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Time-aware life cycle inventories for electricity consumption

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ABSTRACT

Software package *shrecc* is designed to handle electricity mix data across European countries, using data from the Energy-Charts API. With an increasing share of renewable energy in electricity mixes, environmental impact varies by hour, day and season – which is not systematically accounted for in LCA. To remediate this, *shrecc* prepares live-tracked electricity data for use with the *brightway* package, enabling more accurate life cycle impact assessment (LCIA). Through a case study of electric vehicle charging, we demonstrate the importance of temporally granular data. Our findings reveal that relying on annual average electricity mixes can lead to both over- and underestimation of LCIA results, highlighting the need for more time-aware approaches in energy related life cycle assessments.

Metadata

Nr	Code metadata description	*Please fill in this column*
C1	Current code version	v1
C2	Permanent link to code/ repository used for this code version	https://git.list.lu/shrecc_project
C3	Permanent link to reproducible capsule	Due to the licensing requirements associated with the *ecoinvent* database, this approach is not applicable in our case.
C4	Legal code license	MIT license
C5	Code versioning system used	*GitLab*
C6	Software code languages, tools and services used	*python*
C7	Compilation requirements, operating environments and dependencies	**Operating systems:** Linux (Ubuntu 20.04 or newer) Windows 10 (64-bit) or newer **Hardware configuration:** **Minimum**: Standard desktop or laptop with a modern multi-core processor (e.g., Intel i5 or equivalent). **Recommended**: High-performance processor (e.g., Intel i7 or equivalent) with at least 16GB RAM for handling larger datasets and faster data processing. **For advanced users**: If users wish to calculate data from years beyond the supplied data, they may need a high-performance server with greater processing power (e.g., multi-core server CPU, 32GB+ RAM) to manage the increased computational demands. **Other dependencies:** JupyterLab, GitLab, Conda **brightway framework** (since shrecc is built to integrate with it) **Energy-Charts API** (for retrieving data) **Ecoinvent** (for database matching)
C8	If available, link to developer documentation/manual	*https://shrecc.readthedocs.io/en/latest/*
C9	Support email for questions	sabina.bednarova@list.lu thomas.gibon@list.lu

Motivation and significance

The lack of accuracy when representing electricity-producing activities in life cycle assessment (LCA) has been shown to introduce significant bias in impact assessment results, particularly by using annual averages over more granular timeframes [1–4]. Profound changes in the way electricity is currently being produced, namely via an increasing share of intermittent sources in the supply mix of many countries and grids, as well as a substantial rise in international exchanges (current and planned), may lead to LCA studies misrepresenting electricity mixes

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in modelled supply chains over time. Implications of these misrepresentations range from inaccurate life cycle impact assessment (LCIA) results, especially in electricity-intensive systems, to the incompatibility of current LCA databases with upcoming regulations, e.g. the EU Directive on renewable fuels of non-biological origin [5], or national rules regarding electricity-intensive infrastructure [6].

As the use of LCA is becoming mainstream, so is the reliance on commercial databases, such as *ecoinvent* [7] or *sphera* [8], life cycle inventory (LCI) databases containing thousands of electricity mix models. While the choice is broad, these models often leave the practitioner to their own devices when it comes to building an *accurate* representation of electricity use in the LCA system at hand, for two main reasons. On the background[1] side, electricity life cycle inventories (LCIs) are all built on annual averages, representative of [year n-3] in *ecoinvent* and *sphera*. On the foreground side, electricity consumption itself rarely occurs continuously and constantly over a full year. The latter reason is of particular interest as the share of intermittent electricity production increases in most countries, with the direct consequence that a given production mix may change sensibly from one hour to another, one month to another, or one season to another. When consumption also varies, substituting an accurate mix with the average can lead to substantial errors in estimating life cycle impacts [4,9]. Many studies have presented the importance of time-aware electricity mixes, including in the specific context of LCA [10–13] and the creation of dynamic LCIs (a term that includes time-differentiated models) as defined in [14].

A potentially high variability of electricity mixes translates into a potentially high uncertainty of LCIA results, which may reduce the reliability of LCA. In general, uncertainty in LCA is split into location, level, and nature, the latter being split into epistemic and ontic uncertainty [15]. Epistemic uncertainty is *knowledge* uncertainty, and in theory, can be reduced by gaining more knowledge. Ontic uncertainty, also called variability, refers to random processes and in theory, cannot be reduced. Electricity mixes are in nature variable; however, we would like to argue that with appropriate knowledge and proper tools, their variability can be correctly captured. Such high resolution not only improves the accuracy of results but also enables the optimization of studied systems. For example, in scenario analysis, identifying the optimal time to charge an electric vehicle requires high-resolution temporal data. For such application, annual average electricity mix cannot provide the necessary level of detail to identify time-specific optimization. Instead, using high resolution temporal data can reduce the uncertainty in LCIA and optimize studied systems.

Several tools have tried to fill this gap, by providing LCA practitioners with accurate electricity data, at the hourly step or even lower – yet most require some sort of ad-hoc conversion step that LCA practitioners need to take. *Electricity Maps* is a Danish company providing such electricity data services [16]. Their strategy is to use public live data from various transmission operators (TSO), or TSO organizations, combine it with source-specific life cycle greenhouse gas emission factors, and publish the carbon intensity of a given consumption or production mix at the hourly step. Although highly useful for corporate carbon emission reporting, this service does not fully cover the needs of LCA practitioners as electricity mixes are not part of the published data, and greenhouse gases are the only life cycle indicator assessed. As a response to this observation, *EcoDynElec* was developed to match such live data (namely from the European Networks of TSOs for Electricity, ENTSO-E) with emission factors calculated from the *ecoinvent* database [17]. The final product of *EcoDynElec* is therefore a set of time series for the electricity consumption for a given grid, at a given time, compatible with *ecoinvent* – and therefore consistent with the LCI model that an LCA practitioner would have built with *ecoinvent*. Although a significant achievement, a main criticism that can be made with *EcoDynElec* is that it does not provide the specific LCI for a given amount of electricity consumed at a specific time and place – only LCIA results, which may be less useful to a practitioner, as they cannot be readily integrated in a detailed LCI model. Other minor drawbacks are its limited user-friendliness (e.g. users must select which exact neighbouring countries need to be modelled), and its incompatibility with LCA software package *brightway*. Other existing tools include *Futura*, a tool facilitating electricity modelling in LCA [18]; *bentso*, an interface to import ENTSO-E data into a *brightway* project [19]; and more recently, *Peakachu*, also developed for *brightway* [20] – all shown in Table 1 with their main characteristics.

The ability to consider and model exact electricity consumption mixes in LCA systems is key to being able to provide robust and accurate environmental impact assessments for all types of systems [21], and more crucially for electricity-intensive technologies. At the regulatory level, the European Delegated Act on Hydrogen [5], which mandates hourly tracing of electricity from 2030, or increasingly stringent rules for time-matching in renewable electricity certificate trading (e.g. France mandating that all cancellations of EECS guarantees of origin be monthly- instead of annually-matched with their issuance from 2021) show a definite need in the higher-resolution modelling of electricity in LCA.

Software description

The *shrecc* software package allows users to seamlessly incorporate hourly electricity data into their *brightway* projects. It downloads data from the Energy-Charts API for 45 European countries, treats it and converts everything from high and medium voltage to low voltage electricity mix. A user can choose any countries and times, reoccurring or one-off, to be written as a *brightway* 2 or 2.5 electricity database into their chosen project. (Fig. 1, Fig. 2).

Software architecture

The software package is composed of three main elements: *shrecc.download, shrecc.treatment*, and *shrecc.database*. It also comes with pre-calculated, hourly-resolved data, back to 2022, which can be downloaded from the *shrecc_data* repository[2]. In that case, the user only needs to be aware of the functions in *shrecc.database*, including a function to filter the given data for countries and the times needed for the analysis, to match them to ecoinvent processes, as well as functions that create and write a *brightway* (2 or 2.5 – *shrecc* is *brightway*-agnostic) database. For older years, functions from *shrecc.download* will download the production, trade and load data for all available countries for a given year and save them into a dataframe. In *shrecc.treatment*, the data is parsed, matched from ENTSO-E to ecoinvent categories, and re-calculated to a single layer of low voltage electricity mix. This part is recommended to run on a server, as it involves matrix inversion.

A final output of the package is a *brightway* database, written in a user-specified project. Activities created in said database can easily be incorporated into any project.

Software functionalities

Data download

In *shrecc.download*, a function called *get_data()* will download the production, trade and load from the Energy-Charts API. It automatically downloads all available data for all countries in a specified year. Other functions that properly categorise, clean and add missing data get called

[1] Among LCA practitioners, "foreground" refers to the LCA system at hand, built mostly from primary data, whereas "background" refers to the part of the LCA model built from generic activities (from reference databases), generally outside the core scope of the product system.

[2] Accessible at https://git.list.lu/shrecc_project/shrecc_data

Table 1
Comparison with existing tools.

Feature	*ElectricityMaps*	*EcoDynElec*	*bentso*	*Futura*	*peakachu*	*shrecc*
Source for live data	ENTSO-E (and other TSOs worldwide)	ENTSO-E	ENTSO-E	IEA (not live)	ENTSO-E, ClimateTrace	energy-charts.info API (curated ENTSO-E data)
Native support for consumption mix calculation*	yes	yes	no	no	no	yes
Creates inventories	no	no	yes	no	no	yes
Impact indicators	GHG	GHG	All impact indicators	All impact indicators	GHG	All impact indicators
Brightway-friendliness	none	low	high	none	high	high
Compatibility with ecoinvent	none	high	high	high	high	high

*whether the software natively computes consumption mixes from production mixes and exchanges

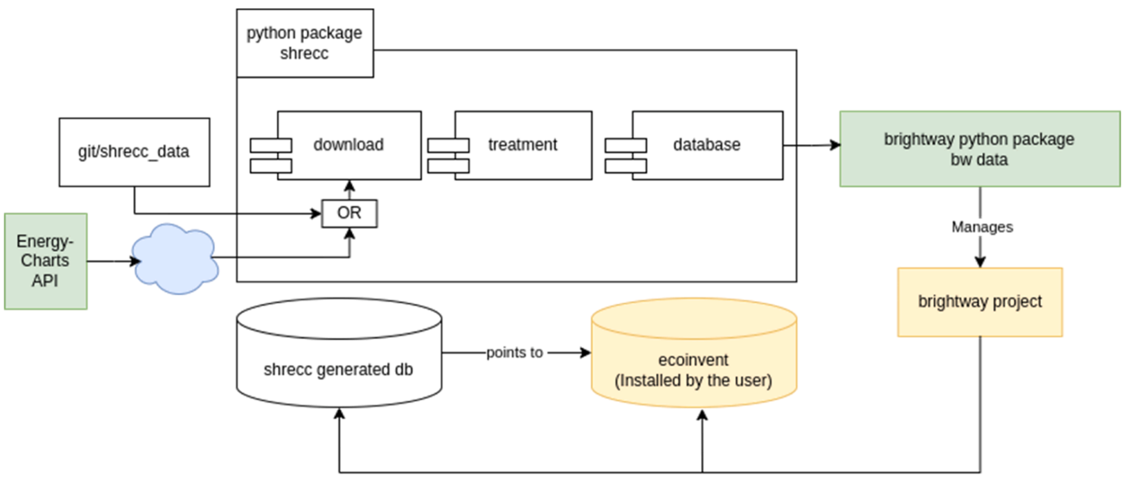

Fig. 1. Software architecture of the shrecc package.

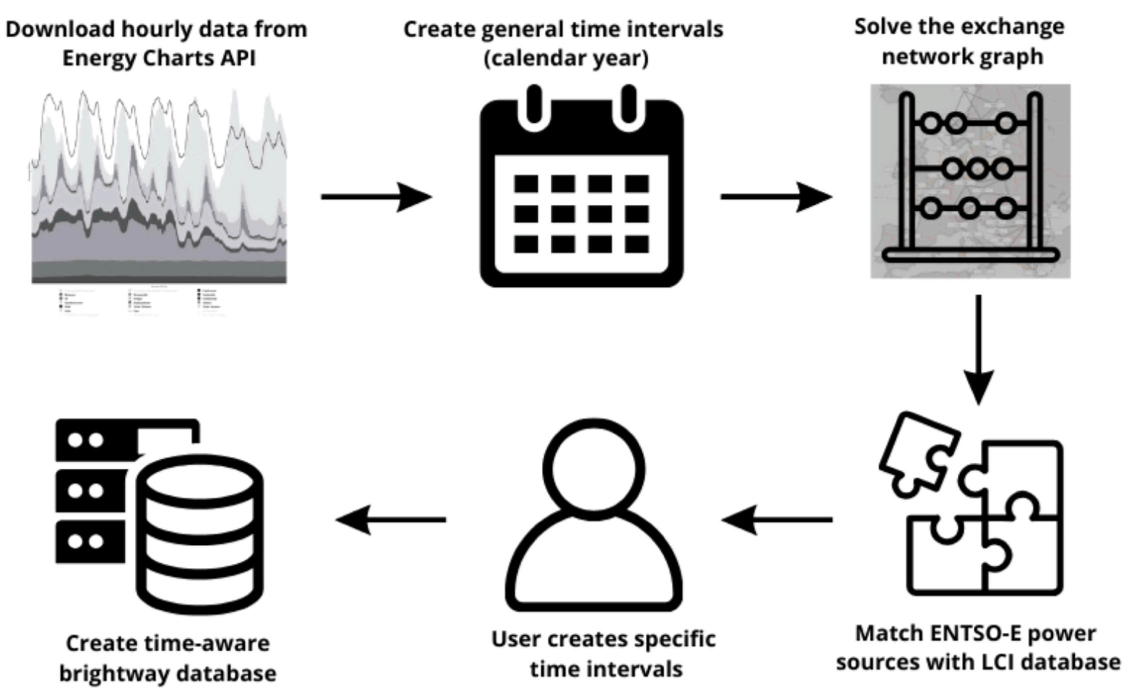

Fig. 2. Conceptual shrecc data flow diagram.

automatically. The downloaded data gets saved into a serialized dataframe, i.e. this step becomes optional for a given calendar year after the first use.

Data treatment

The dataframe provided by *get_data()* needs to be processed. User calls a function called *data_processing()*, which calls other functions to restructure the data into consumption, trade, and demand, making sure no double counts of the imports and exports of countries occur. This function also calls a function that will invert the trade matrix for each hour, making sure that the data is all in a “single layer”, e.g. all electricity sources are represented only once regardless of voltage, as opposed to ecoinvent’s structure, which differentiate low, medium and high voltage (whereby international trade only occurs at high voltage) – all *shrecc* electricity data is considered low voltage. The matrix inversion to calculate the disaggregated consumption mixes is a computationally heavy process, recommended to run on a server. After the data is treated, it is saved as a pickled dataframe, i.e. this step becomes optional for a given calendar year after the first use.

Database creation

The database gets created in two steps. First, the function called *filt_cutoff()* gets called with user specific inputs. This function maps the technologies from the ENTSO-E categorisation (similar to Energy-Charts’s) to the ecoinvent classification and normalizes the consumption mixes to 1 kWh. It also filters the data based on inputs and can apply a “cut off”, to filter the smaller inputs. The cut off is a user-specified float. If desired, the cut off inputs can be summed up and saved as an activity called “the rest”, or it can be completely omitted. Data gets saved into a dataframe. In the second step, which is a database creation, the user needs to have a *brightway* project with an ecoinvent biosphere and technosphere ready. Calling the function *create_database()* will then write a main activity for all pre-filtered countries and times in the *filt_cutoff()* dataframe, and all the interactions as their exchanges. The function also creates exchanges for the distribution network, using an average from all the available countries. A final output of our package is a *brightway* database, with hourly electricity mixes (or combination thereof), written in a user specified project.

Sample code snippets analysis

Notebooks

Example notebooks can be found in *shrecc_project/shrecc/notebooks*.

Illustrative examples

Two functions the user needs to employ, in case of using our pre-calculated 2023 data. More examples can be found in *notebooks/example.ipynb*.

```
filtered_dataframe = filt_cutoff(
      countries=["ES", "IT", "DK"],
      general_range=["2023-06-01 01:00:00", "2023-06-30 23:00:00"],
      refined_range=[9,13],
      freq="D",
      cutoff=1e-3,
      include_cutoff=True,
      path_to_data="your/path/to/data",
)
```

Arguments to generate the low-voltage consumption mix for the exact time and location:

countries (list of str): Countries selected by the user for their database.
times (list of str): Selecting one specific time, can be applied alone.
general_range (list of str): Selecting a general range, e.g. for the month of June, can be applied alone.
refined_range (list of int): Refining range of general range, e.g. mornings of June. Optional. Can only be applied with general_range.
freq (str): Optional. Days to be included, e.g. freq=’D’ selects calendar days, see https://pandas.pydata.org/pandas-docs/stable/user_guide/timeseries.html#offset-aliases. cutoff (float): Optional. Cutoff value for technology values.
include_cutoff (bool): Optional. If True, cutoff is applied and summed at the end to create a new technology "The rest". If False, cutoff is applied but new technology not created.
path_to_data (Path): Optional. location of the data. Default is shrecc/data, where the downloaded files are stored if no other paths are specified.

Returns:

pd.DataFrame: The filtered dataframe of technologies (index) and timesteps (columns).

The functions outputs a dataset containing the low-voltage consumption mix from each source (in kWh per kWh), including grid requirements, as well as transmission and distribution losses, and mapped with *ecoinvent* activities. The dataset can then be directly used to generate a database of all country (in “countries”)-time combinations, directly using *brightway*.

Next, the filtered dataframe is used to create the database. For this step, it is necessary the user has a brightway project ready, with a biosphere and ecoinvent correctly imported.

```
create_database(
      dataframe_filt = Filtered_dataframe,
      project_name = "SHRECCb25",
      db_name = "elec_june_9_13",
      eidb_name = "ecoinvent-3.9.1-cutoff"
)
```

Arguments to write the database:

dataframe_filt (pd.DataFrame): Scaled and filtered dataframe (coming from filt_cutoff()).
project_name (str): BW project name to which the database will be saved.
db_name (str): Name of the BW database to be created.
eidb_name (str): Name of the ecoinvent database. Must be the same as in the BW project.
This function does not return anything; it writes the database into the project.

Impact

The use and impact of *shrecc* is demonstrated here through a small case study of an electric vehicle charging. A first test consists in comparing *shrecc* LCIA results per 1 kWh of low voltage electricity with the impacts of comparable mixes in *ecoinvent*. This is showcased here for most European countries, excluding Eastern Europe and areas trading with Russia and/or Turkey due to limited data. Fig. 3 shows a comparison of the climate change impacts of 1 kWh as directly available in ecoinvent 3.11 (low-voltage mix), with *shrecc*, and data year 2021 for both. Using Energy-Charts data with *shrecc* gives similar results to those of ecoinvent, with three main exceptions: Norway, The Netherlands and Switzerland. In the case of Norway, the difference occurs due to the cut-off system. Cutting off small imports and assigning them as the European average electricity mix can overestimate results in countries that have a very low-carbon electricity consumption mix. In the case of The Netherlands, the main cause is data inconsistencies on the source side (Energy-Charts, ultimately ENTSO-E), namely with solar power being reported as “Others”, a category assigned to a mix of technologies with environmental attributes significantly different from those of solar technologies. This will be addressed in a future version of *shrecc*.

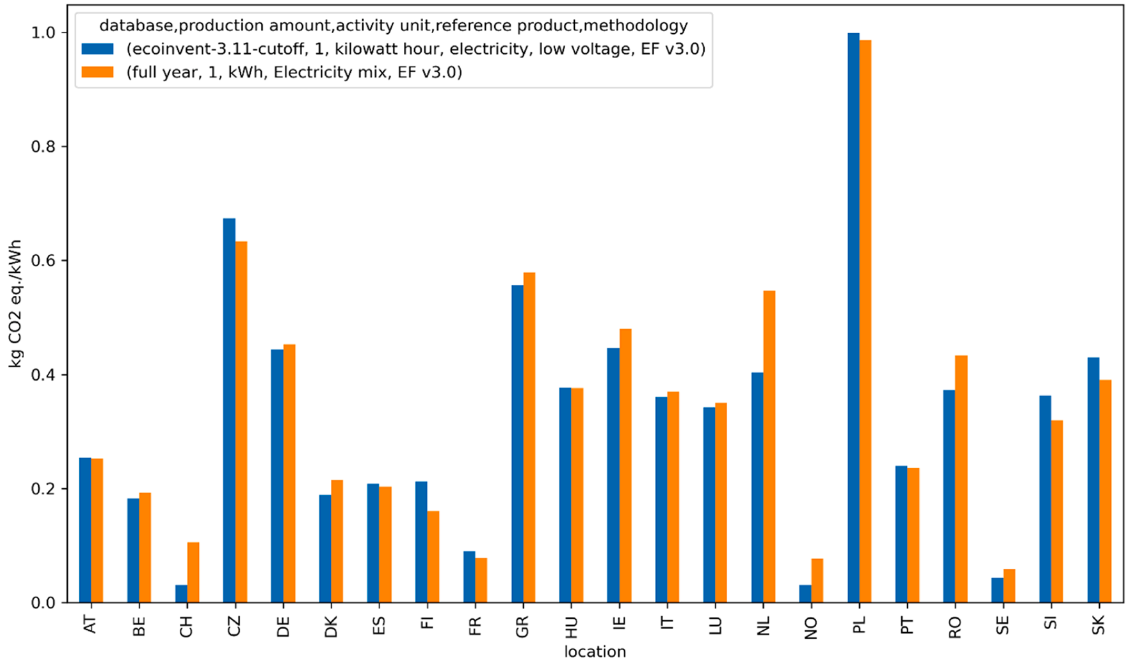

Fig. 3. Greenhouse gas emissions, in kg per kWh, of low-voltage market (consumption) mix in ecoinvent 3.11 (year 2021) and as calculated with shrecc (year 2021), annual average.

However, in the case of Switzerland, the situation is rather different and is explained by *ecoinvent* using market-based rather than location-based modelling to represent the Swiss consumption mix [22]. In this precise case, the comparison is therefore not made between comparable products. Generally, a comparison check is recommended to verify the results given by *shrecc* when a new year is downloaded and processed. In the first step, a check of the annual average of *shrecc* with ecoinvent (for the same year preferably) as shown in Fig. 3, and in case of inconsistencies, the user must check the composition of the mix using the list of exchanges of each low, medium and high voltage activity in ecoinvent compared to the composition of *shrecc* electricity mix (the output of the function filt_cutoff() will provide that). In case of further inconsistencies, users can refer to Energy-Charts API, Electricity Maps, Ember, or any country-specific energy sources to verify the exact composition of the electricity mix, as *shrecc,* by itself, is not able to inform the user about any possible inaccuracies and a manual check is required.

Shrecc can play a crucial part in identifying and supporting the variability of applications that are electricity dependent. Let us illustrate this on an example of an electric vehicle charging, for 8 hours assuming a (rather slow) charging rate of 3.5 kW, capturing 2 different variabilities: day-to-night (diurnal) and season-to-season (seasonal), as well as 3 different countries. We chose Poland for its fossil fuel-heavy electricity mix, France for its very low carbon nuclear heavy electricity mix and Portugal for its high share of renewable energy in the electricity mix. In this comparison, we are using the newest data available from both sources, that is: ecoinvent 3.11 with 2021 data and *shrecc* with 2024 data – as an average LCA practitioner would do in 2025. This is to not only show the variability of the results, but also to show that using *shrecc* tool, one can use the latest data.

Fig. 4 shows the results of the impact assessment for global warming

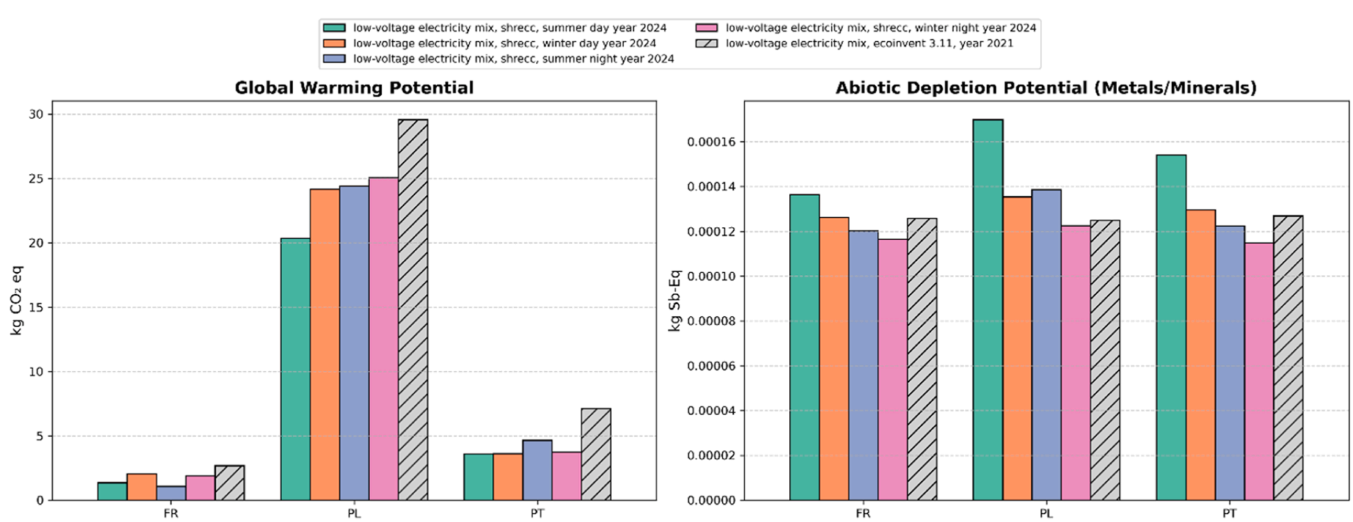

Fig. 4. Global warming potential and abiotic depletion potential in 3 European countries, for the 8-hour charging of an EV at 3.5 kW, using *shrecc* time-aware 2024 data compared to *ecoinvent* 3.11 annual average data.

potential, on the left-hand pane. Seasonal and diurnal variabilities are discernible across all countries. Poland exhibits the highest degree of variability overall; the share of Polish renewable electricity, mainly solar, is 10 times higher in summer than in winter, the rest being predominantly fossil. Portugal also shows great seasonal variability; however its diurnal variability is much lower. We can also observe variability in the French mix, which even though mostly nuclear-based, showcases seasonal variability due to renewable energy (mainly solar and wind power) in the grid. On the selected sample, we see that using *ecoinvent* for a time-specific electricity use case means that the results are overestimated.

Looking at the results for a different impact category, namely abiotic depletion potential (ADP, right-hand pane on Fig. 4), an indicator of mineral resource scarcity, seasonal and diurnal variabilities are also present, which is again directly linked to the amount of renewable energy in the consumption mix. Solar power indeed exhibits the highest per-kWh impact in material depletion between wind power and hydroelectric power. An interesting point to make regarding this impact category is that using *ecoinvent*'s annual average mix, results are this time underestimated. Unlike with global warming potential, in the case of material depletion, charging during the night has the lowest impact, due to the absence of solar power in the mix. Therefore, charging during a summer day leads to the highest ADP impacts, regardless of location in our sample.

Conclusions

A *python* software package that allows LCA practitioners to generate time-aware electricity mix databases for most European countries was created. The implementation is easy-to-use and directly compatible with open-source software *brightway*, allowing users to generate LCIAs with any of the available impact categories. By using such a time-aware database, LCA practitioners can capture the variability of electricity mixes, therefore reducing uncertainty of LCIA and potentially optimizing studied systems. The impact of using time-aware electricity databases is shown via a small case study of electric vehicle charging. Development is still ongoing and focuses on filling data gaps, such as the Dutch production mix, as well as missing datasets, which can be substituted by monthly or annual averages from other sources. It is important to note that *shrecc* provides temporally-resolved electricity mixes: while this improves upon annual averages for attributional LCA, it does not capture marginal mixes, which are typically needed for consequential LCA or for assessing the effects of additional electricity demand. *Shrecc* only uses historical data, which can be a limitation for prospective applications. For future development, a coupling with a machine learning model on weather forecasting or other prospective tools, such as *premise*, could help to better capture future electricity mixes for LCA applications.

CRediT authorship contribution statement

Sabina Bednářová: Writing – review & editing, Writing – original draft, Visualization, Software, Methodology, Formal analysis, Data curation, Conceptualization. **Thomas Gibon:** Writing – review & editing, Writing – original draft, Supervision, Software, Methodology, Formal analysis, Data curation, Conceptualization. **Enrico Benetto:** Writing – review & editing, Supervision, Methodology.

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.

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