Environmental and Climate Technologies
2026, vol. 30, no. 1, pp. 558–569
https://doi.org/10.2478/rtuect-2026-0038
https://content.sciendo.com

Time-Resolved Energy Attribution Model Comparison for Accurate and Transparent Corporate Carbon Reporting

Aleksandrs ŠCEDROVS[1], Pauls SONDORS[2], Maksims FEOFILOVS[3]*, Agris KAMENDERS[4], Francesco ROMAGNOLI[5]

[1,3,4,5] *Institute of Energy Systems and Environment, Riga Technical University, Riga, Latvia*
[2]*SIA AdvanGrid, Katlakalna iela 11, LV-1073, Riga, Latvia*

Received 10.03.2026; accepted 16.10.2026

***Abstract* – Electrification of industrial processes, transport systems, and corporate operations shifts emissions from direct fuel combustion to indirect emissions associated with electricity supply. Most corporate carbon accounting approaches still rely on annual average emission factors, which may misrepresent actual electricity-related emissions and reduce the comparability and reliability of corporate sustainability reporting. Therefore, more precise accounting of greenhouse gas emissions (GHG) for energy related activities is becoming increasingly important for meaningful corporate sustainability reporting. The selection of the data platform and database is summarised, and the attribution model is compared in detail. This study aims to compare four attributional models, production average, direct import, aggregated coupling and direct coupling, for the time-resolved carbon-accounting tool, which uses open ENTSO-E generation and cross-border flow data, smart-meter data and technology-specific life cycle emission factors. A qualitative review with a fictional case study example informs the comparison of attribution methods under consistent energy and emission boundaries.**

***Keywords* – Corporate sustainability; energy management; ESG; GHG protocol; organisation carbon footprint.**

1. INTRODUCTION

1.1. Motivation and Research Rationale

The decarbonisation of economic activities increasingly depends on the accuracy, transparency, and comparability of GHG accounting [1], [2]. Within the European Union, the Corporate Sustainability Reporting Directive (CSRD) and the accompanying European Sustainability Reporting Standards (ESRS) have substantially expanded mandatory climate-related disclosures [3]. Energy-related disclosures are particularly important given the

* Corresponding author.
E-mail address: maksims.feofilovs@rtu.lv

Pauls SONDORS https://orcid.org/0009-0009-2240-7841
Maksims FEOFILOVS https://orcid.org/0000-0002-0797-150X
Agris KAMENDERS https://orcid.org/0000-0002-4695-6775
Francesco ROMAGNOLI https://orcid.org/0000-0003-1814-7310

©2026 Author(s). This is an open access article licensed under the Creative Commons Attribution License (http://creativecommons.org/licenses/by/4.0).

substantial contribution of energy production and consumption to GHG. At the industrial level, changes in energy-related emissions reflect changes in production activity, energy intensity, fuel mix and emission intensity [4]. Understanding these relationships is therefore necessary for identifying effective decarbonisation measures.

Electricity already plays a central role in industrial energy consumption. According to Eurostat's Complete Energy Balances dataset [5], electricity accounted for approximately 33 % of final energy consumption in the EU industry sector in 2023, making it the largest single energy carrier used in industrial production. Decarbonisation pathways anticipate further electrification across industrial and service sectors, alongside improvements in energy efficiency and the expansion of renewable electricity generation [6], [7].

At the European level, the average GHG emission intensity of electricity generation has declined over recent decades alongside renewable deployment and climate policies [8]. However, declining annual averages do not eliminate short-term variation in the generation mix or its emission intensity. In the Baltic and Nordic-Baltic region, increasing wind and solar generation, sector coupling and energy-system integration are expected to reshape electricity supply and demand [9], [10]. Accommodating variable renewable generation requires flexibility, storage and cross-border coordination [11], [12].

In interconnected electricity systems participating in markets such as Nord Pool, cross-border exchanges and generation patterns vary within and between days [13]. Hydrological conditions, demand, renewable availability and trading patterns consequently contribute to differences in electricity carbon intensity over time and between locations [14]–[16]. Industrial demand also requires sufficient differentiation: a process-based TIMES study used energy-audit data from 122 Latvian companies to distinguish process heat, machinery, space heating and other energy uses across industrial subsectors [17]. Such differences in end uses provide an additional reason to examine electricity consumption beyond aggregate annual totals.

Transport electrification further increases the importance of electricity-related emissions. Electric vehicle (EV) deployment is projected to contribute to electricity demand growth over the coming decades [18], [19], while electrification of corporate fleets and wider electric mobility adoption are also relevant in the Baltic and Nordic-Baltic region [20], [21]. Replacing combustion-engine vehicles to EVs shifts operational energy use from direct fuel combustion to electricity consumption [13]. The resulting climate performance depends a lot on the electricity supply mix, as recognised in vehicle life-cycle assessments [23], [24]. Where electricity generation remains dependent on carbon-intensive sources, electrification retains associated upstream emissions [23]. For companies purchasing electricity to operate their fleets, this transition also changes the relative importance of direct combustion emissions and indirect electricity-related emissions in their GHG reporting.

These variations become particularly relevant when electricity consumption is concentrated in specific periods. Research on hydrogen and e-fuel production shows that the number of hours during which electricity meets specified low-carbon thresholds varies considerably throughout the year [25]. Accordingly, an assessment based on annual-average electricity intensity may reach a different conclusion from one that aligns electricity consumption with hourly emission factors. This illustrates why the temporal resolution of electricity data matters when evaluating electrification and identifying opportunities to reduce electricity-related emissions.

The GHG Protocol provides standardised accounting principles, but implementing electricity accounting at higher resolution requires additional methodological choices. In line with GHG Protocol accounting principles, the digital sustainability reporting tools typically combine user-provided activity data with emission factors and present results by scope,

category, product or activity [26], [27], but the ability to represent temporal and geographical differences consequently depends on the underlying data and calculation methods, which currently do not resolve the relationship between the timing of electricity consumption and changes in electricity carbon intensity.

Literature reports approaches for real-time carbon-intensity estimation and marginal emission factors [15], and corporate accounting applications could move towards distinguishing physical electricity attribution from the allocation of contractual electricity attributes. However, currently there is no uniform agreement or guidelines for a framework incorporating high-resolution electricity data to select an attribution approach appropriate to the intended reporting or decision-making purpose. Therefore, this study aims to construct a comparative methodological framework for selecting electricity-attribution approaches for the sustainability tool reporting GHG emissions of electricity consumption.

This is a methodological paper supported by a focused literature review (section 1.2). It reviews existing attribution approaches and compares how they treat domestic generation, cross-border exchange and contractual claims. The models themselves are not new, therefore the contribution is an application-driven evaluation: (i) criteria derived from the requirements of a corporate Scope 2 tool, (ii) a residual-mix adjustment applied after the physical attribution, so that location-based and market-based values stay consistent, and (iii) an assessment of how each model can be implemented with ENTSO-E data

1.2. Electricity Attribution Methods for Time-Resolved Carbon Accounting

Electricity-related GHG emissions can be assigned to consumers using different accounting principles. Production-based accounting describes emissions associated with generation within a defined area; consumption-based accounting additionally considers electricity exchanges. Contractual accounting assigns generation attributes according to eligible purchasing instruments, whereas consequential analysis estimates change in emissions resulting from an intervention. In early methodological comparison [28] demonstrated that alternative treatments of cross-border electricity exchanges produce different emission allocations and policy incentives. A subsequent review [29] compared electricity emission estimation methods and recommended selecting models according to the characteristics of the electricity demand and the objective of the assessment.

A domestic production factor combines the emission factors of generation technologies using their respective electricity outputs as weights. It provides a transparent reference for the generation occurring within a national or regional boundary. However, applying this factor to domestic consumption does not account for differences between the electricity generated within the area and the electricity exchanged with neighbouring systems. The treatment of imports and exports consequently becomes important when the objective is to allocate emissions to electricity consumers [28].

Assigning imports the neighbouring country's domestic production factor is a simplification: that country may itself import and re-export electricity. A network formulation can account for this upstream contribution by linking the balances of the represented areas. However, its output remains an allocation conditional on the mixing assumption, spatial aggregation and available flow data; it is not a direct observation of which generator supplies each individual consumer [16].

The simplest way to include imports is to value them at the production mix of the exporting neighbour. Here this is called direct import; it is a descriptive label, because the sources reviewed do not give this approach a common name. Its weakness is already described above: the neighbour may itself have imported the electricity. Proportional sharing, also called flow tracing, removes this weakness [30], [31]. Electricity from all sources is assumed to mix in

each zone, so everything that leaves a zone, whether consumed there or sent on, has the same mix as everything that entered it. Applied zone by zone, this gives the consumption mix of every zone, including electricity that crossed several borders [16].

Two approaches of proportional sharing exist. In direct coupling, all generation of the zone is mixed with its imports before anything is consumed or exported. In aggregated coupling, each zone first covers its own demand with its own generation, and only the net import or net export is exchanged with the network. The two approaches give similar results for large zones, but differ for small, well-connected countries, where imports are large compared with local generation [32].

Contractual (market-based) accounting is also attributional, but it answers a different question: which generation a buyer has contracted for, and not which generation supplied the grid when the electricity was used. Guarantees of origin (GOs) claimed by buyers must be removed from the residual mix, which for Europe is published annually by the Association of Issuing Bodies [33]; otherwise the same renewable electricity is counted twice, once by the certificate holder and once by location-based users [34], [35].

2. METHODOLOGY

The study evaluates three connected components of a time-resolved electricity carbon-accounting tool: the electricity-data platform, the life cycle inventory database and the electricity attribution model for a tool structure presented in Fig. 1.

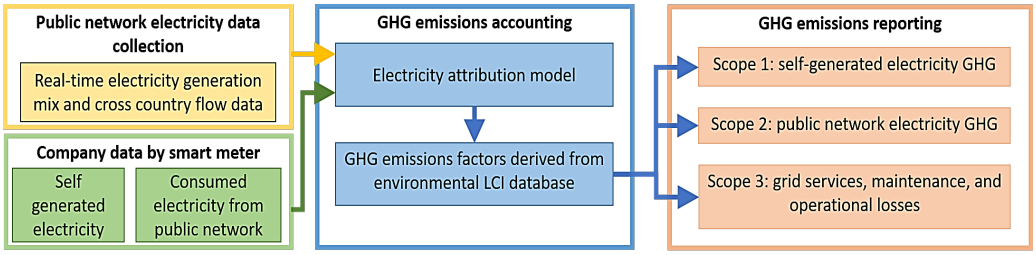


Fig. 1. Tool for Time-Dependent Electricity Carbon Accounting.

The described tool combines generation by technology and physical cross-border flows with company smart-meter data and technology-specific emission factors. Within the scope of this framework the electricity attribution model must deliver an hourly consumption mix by generation technology, built from open data, for location-based Scope 2 reporting, and a basis for the residual-mix adjustment needed for market-based reporting.

2.1. Selecting the Data Sources for Defined Tool

Nord Pool and the ENTSO-E Transparency Platform are screened as candidate sources of electricity activity data [36], [37], taking into consideration data availability for generation disaggregated by technology, directed physical cross-border flows and identifiable areas, time series that can be aligned to hourly company data, coverage of the interconnected areas needed to trace imports, documented access, extraction and reuse conditions. The selected primary platform must support generation and physical-flow inputs over a declared study boundary. Market trades cannot be treated as substitutes for physical flows.

The inventory screening compares *Ecoinvent* 3.11, Environmental Footprint (EF) compliant datasets and EXIOBASE 3 as three distinct data structures [38], [39]. The evaluation are electricity-technology detail, access to inventories or documented factors that separate generation-stage emissions from other life-cycle burdens, geographical and temporal representativeness, transparent system modelling, units and characterisation, updates and access conditions.

Database is selected for its fit to the required technology-factor calculation, rather than labelled universally suitable or unsuitable for corporate accounting. Technology factors must have the possibility to be characterised by IPCC GWP100 impact method for estimation of g CO_2eq per energy unit produced, with the assessment-report version and treatment of gases recorded alongside the database release, system model, dataset identifiers and geography. Another important aspect is ability to distinguish the Scope 1 Scope 2, Scope 3 emission categories.

2.3. Selecting the Electricity Attribution Model

The study evaluates electricity attribution models given Table 1 to analyse their direct relevance to electricity mix attributes, electricity flow tracing, and disaggregation of final GHG emissions at the consumer. Each stage of the framework in Figure 1 places a requirement on the attribution model. Three are set by the framework and treated as pass or fail: an hourly result, a split by generation technology and open data. A model that fails one criterion cannot be used.

TABLE 1. THE ATTRIBUTION MODELS UNDER EVALUATION

Model	Own generation, imports and exports
Production average (PA)	Own generation: all consumption is supplied from the own generation of the zone in the same hour. Imports and exports: not considered.
Direct import (DI)	Own generation: covers consumption first. Imports: the rest comes from the exporting neighbours, with the mix of their own generation. Exports: not considered; the imports of the neighbours are not traced.
Aggregated coupling (AC)	Own generation: covers consumption first. Imports: only the net import is taken from the network. Exports: only the net export joins the network, where it mixes with the inflows and passes through the zone.
Direct coupling (DC)	Own generation: all generation joins the pool of the zone. Imports: all inflows join the same pool. Exports and consumption: both have the mix of the pool.

Considering the findings in literature, Table 2 shows the questions that are used in the study to evaluate the attribution model suitability based on the fictional case study: does the model attribute electricity credibly, does it fit reporting, including contractual claims, and can it be implemented with ENTSO-E open-source data. The questions are built from the issues the literature raises [32], [34]–[36].

Each model is judged on each criterion as strong, moderate, or weak correspondence. No weights or totals are used, because the criteria are not exchangeable: simplicity does not offset wrong attribution of imports.

To complement the evaluation and make the results easier to interpret, the four models applied to one fictional case of three zones in a chain: A to B to C. The fictional case scenario is shown in Fig. 2. For each model, the mix and emission intensity of 1 kWh consumed in zone C are calculated for both hours for comparative purpose. The consumer is in zone C, whose total consumption is 50 kWh in each hour is a small part of total 130 MWh consumed in zone C over 2 hours. Emission intensities are given per kWh and do not depend on the size

of the company, so the company result is the consumption in each hour multiplied by the intensity of that hour. For each electricity attribution model and hour, the mix of 1 kWh consumed in zone C is obtained, giving the shares of renewables (hydro and wind), gas and coal.

TABLE 2. QUESTIONS USED TO EVALUATE THE ATTRIBUTION MODELS

Question	**Reason**
Does the mix include the electricity available to the consumer, including imports?	Consumption- and production-based values in countries differ [16], [32]
Are the original sources of transit imports represented?	Transit flows change results [32]
Does attributed volume equal generated volume, per technology?	Double counting [34], [35]
Does it fit location-based Scope 2 reporting for the consumption zone?	Reported separately [34], [40]
After claims are removed (residual mix), does it still conserve generation?	Residual mixes remove claims [33], [34], [41]
Is open-source data enough?	Data problems related to [36]
Is data gap or error acceptable?	Gaps are common in open data [36], [42]

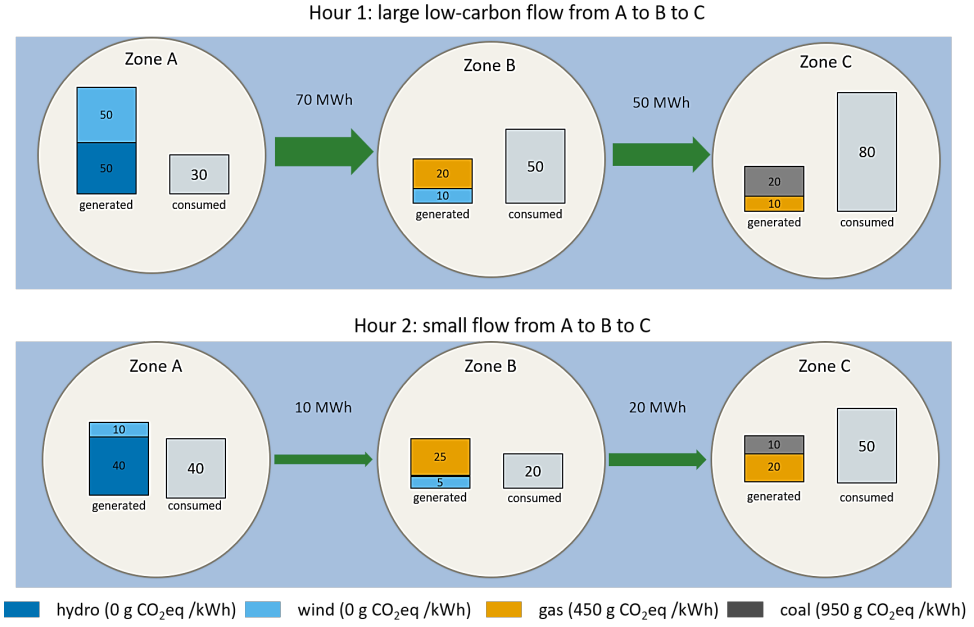


Fig. 2. Example case of three zones with generation by technology, consumption and flows (MWh per hour).

Based on the example, the emission intensity, closure ratio, total emissions attributed to Zone C consumption and the difference to DC attribution is estimated. Emission intensity (g CO_2eq/kWh) is the sum of these shares multiplied by the emission factors of the technologies. The closure ratio is used to check consistency over all zones and both hours, estimated as the emissions attributed to consumers (consumption of each zone multiplied by

its intensity) divided by the emissions generated (generation of each technology multiplied by its emission factor), where a value of 1.00 means that no emissions are lost or counted twice. The company result (kg CO_2eq) is its consumption in each hour multiplied by the intensity of that hour, added for the two hours. The difference to DC is the company result of each model compared with that of direct coupling, in percent. Positive values mean higher emissions than direct coupling.

3. METHODOLOGY

3.1. Data Sources for Developed Model

A comparative evaluation of available electricity data platforms was conducted to identify the most suitable data sources for the proposed electricity carbon attribution model. Two major electricity data platforms were analysed: Nord Pool and ENTSO-E Transparency Platform. Table 3 compares the two platforms suitable for obtaining data for time energy attribution model and the GHG emission intensity accounting. Based on the analysis, ENTSO-E is selected as the primary activity-data source because its documented generation and transmission data support a common network representation. This selection is conditional on area-specific completeness, time alignment and explicit treatment of external supplies. Nord Pool remains relevant for market information and available regional operating data.

TABLE 3. COMPARISON OF PLATFORMS FOR ELECTRICITY GENERATION AND FLOW ANALYSIS

Platform	NORDPOOL	ENTSO-E
Geographical coverage	Nordic and Baltic regions	All European countries
Data focus	Generation data, market prices, trading dynamics	Generation types, cross-border flows, system operation
Access requirements	Registration required; paid access	Free access
Data retrieval method	Web interface, API	Web interface, API
Data resolution	Hourly and daily data	Hourly and daily data

LCI datasets ensure that environmental reporting, including the GHG emissions, is transparent, verifiable, and aligned with international sustainability reporting standards. When more detailed sector-specific information is required, many databases provide specialized datasets for individual products and industrial processes. Table 4 summarizes major LCI databases categorized according to their application areas and characterized by studying their structure and application possibilities.

Based on the comparison presented in Table 3, the *Ecoinvent* 3.11 database was selected as the primary data source for GHG emission estimates in this study. The selection was primarily motivated by the process-based structure of the database and its high level of modelling flexibility, which allows detailed representation Scope 1, Scope 2 and Scope 3 GHG emissions by daring the unit processes data. This approach is consistent with widely adopted GHG accounting frameworks from international standardisation organisation (ISO) [43]–[46] and supports transparent allocation of emissions across different stages of the value chain.

TABLE 4. CHARACTERIZATION OF LCI DATABASES

Criterion	Ecoinvent	Environmental Footprint	EXIOBASE
Database type	Process-based	Process-based	Environmentally extended input–output
Level of detail	Very high (unit and system processes)	Medium (aggregated processes)	Low–medium (sector level)
Ability to modify product systems	High	Limited	Low
Sector coverage	Multi-sector	EU-focused multi sector	Global economic sectors
Geographic coverage	Global with regional datasets	Mainly EU	Global
Number of datasets	More than 20 000 datasets	Around 4000 datasets	Around 200 sectors
Modelling flexibility	High	Medium	Low
Typical application	Product LCA, environmental modelling	PEF/OEF environmental footprint studies	Macro-economic environmental footprint analysis
Compliance with GHG protocol	Compatible with Scope 1-3 accounting	Partially (designed for PEF rather than corporate GHG)	Not suitable for corporate GHG accounting
Suitability for detailed electricity flow model	High	Medium	Low

3.2. Example of Attribution Model Application

The fictional case illustrates how alternative treatments of local generation and cross-border flows affect the electricity mix attributed to consumers. Fig. 3 presents the technology composition of 1 kWh consumed in zone C, while Table 5 summarises the corresponding emission intensities, system-wide emission closure and emissions attributed to the company's 100 kWh consumption.

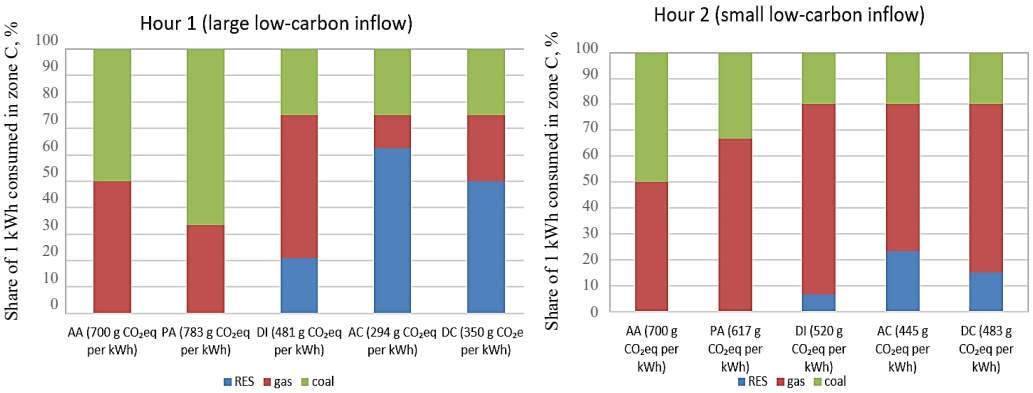


Fig. 3. Mix of 1 kWh consumed in zone C under five models (numbers above the bars are g CO_2e per kWh).

The differences are most pronounced in the first hour, when renewable electricity flows from zone A through zone B towards zone C. PA considers only generation within zone C and therefore produces the highest emission intensity, at 783 g CO_2eq/kWh. DI incorporates imports from zone B but values them using B's production mix, without tracing its renewable imports from zone A. Its resulting intensity is 481 g CO_2eq/kWh. Both coupled models

account for the upstream contribution from zone A, giving lower intensities of 294 g CO_2eq/kWh for AC and 350 g CO_2eq/kWh for DC. Their difference reflects the allocation convention: AC prioritises local generation for local consumption, whereas DC assigns the same mixed attributes to consumption and exports. In the second hour, the smaller renewable contribution from zone A reduces the difference between the coupled models.

For the company consuming 50 kWh in each hour, the attributed emissions range from 36.9 kg CO_2eq under AC to 70.0 kg CO_2eq under PA and the annual-average reference. The annual-average and PA results coincide because consumption is equally distributed between the two hours and the reference factor equals the mean of the hourly production factors. Nevertheless, the annual-average approach conceals the hourly variation represented by PA. Relative to DC, the company result is 68 % higher under these two approaches, 20 % higher under DI and 11 % lower under AC.

TABLE 5. EMISSION INTENSITY AND CONSISTENCY CHECK OF CASE STUDY OUTPUTS

Model	Hour 1, g CO_2eq/kWh	Hour 2, g CO_2eq/kWh	Closure ratio	Final load, kg CO_2eq	Difference to DC
Annual average (reference)	700	700	1.84	70.0	+68 %
Production average (PA)	783	617	1.86	70.0	+68 %
Direct import (DI)	481	520	1.30	50.1	+20 %
Aggregated coupling (AC)	294	445	1.00	36.9	–11 %
Direct coupling (DC)	350	483	1.00	41.6	–

The closure ratio provides a separate assessment of consistency across the entire system. AC and DC both achieve a ratio of 1.00, while the annual-average reference, PA and DI allocate more emissions to consumption than are generated within the defined boundary. However, the different company results under AC and DC demonstrate that aggregate emission conservation does not uniquely determine the allocation to individual consumers.

3.3. Attribution Model Selection and Discussion

Model selection must consider both system-wide consistency and the suitability of the allocation convention for the intended application. PA ignores imports and exports and attributes generation to the wrong consumers, but at the same time is the easiest to implement and explain. DI includes imports but loses the original source when the neighbour itself imported the electricity, as zone B does in hour 1; it needs only direct-neighbour flows and is easy to explain. AC, and DC trace imports to their original sources, balance the emissions and stay consistent after the residual-mix adjustment. They differ in one assumption: in AC a zone that imports on balance uses its own generation locally first, so it is not passed on even if the zone also exports; in DC, generation and imports are mixed before anything leaves the zone. DC is the approach used in published flow-traced European data [16], [32], which allows cross-checking. AC also needs the load of every zone to classify imports and exports, so it is the most sensitive to data errors, but both are harder to explain then rest of attribution models as they process more data and therefore also are more data-demanding.

No model is best on every question investigated as defined in Table 2. PA and DI are simple and need little data, but they do not trace imports consistently and cannot represent claims. DC and AC conserve generation and respond to claims but need complete flow data and spread errors. For the defined tool the results support DC as the default physical attribution; AC is suitable only when the information related to consumption of the exact type of mix is

available for the consumer (e.g., information on bought energy mix, currently not traced); DI and PA only as flagged fallbacks when flows are missing.

The limitations of the study are mostly connected to the simplified fictional example used for electricity grid evaluation; the application of green certificates is not investigated and the judgements are qualitative. The emission factors are annual values per technology applied to hourly generation, so the hourly result changes only through the mix and not through the factors. Validation with real network data and a sensitivity analysis of data gaps remain for future studies. Moreover, ENTSO-E data can have gaps, revisions, and flows from zones outside the data area are missing. These errors can enter the result directly, and under AC and DC they spread downstream. Therefore, an appropriate handling procedure for errors must be defined for the tool when used in practice.

4. CONCLUSIONS

This study analyses the model for calculating energy-related GHG emissions that integrates real-time electricity system data, life cycle emission factors, and company-level energy production information. The proposed approach addresses limitations of conventional corporate carbon accounting tools that rely on static national-average electricity emission factors and therefore do not adequately capture the dynamic and interconnected nature of modern energy systems.

Four attributional electricity models, production average, direct import, aggregated coupling and direct coupling, were compared qualitatively by judgements related to their physical attribution, reporting fit including a residual-mix adjustment, and implementability with ENTSO-E data. The models require different inputs from the ENTSO-E Transparency Platform. No model was best on every criterion: the simple models are easy to implement but inconsistent; the coupling models are consistent but need complete flow data.

For the scope of carbon reporting tool, direct coupling is the most suitable physical basis, while simpler models have fallbacks related to a residual-mix adjustment after the attribution. The direct coupling allows the integration of LCI datasets for technology-specific emission factors that distinguish between direct operational emissions and upstream supply-chain emissions.

The contribution is the evaluation and the implementation rules. The findings are qualitative, therefore future work should repeat the comparison on real ENTSO-E data, test the sensitivity to data gaps, extend to including the residual-mix based on renewable energy certificates for energy consumption. Future work should document the complete dataset mapping and factor configuration, validate the implementation with observed network data, and address storage, losses, missing data, residual mix handling and contractual temporal matching.

FUNDING STATEMENT

This work has been supported by the European Union “NextGenerationEU fund” within the project “Development of a digital carbon footprint management and sustainability reporting tool” No. 2.2.1.3.i.0/1/24/A/CFLA/003.

ACKNOWLEDGEMENTS

The authors acknowledge the use of ChatGPT (OpenAI) for language editing and grammar correction during the preparation of the manuscript. The tool was used solely to improve the clarity and readability of the text. All scientific content, analysis, and interpretations remain the responsibility of the authors.

REFERENCES

[1] Gillenwater M. Examining the impact of GHG accounting principles. *Carbon Management* 2022:13(1):550–553. https://doi.org/10.1080/17583004.2022.2135238

[2] Comello S. D., Reichelstein J., Reichelstein S. Corporate carbon reporting: Improving transparency and accountability. *One Earth* 2023:6(7):803–810. https://doi.org/10.1016/j.oneear.2023.06.002

[3] Hummel K., Jobst D. An Overview of Corporate Sustainability Reporting Legislation in the European Union. *Accounting in Europe* 2024:21(3):320–355. https://doi.org/10.1080/17449480.2024.2312145

[4] Dolge K., Blumberga D. Key Factors Influencing the Achievement of Climate Neutrality Targets in the Manufacturing Industry: LMDI Decomposition Analysis. *Energies* 2021:14(23):8006. https://doi.org/10.3390/en14238006

[5] European Commission. Eurostat. Complete energy balances (nrg_bal_c). 2024. [Online]. [Accessed 15.02.2026]. Available: https://ec.europa.eu/eurostat/databrowser/view/nrg_bal_c/default/table

[6] IEA. Tracking Clean Energy Progress 2023, IEA, Paris. [Online]. [Accessed 15.02.2026]. Available: https://www.iea.org/reports/tracking-clean-energy-progress-2023

[7] Phan N. A., Hellsmark H., Göransson L., Johnsson F. Electrifying tensions: Stakeholder narratives to electrification of industry and transport in Sweden. *Energy Research & Social Science* 2025:126:104142. https://doi.org/10.1016/j.erss.2025.104142

[8] European Environment Agency (EEA). Greenhouse gas emission intensity of electricity generation in Europe. EEA Indicator Report, 2025.

[9] Lund P. D., Skytte K., Bolwig S., Bolkesjö T. F., Bergaentzlé C., Gunkel P. A., Kirkerud J. G., Klitkou A., Koduvere H., Gravelsins A., Blumberga D., Söder L. Pathway Analysis of a Zero-Emission Transition in the Nordic-Baltic Region. *Energies* 2019:12(17):3337. https://doi.org/10.3390/en12173337

[10] Pakere I., Freimanis R., Alena-Ozolina S., Asaris P., Demurtas A., Gorner M., Yearwood J. Cost-Optimal Policy Strategies for Reaching Energy Efficiency Targets and Carbon Neutrality. *Environmental and Climate Technologies* 2023:27(1):999–1014. https://doi.org/10.2478/rtuect-2023-0073

[11] Göransson L., Lund P. D., Vuille F., Widén J. The benefit of collaboration in the North European electricity system. *Energies* 2019:12(24):4648. https://doi.org/10.3390/en12244648

[12] ENTSO-E. Ten-Year Network Development Plan 2022: System needs and investment opportunities for the European electricity grid. European Network of Transmission System Operators for Electricity. [Online]. [Accessed 15.02.2026]. Available: https://eepublicdownloads.blob.core.windows.net/public-cdn-container/tyndp-documents/TYNDP2022/public/system-needs-report.pdf

[13] Ergemen Y. E., Haldrup N., Rodríguez-Caballero C. V. Common long-range dependence in a panel of hourly Nord Pool electricity prices and loads. *Energy Economics* 2016:60:79–96. https://doi.org/10.1016/j.eneco.2016.09.008

[14] Bertolini M., Duttilo P., Lisi F. Accounting carbon emissions from electricity generation: A review and comparison of emission factor-based methods. *Applied Energy* 2025:392:125992. https://doi.org/10.1016/j.apenergy.2025.125992

[15] Leerbeck K., Bacher P., Junker R. G., Goranovic G., Corradi O., Ebrahimy R., Tveit A., Madsen H. Short-term forecasting of CO_2 emission intensity in power grids by machine learning. *Applied Energy* 2020:277:115527. https://doi.org/10.1016/j.apenergy.2020.115527

[16] Tranberg B., Corradi O., Lajoie B., Gibon T., Staffell I., Andresen G. B. Real-time carbon accounting method for the European electricity markets. *Energy Strategy Reviews* 2019:26:100367. https://doi.org/10.1016/j.esr.2019.100367

[17] Allena-Ozolina S., Jaunzems D., Pakere I., Blumberga A., Bazbauers G. Decarbonisation Pathways of Industry in TIMES Model. *Environmental and Climate Technologies* 2021:25(1):318–330. https://doi.org/10.2478/rtuect-2021-0023

[18] IEA. Global EV Outlook 2025, IEA, Paris, 2025. [Online]. [Accessed 15.02.2026]. Available: https://www.iea.org/reports/global-ev-outlook-2025

[19] Lee Y., *et al.* Electrification pathways toward transport decarbonization with a systematic review. *Clean Technologies and Environmental Policy* 2025:27:7855–7877. https://doi.org/10.1007/s10098-025-03321-7

[20] Santos R. C. O. Systematic literature review of electric vehicles in electrical system expansion planning. *Energy Reports* 2025. https://doi.org/10.1016/j.rineng.2025.104500

[21] Hawkins T. R., Singh B., Majeau-Bettez G., Strømman A. H. Comparative Environmental Life Cycle Assessment of Conventional and Electric Vehicles. *Journal of Industrial Ecology* 2013:17:53–64. https://doi.org/10.1111/j.1530-9290.2012.00532.x

[22] Santero N., *et al.* Electrifying light vehicles in the United States shows emission reduction potential for all vehicle types and powertrains. *Communications Sustainability* 2026:1:23. https://doi.org/10.1038/s44458-025-00032-4

[23] Alwosheel A., Koroma M. S. Context matters: Life cycle emissions and policy implications of electric vehicles in evolving carbon-intensive energy systems. *Energy* 2025:338:138845. https://doi.org/10.1016/j.energy.2025.138845

[24] Mendziņš, K., & Barisa, A. Electric vs. Internal Combustion Vehicles: A Multi-Regional Life Cycle Assessment Comparison for Environmental Sustainability. *Environmental and Climate Technologies* 2024:28(1):855–862. https://doi.org/10.2478/rtuect-2024-0065

[25] Besseau R., *et al*. (2024). Assessing the carbon intensity of e-fuel production: A temporal analysis of electricity supply. *Applied Sciences* 2024:14(22):10299. https://doi.org/10.3390/app142210299
[26] Hąbek P. Evaluating ESG Software Solutions for Sustainability Reporting in the Manufacturing Sector. *Management Systems in Production Engineering* 2025:33(3):420–432. https://doi.org/10.2478/mspe-2025-0041
[27] Garzón Marsal A. Definition of a software tool for carbon footprint reporting (Master's thesis). Universitat Politècnica de Catalunya, 2024. [Online]. [Accessed 15.02.2026]. Available: https://upcommons.upc.edu/bitstreams/61714fe0-b980-428f-baed-ca09b5163754/download
[28] Jiusto S. The differences that methods make: Cross-border power flows and accounting for carbon emissions from electricity use. *Energy Policy* 2006:34(17):2915–2928. https://doi.org/10.1016/j.enpol.2005.05.002
[29] Ryan N. A., Johnson J. X., Keoleian G. A. Comparative assessment of models and methods to calculate grid electricity emissions. *Environmental Science & Technology* 2016:50(17):8937–8953. https://doi.org/10.1021/acs.est.5b05216
[30] Bialek J. Tracing the flow of electricity. *IEE Proceedings - Generation, Transmission and Distribution*, 1996:143(4):313–320. https://doi.org/10.1049/ip-gtd:19960461
[31] Kirschen D., Allan R., Strbac G. Contributions of individual generators to loads and flows. *IEEE Transactions on Power Systems* 1997:12(1):52–60. https://doi.org/10.1109/59.574923
[32] Schäfer, M., Tranberg, B., Jones, D., & Weidlich, A. (2020). Tracing carbon dioxide emissions in the European electricity markets. *International Conference on European Electricity Market*, *arXiv*2008.00893. https://doi.org/10.1109/EEM49802.2020.9221928
[33] AIB (Association of Issuing Bodies). European Residual Mix. 2026. [Online]. [Accessed 14.10.2026]. Available: https://www.aib-net.org/facts/european-residual-mix
[34] Meng X., Wu J., Zhang Y., Ren J., Yue D., Manzardo A. Critical review: a standardized blueprint for green certificate integration in life cycle assessment. *Carbon Footprints* 2025:4(4):29. https://doi.org/10.20517/cf.2025.51
[35] Holzapfel P., Bach V., Finkbeiner M. Electricity accounting in life cycle assessment: the challenge of double counting. *The International Journal of Life Cycle Assessment* 2023:28:771–787. https://doi.org/10.1007/s11367-023-02158-w
[36] Hirth L., Mühlenpfordt J., Bulkeley M. The ENTSO-E Transparency Platform – A review of Europe's most ambitious electricity data platform. *Applied Energy* 2018:225:1054–1067. https://doi.org/10.1016/j.apenergy.2018.04.048
[37] European Commission. Commission Regulation (EU) No 543/2013 of 14 June 2013 on submission and publication of data in electricity markets. *Official Journal of the European Union* 2013 L: 163
[38] Wernet G., *et al*. The ecoinvent database version 3 (part I): overview and methodology. *The International Journal of Life Cycle Assessment* 2016:21:1218–1230. https://doi.org/10.1007/s11367-016-1087-8
[39] Stadler K., Wood R., Bulavskaya T., Södersten C.-J., Simas M., Schmidt S., Usubiaga A., Acosta-Fernández J., Kuenen J., Bruckner M., Giljum S., Lutter S., Merciai S., Schmidt J. H., Theurl M. C., Plutzar C., Kastner T., Eisenmenger N., Erb K.-H., de Koning A., Tukker A. EXIOBASE 3: Developing a Time Series of Detailed Environmentally Extended Multi-Regional Input-Output Tables. *Journal of Industrial Ecology* 2018:22:502–515. https://doi.org/10.1111/jiec.12715
[40] Greenhouse Gas Protocol. GHG Protocol Scope 2 Guidance: An amendment to the GHG Protocol Corporate Standard. World Resources Institute & World Business Council for Sustainable Development, 2015.
[41] Holzapfel P., *et al*. Replacing location-based electricity consumption with market-based residual mixes in background data to avoid possible double counting: a quantitative analysis of effects and challenges. The *International Journal of Life Cycle Assessment* 2024:29:1279–1289. https://doi.org/10.1007/s11367-024-02294-x
[42] Electricity Maps. Methodology. [Online]. [Accessed: 15.10.2026]. Available: https://electricitymaps.com/methodology
[43] ISO. ISO 14044: Environmental management – Life cycle assessment – Requirements and guidelines. 2006.
[44] ISO. ISO 14067: Greenhouse gases – Carbon footprint of products – Requirements and guidelines for quantification. 2018a.
[45] ISO. ISO 14064-1: Greenhouse gases – Specification with guidance at the organization level for quantification and reporting of greenhouse gas emissions and removals, 2018b.
[46] ISO. ISO 14069: Greenhouse gases – Quantification and reporting of greenhouse gas emissions for organizations, 2013.