minor temporal fluctuations. Therefore, the high CV value is almost exclusively attributable to electricity production from solar parks, which are subject to daily and seasonal fluctuations. The high CV of ODP is due to the flexible use of gas-fired power plants. In the case of WU, water reservoir power plants are responsible, but these hardly play a role in German power generation.

The impact categories EU_m, EU_t, and POCP show CVs between 10 % and 15 %. In contrast, a low CV of less than 10 % can be observed for AP, ET, HT_c, HT_nc, and PM. Accordingly, the environmental impacts of these categories are only subject to minor temporal fluctuations.

Table 4 lists the CVs of all impact categories for all countries analyzed. The general trends for Spain, France, and Italy are transferable from Germany. Since French electricity generation is primarily based on nuclear power, IR, RU_m, and RU_fo values deviate only slightly over the year. The extremely high CV value for LU of Italian electricity generation is caused by the operation of ground-mounted solar parks, which account for a larger share of PV electricity generation in Italy than in the other countries. In contrast, the Polish electricity generation analysis shows that the CVs are lower than those of other countries. This is because Polish electricity generation is mainly based on fossil fuels (Table 1), and therefore, the volatile feed-in behavior of renewable energy producers is less relevant.

The results in this section show that many impact categories are subject to strong fluctuations over time. This is particularly evident in Germany, Spain, France, and Italy. The partially high CV values confirm that using annual average electricity mixes in LCAs can lead to a significant under- or overestimation of the environmental impact of product systems. By using dynamic electricity profiles instead of an annual average electricity mix from LCA databases, more accurate results can be obtained when determining the environmental performance

Table 4
Coefficients of variation (CV) of environmental impacts of electricity generation for all countries analyzed.

Impact category	DE [%]	FR [%]	IT [%]	ES [%]	PL [%]
AP	9	9	13	13	7
GWP	16	24	11	17	8
ET	9	6	5	7	5
RU_fo	16	5	12	14	7
EU_f	17	15	21	11	9
EU_m	14	9	11	13	7
EU_t	11	13	10	13	7
HT_c	3	5	17	4	5
HT_nc	7	5	4	6	5
IR	24	6	36	17	17
LU	17	31	51	30	6
RU_m	18	7	9	10	11
ODP	18	22	8	17	7
PM	8	4	10	6	4
POCP	11	15	9	14	7
WU	22	11	18	25	10

of product systems. Product systems whose electricity production or consumption does not have a constant profile are of particular interest. Examples include heat pumps, which consume electricity primarily during the winter months. Another application is electric cars, which, in uncontrolled cases, are mainly charged at night.

In addition to determining the environmental impact of such technologies, the dynamic LCA electricity models can also be used to determine the potential for environmentally optimized operation of these systems. For example, analyzing when an electric car should have been charged or when a heat pump should have been producing heat is possible. However, it should be noted that the provided dynamic environmental profiles of electricity generation can only be used to determine the retrospective potential of such an operating mode, as the electricity grids are subject to significant changes due to the expansion of renewable electricity generation plants. Nevertheless, such a retrospective analysis could drive innovation towards more environmentally optimized operations. In order to derive strategies for the future operation of systems, an ex-ante analysis by developing temporally resolved prospective scenarios is required. However, the presented dynamic LCA models can serve as a basis for these future scenarios.

Depending on the goal and scope of an LCA, it may be appropriate to apply the consequential approach and thus consider marginal electricity suppliers for short-term, environmentally optimized adjustments to the operating mode of electricity-consuming systems. A method for short-term forecasting of the time-varying environmental impact of electricity generation is presented in [20].

3.2. Comparison of consumption-based and production-based electricity models

Fig. 5a compares the annual mean GWP per kWh of the consumption-based modeled electricity mix with the production-based one. In contrast, Fig. 5b does not compare the annual averages of the two modeling approaches but instead shows the relative deviation of the GWP for the production-based electricity mix from the consumption-based mix for each hour of the year as box plots.

In Germany, Spain, Italy, and Poland, the annual mean production-based carbon intensity of electricity generation is higher than the annual mean consumption-based carbon intensity. This means that electricity imported from trading partners is associated with lower greenhouse gas emissions than domestic electricity generation. While the average difference is relatively small in Germany and Spain, it is much more considerable in Italy and Poland. In Italy, the production-based electricity mix at the high-voltage level, i.e., without transmission and transformation losses, emits an average of 0.463 kg CO_2-eq/kWh. However, Italy imports electricity that is produced with lower greenhouse gas emissions. This is shown in Table 5, which lists Italy's

Table 5
Countries from which Italy imports electricity. In addition, the share of electricity imports of the entire electricity consumption is listed with the associated GWP of the imported electricity.

Exporting countries	Italian electricity imports [%]	Share of imports in Italian electricity consumption [%]	GWP production-based high voltage [kg CO_2-eq/kWh]
Austria	2.9	0.5	0.153
France	31.8	5.7	0.069
Greece	2.3	0.4	0.540
Montenegro	6.2	1.1	0.646
Slovenia	12.2	2.2	0.349
Switzerland	44.5	8.0	0.021

electricity imports and the respective GWP of the imported electricity at high-voltage levels. More than 13 % of the electricity consumed in Italy originates from Switzerland and France, where electricity generation is associated with much lower greenhouse gas emissions. As a result, the average CO_2-eq emissions of the Italian electricity mix related to electricity consumption are lower than those related to production. However, the hourly differences in greenhouse gas emissions between the two modeling approaches are subject to strong fluctuations, as shown by the box plot for Italy in Fig. 5b. The relative deviation is between 10 and 15 % in half of the hours. However, there are also times when the production-based approach leads to 20 % higher greenhouse gas emissions.

The same trend can be observed in Poland for the annual mean difference. Although Poland imports only about 9 % of the electricity it consumes, all the imported electricity, regardless of the trading partner, is associated with lower greenhouse gas emissions since Polish electricity generation is primarily based on fossil fuels, mainly lignite and hard coal. Thus, the imports reduce the annual mean consumption-based carbon intensity compared to the production-based intensity. However, due to the lower share of electricity imports, there is less variation in hourly CO_2 deviations of both electricity models for Poland than for Italy.

In France, on the other hand, annual mean CO_2-eq emissions from electricity consumption are higher than those from electricity production. This is because domestic electricity production already has a low GWP due to the high share of nuclear power. However, imported electricity from Belgium, Germany, Italy, Spain, and the United Kingdom is associated with higher greenhouse gas emissions. Only electricity imports from Switzerland emit less CO_2-eq emissions. In terms of hourly variations, France shows the greatest relative variations. Fig. 5b reveals that the GWP of the consumption-based and production-based electricity mixes differ significantly at certain times of the year. While 50 % of the results show an hourly deviation of 5 to 15 %, maximum

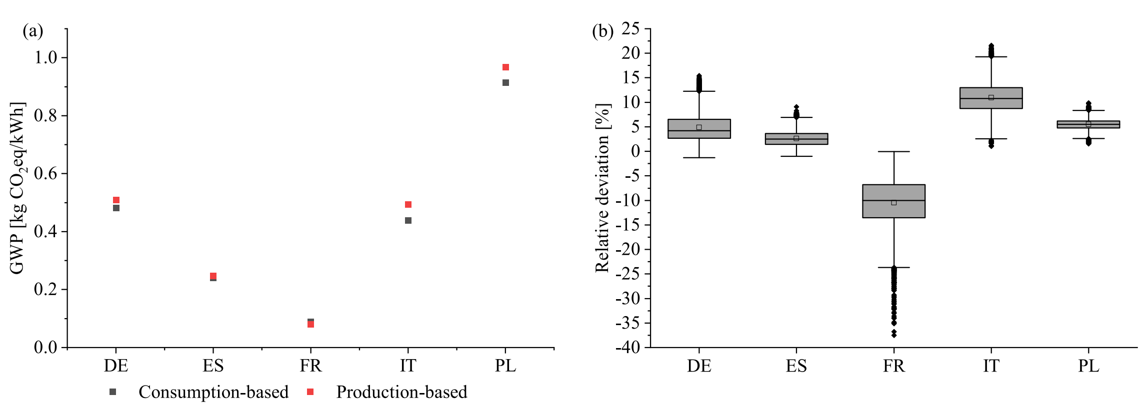

Fig. 5. (a) annual mean GWP of the consumption-based and production-based electricity generation; (b) box plots of the relative hourly deviations of greenhouse gas emissions between production-based and consumption-based electricity mixes.

deviations of almost 40 % can be observed. The negative values for France imply that the production-based emissions are lower than the consumption-based emissions.

Following Tranberg et al., the consumption-based carbon intensity is lower than the production carbon intensity in countries with a high share of fossil fuel power producers due to electricity imports [14]. This pattern is reversed for countries with a low share of fossil power producers.

Fig. 6 shows a radar chart comparing the annual mean consumption-based and production-based electricity generation LCA results for all impact categories by setting the higher result to 100 % and scaling the lower result accordingly. Therefore, the following analyses only refer to the average annual results. Similar to the GWP shown in Fig. 5b, the differences in the results of the other impact categories of the two electricity mixes can also vary much more in individual hours.

For the French electricity mix, the results of the two electricity models differ by 4.5 % on average in all impact categories. The consumption-based modeling leads to lower impacts in only 2 of 16 impact categories: RU_fo and IR. Significant deviations of more than 10 % are observed for EU_f and LU. As can be seen in Table 1, France generates very little electricity from biomass and PV compared to the electricity trading partners. These two electricity generation technologies are associated with a transformation of land and, therefore, an impact in the LU impact category. Thus, imported electricity has much higher LU impacts. The higher EU_f results of the consumption-based approach are caused by imported coal-based electricity since France does not use lignite for electricity generation. However, among the electricity trading partners are countries, such as Germany, which use lignite as an energy source for electricity production.

The average deviation of the LCA results for the German electricity mix is 5.2 %, with consumption-based modeling showing higher impacts in only 4 impact categories. The deviation is significant for IR and WU. Around 14 % of Germany's electricity imports come from Norway, which accounts for 1 % of Germany's electricity consumption. As Norway generates more than three-quarters of its electricity from water reservoir plants, and this type of electricity generation causes high water consumption, Germany's consumption-based electricity mix has a significantly higher water consumption than the production-based mix. The same applies to imports from Switzerland, which also generates more than 20 % of its electricity with water reservoir plants. The higher ionizing radiation of the consumption-based electricity mix is because the last nuclear power plant in Germany was decommissioned in April 2023 [50]. Therefore, in 2022, the reference year of this study, only small capacities of nuclear power plants were under operation. However, 29 % of Germany's imports come from France, where nuclear power is the largest electricity producer.

The deviation of the LCA results is highest for the Italian electricity mix, with an average of 14.7 %. Thereby, the impacts of the production-based electricity mix are higher in 11 of 16 impact categories. Differences of more than 10 % are observed for the following impact categories: GWP, EU_f, HT_c, IR, ODP, POCP, and WU. IR stands out with 94.4 % lower impacts of the production-based approach. This is due to electricity imports of the consumption-based electricity mix from France. In contrast, Italy does not operate nuclear power plants, resulting in very little ionizing radiation in domestic electricity generation. However, the consumption-based electricity mix emits less greenhouse gas emissions because, as described in Fig. 5, a large share of Italy's electricity imports comes from Switzerland and France, whose electricity mix is associated with a lower GWP. Electricity imports from Switzerland also account for the higher water consumption of the consumption-based electricity mix. While there is no lignite-fired power generation in Italy, it plays a significant role in Slovenia, Montenegro, and Greece. Although the imported electricity volumes from these countries are not large, they result in higher EU_f impacts of consumption-based electricity generation. In contrast, the production-based electricity mix has higher values than the consumption-based

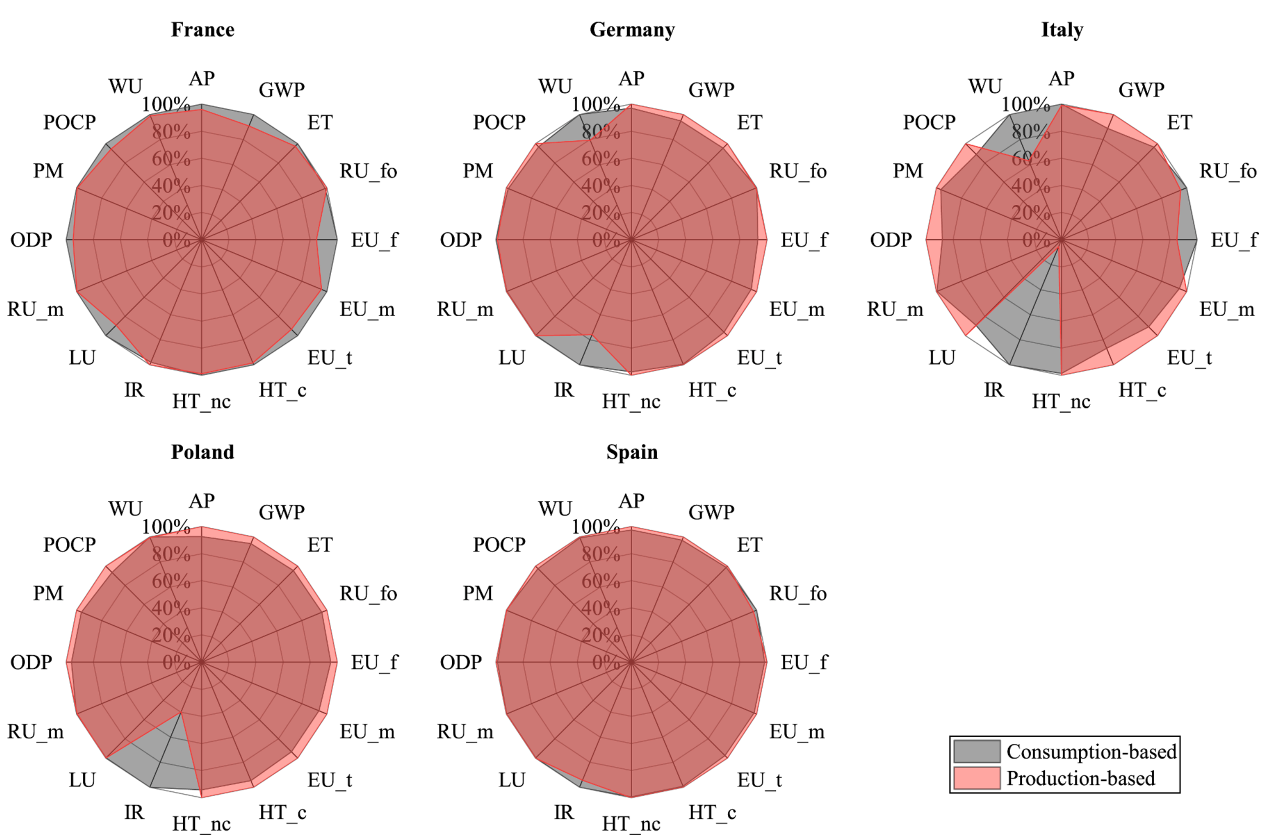

Fig. 6. Relative environmental impacts of consumption-based and production-based electricity generation.

electricity mix for the HT_c, ODP, and POCP categories. This is due to the use of coal gas for electricity generation in Italy, which is associated with high impacts in these categories.

In Poland, the average deviation of the LCA results is 7.9 %. The production-based approach leads to higher impacts in 13 impact categories. A significant deviation can only be observed for IR, as Poland does not operate any nuclear power plants but imports nuclear power from other countries.

The slightest deviation in the average LCA results is observed for Spain with 1.8 %. The two electricity mixes are similar because in Spain only 5 % of the electricity consumed originates from electricity imports.

The comparison of the results of the two modeling approaches shows that even the annual average results differ significantly for most countries. Looking at the hourly deviations for GWP, all countries show significant variations in the differences in greenhouse gas emissions between the two electricity mixes. This pattern can also be transferred to other impact categories. Therefore, electricity imports significantly impact electricity emissions in many countries. The difference between the consumption-based and production-based electricity mixes highlights the importance of including cross-border electricity flows in assessing the environmental profile of electricity. Although the proposed methodology is more complex than the production-based analysis due to the inclusion of cross-border electricity flows, it better reflects the reality of the integrated European electricity market.

4. Conclusions

The dynamic assessments show that the impacts of the different environmental categories vary considerably depending on the time of electricity generation. As Poland's electricity generation is primarily based on fossil fuels and, therefore, the fluctuating feed-in of renewable energy sources plays a minor role, the environmental impact of Polish electricity generation shows the slightest temporal variation. In contrast, electricity generation in Germany, France, Italy, and Spain has coefficients of variation above 10 % for most impact categories. In some cases, the variation is even higher than 20 %. The largest temporal variation, with a coefficient of variation of more than 50 %, is observed for the land use category in Italy.

In addition, the analysis shows that the results of the consumption-based and production-based modeling approaches differ significantly for most countries. With an average deviation in environmental impacts of around 15 %, the difference is most significant for Italy. Therefore, especially for countries with high electricity imports and exports, LCA studies should not only be based on the environmental impacts of domestic electricity production but should also consider cross-border electricity flows.

The study's results highlight the need to implement dynamic electricity mix models in LCA studies that examine product systems with time-varying electricity consumption, like electric heating systems such as heat pumps or the charging of electric cars. However, using dynamic electricity models leads to more accurate results in almost all LCA studies of electricity-consuming product systems, as the electricity consumption of most product systems varies over time, and the level of environmental impact, therefore, depends on the time of the actual electricity consumption. Due to the supply of the developed dynamic environmental profiles of electricity generation as supplementary material, the dynamic approach can be easily transferred into further LCA studies. In addition to determining the environmental impact of electricity-consuming technologies, the dynamic LCA electricity models can also be used to determine the potential for environmentally optimized operations. However, only the retrospective optimization potential of such technologies can be determined, as the provided dynamic environmental profiles are based on empirical data. Future studies can extend the model for developing prospective scenarios to enable the application of ex-ante LCA analyses. In addition, it would be advisable to expand the model to include also dynamic marginal electricity mixes so that environmental profiles are available for both attributional and consequential LCA studies.

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CRediT authorship contribution statement

Gabriel Naumann: Writing – original draft, Visualization, Software, Project administration, Methodology, Investigation, Formal analysis, Conceptualization. **Jacopo Famiglietti:** Writing – review & editing, Investigation, Conceptualization. **Elke Schropp:** Writing – review & editing, Visualization, Validation, Investigation, Conceptualization. **Mario Motta:** Supervision, Funding acquisition. **Matthias Gaderer:** Supervision, Funding acquisition.

Declaration of competing interest

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

Data availability

Data will be made available on request.

Appendix A. Supplementary material

Supplementary data to this article can be found online at https://doi.org/10.1016/j.enconman.2024.118520.

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