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From Papers to Power Plants: A Taxonomy of Power Flow Tracing Methods in Research and Practice

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Abstract

Power flow tracing (PFT) methods algorithmically reconstruct how electricity generators supply specific loads and contribute to network losses, enabling physically grounded attribution of electricity flows across a grid. Despite nearly three decades of research, the field lacks a unified conceptual framework that integrates academic and industry perspectives. In this paper, we address this gap by conducting a multivocal literature review (MLR) covering 52 academic and industry sources published between 2019 and 2025, and developing a taxonomy of PFT methods structured along six dimensions and 20 characteristics: input, output, tracing approach, application area, topology model, and level of analysis. Our analysis reveals that linear-equation-based methods embodying the proportional sharing principle dominate both academic and practitioner contexts, and that emissions attribution and renewable energy certification have emerged as the primary application areas, primarily driven by tightening sustainability reporting requirements. While PFT methodologies themselves exhibit considerable maturity, we find that limited data availability, granularity, and quality represent the central barrier to broader practical adoption. We discuss how digital technologies can support the measuring, reporting, and verification of electricity data to overcome these barriers, and propose a research agenda from a data perspective. Our taxonomy supports policymakers and grid operators in selecting suitable PFT methods for regulatory, technical, and operational contexts.

Keywords: Electricity Pricing; Grid Management; Guarantees of Origin; MRV; Multivocal Literature Review; Power Flow Tracing; Scope 2 Emissions; Taxonomy

1 Introduction

Today's electricity system is characterized by the widespread integration of Distributed Energy Resources (DERs), an increasing number of prosumers who not only consume but also produce electricity, and fundamental electricity market changes such as the emergence of Peer-to-Peer (P2P) energy trading platforms that allow these prosumers to trade their excess electricity. While these trends are essential for achieving the EU's 2050 net-zero goal, they significantly increase technical and economic system complexity: First, electricity generation from Renewable Energy Sourcess (RESs), such as rooftop Photovoltaic (PV) systems, fluctuates significantly. Feed-in as well as consumption are not necessarily grid-oriented because prosumers may act according to economic incentives that do not reflect grid constraints. Hence, pricing mechanisms must be dynamized to provide appropriate signals that address both temporal and spatial coordination challenges: Regarding the former, time-varying tariffs can incentivize behavior that shifts demand to hours with high renewable energy generation or reduces demand peaks, as exemplified by Kaur and Singh (2023) for electric vehicles. Regarding the latter, grid-aware or locational pricing signals are needed to address spatial grid constraints by providing location-specific incentives that reflect local network conditions and congestion, as illustrated by Pease *et al.*, (2023). Second, ensuring grid stability is becoming increasingly difficult, particularly in the absence of appropriate incentivization mechanisms such as dynamic tariffs, due to fluctuating supply and demand. This is reinforced by the fact that renewable energy sources (especially PV systems) often produce electricity during times of lower demand (i.e., daytime hours). Third, the increasing number of plants and grids makes it difficult to determine the origin of electricity, which is essential, among other things, to provide consumers with transparency about their electricity's carbon footprint. Einolander (2025), for example, shows large discrepancies between Guarantee of Origin-based claims and physical availability of RES.

In this light, fair implementation of dynamic pricing, accurate certification of electricity origin (e.g., from RES), and reliable maintenance of grid stability with fluctuating supply remain significant challenges in practice: Traditional and widespread approaches, such as constant flat rates for tariffs, guarantees of origin for renewable energy certification, or the MW-Mile method for calculating transmission costs based on the distance and amount of power generally do not appropriately account for real-world conditions (e.g., congestion or line losses). This can lead to inequitable cost allocation, limited transparency, and low accuracy (Gernaat *et al.*, 2020; Körner *et al.*, 2024; Nojeng *et al.*, 2014) and illustrates the need for reliable approaches to trace electricity flows that respect physical constraints. However, accurately tracing the physical flow of electricity from generators to loads is very challenging because electrons cannot be tagged and follow complex network paths governed by Kirchhoff's laws (Bialek, 1996).

Against this background, several Power Flow Tracing (PFT) methods have been proposed. By algorithmically reconstructing how generators supply specific loads and contribute to line losses, PFT can provide a more accurate allocation of electricity that integrates real-world conditions, thereby enabling more realistic tracing results. In recent years, researchers and practitioners have proposed numerous PFT methods that differ, among other things, in their data foundation (e.g., historical vs. real-time data), tracing approach (e.g., based on linear equations vs. graph theory), and application area (e.g., electricity pricing vs. emissions allocation). Despite the considerable body of research in PFT, there is still no unified conceptual framework that compares these methods and integrates insights from both academia and industry.

In this paper, we address this gap by conducting a Multivocal Literature Review (MLR) following Garousi *et al.*, (2019) that incorporates both peer-reviewed studies (e.g., journal articles) and gray literature (e.g., white papers). By doing so, we ensure that insights from practitioners such as utilities, regulators, and technology providers can be included alongside scholarly research. We define PFT as the allocation step that disaggregates solved power flows to network participants and categorize and evaluate six fundamental kinds of tracing approaches: circuit-theoretic, graph-theoretic, linear-equation–based, optimization-driven, electrical-distance–based, and game-theoretic approaches. Further, by presenting a structured taxonomy and comparative analysis, we allow for a more distinct classification of PFT methods, including other relevant dimensions such as data foundation and application areas. We aim at guiding stakeholders in selecting suitable PFT methods for their specific use cases. By highlighting the theoretical foundations and practical applications of these methods, we also explore their potential for further development as well as wider adoption in the energy sector. Therefore, we aim at answering the following research question:

How can power flow tracing methods in research and practice be structured to contribute to different application areas in the energy sector?

The remainder of this paper is structured as follows: In Section 2, we present the background of our research by outlining the different approaches for tracing electricity and discuss related literature in this context. In Section 3, we outline our methodology based on a MLR following Garousi *et al.*, (2019). In Section 4, we compare different PFT approaches and explore their applications in different contexts. In Section 5, we then discuss opportunities for further developing PFT approaches by taking a data perspective. Finally, in Section 6, we conclude with an outlook on future research avenues and practical implications for industry stakeholders.

2 Background and Related Literature

The electricity sector has evolved from a centralized, unidirectional supply chain, where large generators feed transmission grids that in turn feed distribution grids, to a highly decentralized ecosystem. Deregulation and the entry of numerous small-scale renewable generators and prosumers have introduced bidirectional flows and temporal variability in both injections and withdrawals of electricity. These developments complicate existing challenges in allocating grid usage and losses equitably among market participants and certifying the origin of electricity, while also creating new use cases for PFT methods.

Two fundamentally distinct types of methods have emerged for tracing power flows and related attributes such as Scope 2 emissions: *balance sheet tracing* and *physical tracing*.

Balance sheet tracing treats electricity as a fungible commodity and, hence, relies on contractual accounting: registries track certificates that correspond to renewable generation, but electricity may be physically consumed at a different location or time than it was generated. This approach decouples physical realities of grid operation from contractual attributes, focusing on aggregated volumes over financial or calendar periods rather than granular flows.

This leads to criticism that such methods offer low spatio-temporal resolution and poor alignment with actual grid behavior (Einolander, 2025). Volumes and attributes are captured through contracts and certificates (e.g., a guarantee of origin allows one to certify 1 MWh of electricity as "green" through the same amount of electricity being generated by a RES in the EU within the last year). While simple balance sheet methods are practical for high-level accounting and more complex balance sheet methods for fine-granular accounting exist in research and practice (e.g., Körner *et al.*, (2024)), they typically neglect physical constraints of grid flows. For reporting Scope 2 emissions, for example, balance sheet methods (e.g., "market-based" accounting in the Greenhouse Gas (GHG) Protocol) are widely used, but their assumptions may not reflect the actual emissions related to physical consumption (which is why the GHG Protocol also requires "location-based" accounting).

Physical tracing (i.e., PFT), on the other hand, seeks to solve the allocation problem based on physical flows, often by enforcing Kirchhoff's circuit laws: First, the junction rule which describes that the sum of the currents entering and leaving each network node is zero. Second, the loop rule which says that the sum of the voltage changes around each closed loop is zero (Kirchhoff, 1845). PFT approaches operationalize these physical laws, often under simplifying assumptions, to map generator contributions to loads and line losses. Originally developed for transmission loss allocation (Bialek, 1996; Kirschen *et al.*, 1997), PFT has since been proposed for a variety of use cases such as emissions allocation (e.g., Z. Lu *et al.*, (2024)), curtailment (e.g., T. Wu *et al.*, (2019) and load shedding (e.g., Jiandong *et al.*, (2019)). Unlike balance sheet tracing, physical tracing enables location- and time-specific attribution, providing a high-resolution view on which generators serve which loads and how losses are incurred. As such, "location-based" accounting methods for Scope 2 emissions consumption or imports may use physical tracing results to better align emissions attribution with actual system usage. In this light, practical applications of PFT are mainly driven by corporate sustainability reporting requirements (e.g., EU Corporate Sustainability Reporting Directive), and the demand for transparent, granular network insights (e.g., from consumers).

A wide range of PFT methods and variations thereof have been developed to address the differing requirements of the various use cases. For instance, the original PFT method of Bialek (1996) is based on linear equations and assumes that power flows converging at a node are proportionally divided among the outgoing branches based on their respective contributions ("proportional sharing principle") and has been modified by several authors, such as Angaphiwatchawal *et al.*, (2024), who adapt it for managing the voltage impact in distribution grids, or Enshaee and Yousefi (2019), who propose an updated method for attributing responsibility for reactive power flows and losses in transmission lines to sources and loads. In contrast, Y. C. Chen and Dhople (2020) and C. Wang *et al.*, (2022) derive their method strictly from circuit theory, thereby refraining from using the proportional sharing principle. Beyond classical tracing, decomposition-based allocations define elementary import/export building blocks to align partial flows with commercial exchange patterns and capture counter-flows, offering a complementary lens for cross-border analysis (Schäfer *et al.*, 2017).

Consequently, previous literature in this area has focused on specific tracing approaches but does not offer a systematic framework that provides a detailed comparison of existing methods. While some papers address individual use cases such as emissions allocation, they rarely analyze how methodological choices affect suitability for these and other application areas. This limits the ability of stakeholders to choose appropriate tracing methods based on their specific goals or data availability. In response, this paper offers a comprehensive review and classification of PFT methods across tracing approaches, data foundations, and application areas.

3 Methodological Approach

In this paper, we employ a qualitative review to develop a taxonomy of power flow tracing (PFT) methods. Our aim is to systematically classify existing methods based on their tracing approaches and application areas. To achieve this, we conduct a MLR and use the resulting insights to construct a taxonomy that captures key conceptual and practical distinctions.

Taxonomy development is a well-established approach for structuring fragmented or multidisciplinary knowledge domains, e.g., on the interface of sustainability and Information Systems (IS) (e.g., Babel *et al.*, (2024) or Böttcher *et al.*, (2024)). In our case, the taxonomy aims to synthesize diverse academic and industry perspectives on PFT and provide a comparative framework for researchers and practitioners in the energy sector.

3.1 Multivocal Literature Review

We apply a MLR approach, following the guidance of Garousi *et al.*, (2019), to synthesize and compare academic and gray literature on PFT. MLRs are increasingly recognized as valuable in energy and IS research, particularly when conceptual or methodological synthesis is required across both scholarly and practitioner domains. For instance, Kvalvik *et al.*, (2023) review data governance publications to detect and categorize endeavors backing up data sharing in smart cities by combining academic sources with practitioner documents. Similarly, Itodo and Ozer (2024) include peer-reviewed articles in combination with gray literature to consolidate knowledge on zero-trust implementation and to identify gaps in literature. These examples illustrate that MLRs are particularly suited to fields where knowledge is spread across various types of sources. This includes academic publications, less formal but practically significant materials, and novel research papers that have not (yet) undergone peer review. Fields relevant for MLRs application often involve emerging practices, digital technologies, new methods, and implementation insights, which highlights its suitability for PFT. Accordingly, we perform an MLR to answer our research question.

We illustrate our MLR process as a PRISMA diagram following Page *et al.*, (2021), which outlines the flow from identification to final inclusion of literature (cf. Figure 1). To cover a broad spectrum of recent literature, we collect literature published between 2019 and 2025 using the following search string in the abstract search:

*(power OR electricity) AND flow AND trac**

While we acknowledge that some streams of literature may employ alternative terminology, we define our scope around the widely recognized term power flow tracing. Complementary results using other wordings are incorporated through forward and backward snowballing, as outlined by Garousi *et al.*, (2019).

We apply this query across the four academic databases ACM Digital Library, AIS eLibrary, Emerald Insight, and IEEE Xplore, which we choose according to their relevancy in energy and IS research. To capture gray literature, we additionally search Google and arXiv (a repository which hosts preprints and emerging research). For Google, we use the simpler search string "power flow tracing" because the search engine's advanced search does not allow our complex search string.

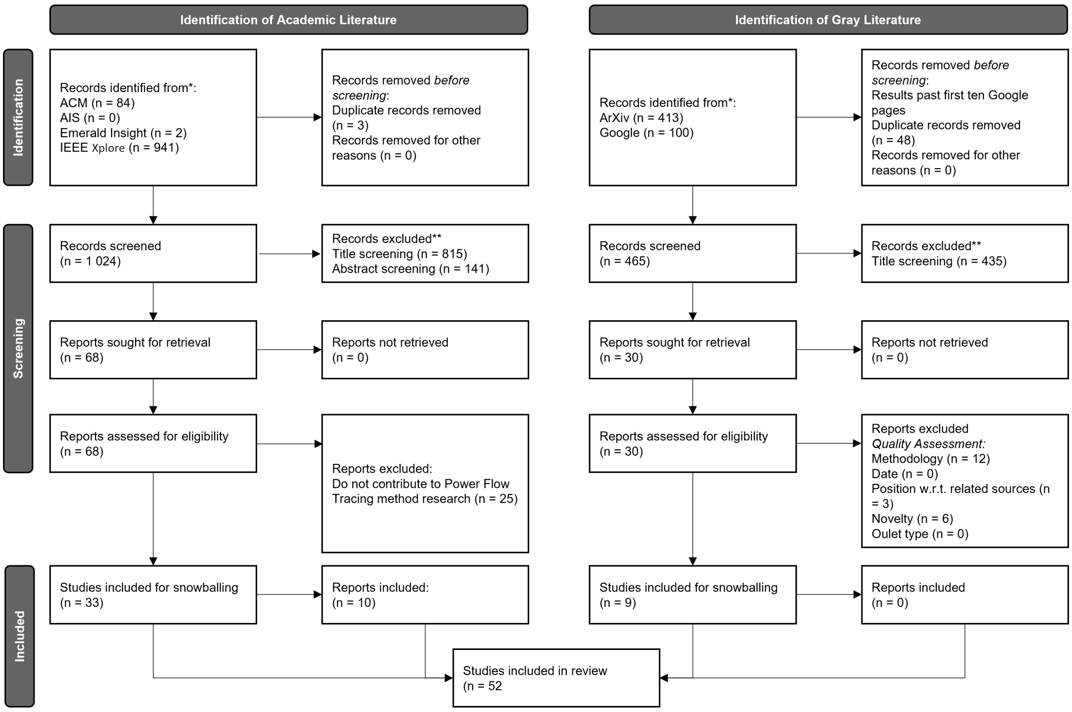

Figure 1: PRISMA Flow Diagram following Page *et al.*, (2021)

Following Garousi *et al.*, (2019), we apply an effort-bound approach and analyze the first ten pages of results sorted by relevance because of the large number of hits. After identifying sources, we remove duplicates and screen the remaining documents based on titles and abstracts. We include sources that explicitly describe, apply, or evaluate PFT methods and application areas, while we exclude those that do not focus on PFT or lack methodological detail. During the eligibility phase, we evaluate full text. To be included, both academic and gray literature must clearly focus on PFT. For academic literature, the paper must thematize it in the results section, and for gray literature, it must make up the majority of the text. To get more information on gray literature results, we also screen corresponding websites and use, for example, their FAQ sections for reference.

By following the established approach of Garousi *et al.*, (2019) and integrating both academic and practitioner perspectives, we provide a comprehensive overview of the PFT landscape that allows us to identify trends that a purely academic review would likely miss. Hence, our methodological approach offers a solid foundation for the conceptual framework we present in the next section to structure PFT methods.

#	Author (year)	Publication Type	Tracing Approach	Application Focus
1	Aarhus University (2023)	Website	Linear equation	Renewables
2	Angaphiwatchawal *et al.*, (2024)	Conference article	Linear equation	Voltage
3	Bai and Crisostomi (2020)	Conference article	Linear equation	P2P trading
4	Bhand and Debbarma (2021)	Journal article	Graph	Distribution
5	Budi *et al.*, (2020)	Conference article	Linear equation	Distribution
6	Y.-X. Chen *et al.*, (2019)	Conference article	Circuit theory	Frequency
7	Y. C. Chen and Dhople (2020)	Journal article	Circuit theory	Agnostic
8	Deacon *et al.*, (2021)	Conference article	Graph	P2P trading
9	Dudkina *et al.*, (2022)	Conference article	Graph	Renewables
10	Dudkina *et al.*, (2024)	Conference article	Graph	Renewables
11	Electricity Maps (2025b)	Conference article	Graph	Renewables
12	Eleks (2025)	Website	Linear equation	Emissions
13	Enshaee and Yousefi (2019)	Journal article	Linear equation	Transmission
14	Fei and Moses (2019)	Conference article	Circuit theory	Distribution
15	Hofmann (2020)	Preprint	Linear equation	P2P trading
16	Hofmann and Schlott (2022)	Website	Linear equation	Nodal Pricing
17	J. Hu *et al.*, (2024)	Preprint	Linear equation	Emissions
18	Jiandong *et al.*, (2019)	Conference article	Linear equation	Overload
19	Jiang and Zhang (2021)	Conference article	Circuit theory	Voltage
20	Lawal *et al.*, (2019)	Journal article	Graph	Congestion
21	Li *et al.*, (2023)	Conference article	Linear equation	Emissions
22	Liang *et al.*, (2023)	Conference article	Linear equation	Emissions
23	Liu *et al.*, (2020)	Journal article	Linear equation	Voltage
24	Lou *et al.*, (2024)	Journal article	Graph	P2P trading
25	X. Lu and Zou (2021)	Conference article	Circuit theory	Transmission
26	Z. Lu *et al.*, (2024)	Journal article	Linear equation	Emissions
27	S. Ma *et al.*, (2022)	Conference article	Graph	Emissions
28	F. Ma *et al.*, (2023)	Conference article	Graph	Emissions
29	Patel *et al.*, (2019)	Journal article	Overview	Transmission
30	Pease *et al.*, (2023)	Preprint	Linear equation	Transmission
31	Qing and Xiang (2024)	Conference article	Linear equation	Emissions
32	Ren *et al.*, (2023)	Conference article	Linear equation	Emissions
33	Sang *et al.*, (2023)	Journal article	Linear equation	Emissions
34	Schäfer *et al.*, (2019)	Conference article	Linear equation	Im-/Export
35	Shuai *et al.*, (2021)	Conference article	Graph	Transmission
36	Ströher and Strüker (2024)	White Paper	Overview	Overview
37	Sun *et al.*, (2023)	Journal article	Linear equation	Emissions
38	Tijani *et al.*, (2019)	Journal article	Optimization	Transmission
39	Tranberg *et al.*, (2019)	Journal article	Linear equation	Emissions
40	University of Helsinki (2023)	Website	Linear equation	Emissions
41	Vlaisavljevic *et al.*, (2019)	Conference article	Electrical distance	Redispatch
42	C. Wang *et al.*, (2022)	Journal article	Circuit theory	Emissions
43	P. Wang *et al.*, (2023)	Conference article	Linear equation	Emissions
44	D. Wang *et al.*, (2024)	Conference article	Linear equation	Distribution
45	T. Wu *et al.*, (2019)	Conference article	Linear equation	Curtailment
46	Yan *et al.*, (2021)	Conference article	Linear equation	Emissions
47	Yang *et al.*, (2023)	Conference article	Linear equation	Emissions
48	X. Yu (2022)	Conference article	Graph	Planning
49	M. Yu *et al.*, (2023)	Conference article	Graph	Loss allocation
50	Zhang *et al.*, (2023)	Conference article	Linear equation	Emissions
51	Zhao *et al.*, (2023)	Conference article	Linear equation	Distribution
52	Zuo *et al.*, (2024)	Conference article	Game theory	Emissions

Table I: Overview of the Results of Our Multivocal Literature Review

3.2 Taxonomy Development

We develop our taxonomy to structure the approaches identified in our MLR, following the recognized method of Nickerson *et al.*, (2013). As recommended, we first define a meta-characteristic that forms the basis of our taxonomy: *methods and application areas for power flow tracing approaches*. This meta-characteristic guides the identification of relevant taxonomy characteristics and dimensions. We then define both objective and subjective ending conditions, based on the list proposed by Nickerson *et al.*, (2013). Our objective ending conditions include that no new dimensions or characteristics are added and that each characteristic is unique within its dimension. The subjective end conditions include that the taxonomy is concise, robust, comprehensive, extendable, and explanatory.

Since several publications in our final literature set (cf. Table I) already provide some form of differentiation of PFT methods, we begin with a conceptual-to-empirical (i.e., deductive) approach. Consequently and in line with Nickerson *et al.*, (2013), we conceptualize taxonomy dimensions without examining specific objects in our first iteration. To do so, we define and use a subset of all sources that do not solely propose new methods (i.e., empirical objects), but also offer overviews, classifications, or conceptual discussions of PFT, specifically the publications [13; 26; 29; 36; 38; 42; 51] according to Table I. Based on these publications, we derive an initial set of characteristics by coding each of these publications using the MAXQDA software. In the second iteration, we follow an empirical-to-conceptual approach. Here, we identify a second subset of objects and determine recurring attributes across the reviewed literature through inductive coding. This subset consists of all journal articles from our MLR results not already analyzed in the first iteration, as journal articles are typically longer and thus tend to offer more detailed descriptions of methods and application areas. After the second iteration, our objective ending conditions are not yet fulfilled, as dimensions and characteristics continue to change (cf. Appendix A). Consequently, we conduct a third iteration, again following an empirical-to-conceptual approach. This time, we use all gray literature results, as these may provide new real-world insights relevant to our taxonomy. Since our dimensions and characteristics change again, we proceed to a fourth iteration, which also follows an empirical-to-conceptual approach. For this iteration, we analyze all remaining conference proceedings. At this stage, we do not identify any new or modified information. Consequently, our taxonomy remains unchanged between the third and fourth iteration. Together with the fact that each characteristic is unique, this indicates that our taxonomy meets all objective ending conditions. With six distinct and comprehensive dimensions and 20 corresponding characteristics that allow for the classification of every object, we also consider our subjective ending conditions to be fulfilled. We thus conclude the taxonomy development process.

Our final taxonomy is structured along six dimensions that reflect relevant methodological decisions when implementing a PFT approach for a particular use case. For each dimension, we define a set of distinct characteristics that allow consistent classification of each PFT method. We discuss each dimension and characteristic in the subsequent section.

4 Results

The aim of this paper is to provide a structured understanding of PFT methods and their application areas by synthesizing academic and industry perspectives through a MLR. To do so, we develop a taxonomy that classifies existing PFT approaches along conceptually grounded dimensions and corresponding characteristics. We provide our results in two stages. First, we analyze the set of publications we identify through our MLR, assigning each to a corresponding tracing approach and application area. Second, we describe the taxonomy itself, including its six dimensions and 20 characteristics.

4.1 Literature Analysis

Our reviewed body of literature (cf. Table I) reflects a diverse set of PFT methods applied across various application areas, each with differing levels of methodological complexity and data requirements. We observe several dominant tendencies related to publication types and methodological preferences, which we illustrate in Figure 2 and discuss below, drawing on the taxonomy dimensions we present in Section 4.2.

First, academic literature represents the majority of results that we classify as relevant based on our MLR. This implies significant research interest in PFT methods, whereas they remain a niche topic among practitioners, particularly in the early publication years of our data set. Notably, our final set includes a substantial number of conference articles (n = 31), reflecting both active discussion and rapid progress in the field, but also indicating a lack of enduring, general findings.

Second, we see a recent increase in relevant gray literature, while academic publication numbers remain relatively stable. For example, we include only one relevant preprint between 2019 and 2021, whereas we add seven relevant gray literature documents from 2023 to 2025. This trend suggests that PFT methods are reaching a level of maturity that enables practical implementation. Growing practitioner interest further indicates that PFT is moving beyond theory and offers promising ecological, economic, or regulatory applications.

Third, linear equation-based methods represent the large majority of results overall and are, to our knowledge, the only approach adopted by practitioners, followed by graph-based and circuit-theoretic tracing approaches. Other approaches are the main focus of only one publication each. This reflects a clear methodological preference. In the subsequent section, we shed light on this preference by presenting different tracing approaches and highlighting the differences between them. We also illustrate that PFT methods differ not only in their tracing approach, but also along a range of dimensions relevant to their design and implementation.

Finally, a significant proportion of our resulting publications, particularly the most recent ones, focus on the tracing of emissions and renewable energies (i.e., proofs of origin for electricity). Most of these works are motivated by increasingly stringent environmental regulations (e.g., the Corporate Sustainability Reporting Directive in the EU) and a growing market demand for greater transparency regarding sustainability metrics (e.g., from environmentally conscious consumers). This trend suggests not only that PFT represents a promising approach for achieving such transparency, but also that recent regulatory and market pressures are likely key drivers in the ongoing development of PFT methods.

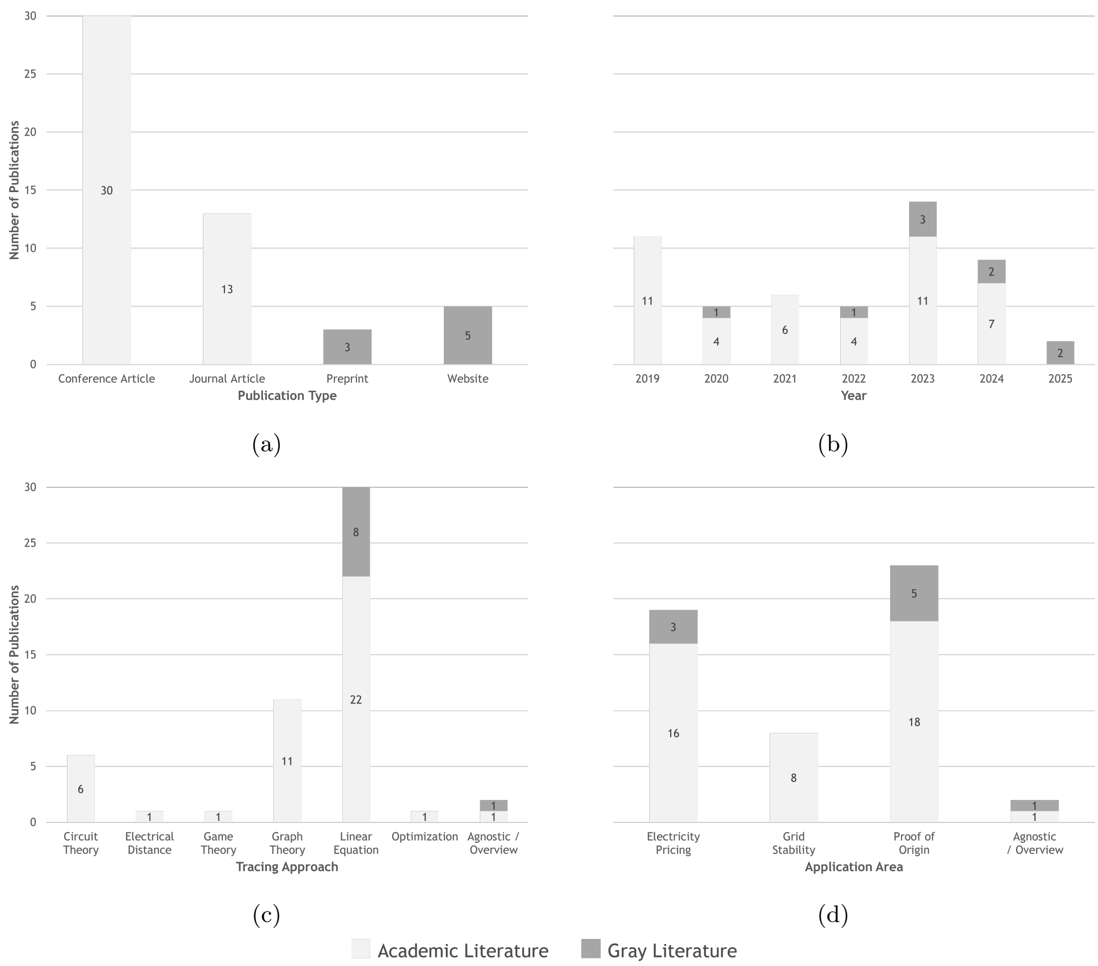

Figure 2: Number of academic and gray literature results a) by publication type, b) over time, c) by tracing approach, and d) by application area

4.2 Taxonomy of Power Flow Tracing

Based on our MLR (cf. Section 3), we introduce a taxonomy that provides a structured framework for comparing and evaluating PFT methods, going beyond the mere distinction of tracing approaches illustrated in Figure 2. Our taxonomy synthesizes recurring patterns and distinguishing criteria observed across our reviewed sources and organizes them into dimensions with corresponding characteristics (cf. Figure 3). In the following, we describe each dimension. Across all dimensions, we define PFT narrowly as the allocation step that disaggregates already-solved flows to participants (cf. Section 1). Our taxonomy, however, also covers prerequisites to conduct PFT (i.e., topology specification, data inputs/outputs, and the underlying power flow solutions).

Dimension	Characteristics						Exclusive (Yes/No)
Input	Historic		Real-Time		Simulation		No
Output	Static			Dynamic			Yes
Tracing Approach	Circuit Theory	Electrical Distance	Game Theory	Graph Theory	Linear Equation	Optimization	Yes
Application Area	Electricity Pricing		Grid Stability		Tracing of Origin and Emissions		No
Topology Model	AC		DC		Hybrid		Yes
Level of Analysis	Transmission Grid		Distribution Grid		Microgrid		No

Figure 3: Taxonomy of Power Flow Tracing Methods

Input

Our input dimension refers to the temporal and contextual source of the system data and solved power flows that serve as inputs to the tracing stage. It distinguishes whether a method depends on recorded historical data, operates with real-time inputs, or is based on simulations. Approaches relying on a *historical* data foundation use archived system data to perform retrospective allocation of power flows. For example, Bai and Crisostomi (2020) reconstruct power losses over previous days using recorded line current and bus injection data. Ex-post approaches such as those described by Tranberg *et al.*, (2019) utilize dispatch data that, while not as timely, enable an in-depth understanding of energy consumption and sourcing during a given time period without direct access to system data. These ex-post scenarios support the clarification of responsibility, for example, by providing a physically more accurate approach to transmission costs.

Real-time approaches use (near) real-time data about the analyzed system to perform PFT. For instance, Dudkina *et al.*, (2022) employ real-time flow data to allocate electricity consumption from RES for the hydrogen production process. Similarly, Yan *et al.*, (2021) provide a real-time carbon flow algorithm for emissions tracing. Also, Hofmann (2020) applies tracing to time-resolved data reflecting power generation and consumption cycles at the granularity of hours for all of Europe. Real-time approaches require a continuous data stream (e.g., through sensors) and allow for the real-time monitoring of evolving hotspots to take corrective actions (e.g., redispatch or curtailment) as necessary.

Simulation-based PFT relies on simulated data rather than real measurements. For example, Li *et al.*, (2023) utilize power flow simulations to examine carbon allocation strategies under sector-coupled scenarios. Z. Lu *et al.*, (2024), in a related context, utilize simulated data to analyze market power behavior under different topological structures using PFT. Simulation-based approaches can examine policy, infrastructure, and market design under experimental settings, even if the data used are not physical measurements. Measurements can be complemented by estimates in case of missing or delayed data, as exemplified by Electricity Maps (2025b). Hence, this dimension is non-exclusive.

Output

Our second dimension, output, specifies the nature of the system state over time for power flow analysis. It explains whether the tracing is applied to a single solved snapshot or to a time series of solved operating points. This distinction is important for determining the applicability of PFT in dynamic grid operations or planning scenarios. Within this dimension, we differentiate between two characteristics: static and dynamic.

Static methods apply tracing to a single snapshot of the grid, usually a power flow solution at steady state. By doing so, these methods rely on the assumption that the system variables (e.g., related to generation, load, and topology) would remain unchanged during the analysis. The cost allocation method proposed by Lou *et al.*, (2024), for example, uses a static tracing model to calculate costs in a P2P electricity market setting. This approach is based on fixed power injections and withdrawals and provides an accurate but limited view of energy consumption and contribution over time. Similarly, Zhao *et al.*, (2023) propose a virtual contribution-based methodology for loss allocation using single-time-step analysis. Although the paper mentions general distributed network dynamics, the primary PFT approach uses static assumptions and calculates losses for pre-chosen operating points. Static methods are computationally inexpensive and particularly appropriate for regulation or billing domains where straightforward allocation logic is needed under fixed operational conditions.

In contrast, *dynamic* approaches apply tracing across evolving operating points (e.g., consecutive solved power flows) or embed system dynamics prior to tracing. These approaches trace how power flows and characteristics (such as associated emissions or costs) change over time as a result of system changes. For example, Liu *et al.*, (2020) propose a 'dynamized' PFT method based on differential transformation. Rather than solving numerous static snapshots sequentially, their approach incorporates dynamics directly into tracing, allowing the method to account for changes over time. Similarly, Qing and Xiang (2024) establish a dynamic carbon emission factor model for accurate carbon emission flow perception.

Tracing Approach

This dimension refers to the theoretical principles used to allocate contributions based on a solved operating point. As illustrated in Figure 2, we distinguish between six groups of tracing approaches: circuit theory, electrical distance, game theory, graph theory, linear equation, and optimization.

Circuit-theoretic approaches rely on basic electrical laws, such as Ohm's and Kirchhoff's laws, to model power flow allocation. These approaches treat the power system as an electrical circuit and trace the flow of active or reactive power based on physical quantities such as current, voltage, and impedance. An example can be found in Y. C. Chen and Dhople (2020), who formulate an analytical method that uses elementary circuit principles to trace power from sources to sinks.

Electrical distance metrics quantify how "far" a node is from another node in electrical terms. Originating from Visakha *et al.*, (2004), this approach is based on a network matrix that provides the relative locations of loads with respect to generators. The original relative electrical distance method, however, does not allow for approximating the contribution of individual generators and loads but rather allocates costs based on (the contractual deviation of) a predefined desired schedule. For this reason, it may not be classified as a PFT method in the narrow sense, but we include it for completeness. Current literature does not focus on this basic electrical distance anymore. However, more sophisticated approaches, such as Vlaisavljevic *et al.*, (2019), integrate electrical distance in their methods.

Game-theoretic methods approach tracing as a problem of cooperative or non-cooperative games, focusing on fairness and strategic behavior. These methods are particularly relevant when balancing economic interests, market actors, or emission responsibilities. Zuo *et al.*, (2024) apply cooperative game theory to allocate carbon emissions across market participants in a hybrid power market. This method ensures that cost and emission responsibilities are fairly shared among participants based on their marginal contributions, reflecting a Shapley value-inspired allocation. Game-theoretic considerations do, of course, not alter the physical conditions of the grids. Thus, game-theoretic approaches typically aim to balance real-world grid constraints and fairness considerations.

Graph-theoretic methods model networks as graphs of nodes and edges, using topological and flow properties to allocate power paths. Generally, methods based on graph theory use the proportional sharing principle, assuming that power flows converging at a node are proportionally divided among the outgoing branches based on their respective contributions (Ströher and Strüker, 2024). For example, Bhand and Debbarma (2021) construct transaction-specific graphs in unbalanced distribution grids, and X. Yu (2022) use a graph-theoretic PFT approach as foundation for a network analytics tool.

Linear equation-based methods use algebraic formulations to trace power by solving systems of linear equations. These methods can be derived from simplified power flow models or from approximated energy flow constraints. For instance, Z. Lu *et al.*, (2024) formulate a market-clearing model based on linear equations, using distribution factors to link generator injections to load allocations, enabling carbon flow tracing in multi-market systems. Research in power engineering suggests that linear equation- and graph-based methods based on the proportional sharing principle are fundamentally equivalent and yield the same results. Ansyari *et al.*, (2007), for example, demonstrate this by comparing different linear equation- and market-based approaches, and Achayuthakan *et al.*, (2010) further provide a mathematical proof of the link between linear equation- and graph-based methods.

Optimization-based methods treat tracing as a constrained optimization problem. These methods balance accuracy and computational tractability but often require heuristic simplifications, such as ignoring loop flows or assuming convexity. Like game-theoretic approaches, they aim to find a solution that respects physical grid constraints while integrating other considerations, such as fairness (Ströher and Strüker, 2024). Optimization methods can be classified into deterministic methods, which always deliver the same output for the same input, and non-deterministic methods, which may yield varying outputs for identical inputs. Deterministic methods are classical or conventional methods based on mathematical programming such as linear and nonlinear programming. Against the background of their drawbacks, such as the weak search capabilities for a global optimum, non-deterministic approaches such as particle swarm optimization, as well as hybrid optimization approaches, combining two or more optimization techniques, have been proposed by researchers (Tijani *et al.*, 2019).

Application Area

PFT methods are crucial for analyzing and optimizing power systems across a range of application areas in the evolving energy landscape, as they can provide valuable insights into the physical flow of energy, which traditional accounting methods often overlook. In this light, it is important to note that PFT complements, but does not replace, power flow calculation in these application areas by allocating usage, losses, emissions, or attributes on top of solved power flows. With regard to application areas for PFT, we distinguish between electricity pricing, grid stability, and proofs of origin.

In *electricity pricing*, PFT is essential for fair cost allocation based on physical usage. A primary application is the allocation of transmission and distribution losses, especially in complex networks with DERs and bidirectional flows. While various loss allocation methods, such as pro rata, MW-mile, and contract path, exist, PFT is grounded in physical power flow, enabling accurate allocation of losses to both generators and loads. PFT is also used to allocate transmission service costs, capital, and operational expenditures of network assets fairly by quantifying each participant's actual network usage (Shuai *et al.*, 2021). These cost allocation principles extend to cross-border transmission infrastructures, where PFT can enable fair cost-sharing among multiple countries based on actual physical usage patterns. In this context, PFT can disentangle the spatio-temporal patterns of physical imports and exports in large-scale electricity systems (Schäfer *et al.*, 2019), addressing the substantial investments and complex jurisdictional challenges in cross-border transmission applications. Concepts like "price tracing" extend PFT to interlink locational marginal prices, increasing transparency in price structures and enabling the derivation of usage-based network tariffs aligned with these marginal prices. Cost allocation, including emission costs, can be linked to the operation and constraints of network assets. Some approaches also integrate energy and carbon prices to formulate nodal integrated prices based on tracing energy and carbon emission flows, as exemplified by S. Ma *et al.*, (2022), who propose a nodal energy-carbon integrated price strategy that includes a nodal energy producing price, a nodal energy transmission price, and a carbon price.

Regarding *grid stability*, PFT can provide insights into power flows for analysis and operational decision-making: voltage stability, which is heavily influenced by reactive power, benefits from PFT analysis of reactive power distribution for control and optimization. Tracing reactive power enables the quantification of coupling between nodes and the identification of voltage weak points. Modified PFT methods have been proposed to mitigate voltage impacts in contexts such as local energy markets, as shown by Angaphiwatchawal *et al.*, (2024). Similarly, Y.-X. Chen *et al.*, (2019) propose a PFT method for frequency stability, and Jiandong *et al.*, (2019) address line overload shedding. PFT can also contribute to congestion management by identifying which generators or loads contribute to congestion and, for example, penalizing them, as illustrated by Lawal *et al.*, (2019). Congestion management can be particularly relevant in cross-border interactions. However, the costs tend to be relatively insensitive to the precise tracing or decomposition approach (Stavropoulos *et al.*, 2025). PFT can also be incorporated into load curtailment strategies to support decision-making on where and how much load to curtail for system restoration after contingencies, based on flow relationships (T. Wu *et al.*, 2019).

Additionally, PFT is used for *tracing of origin and emissions*, i.e., tracing electricity from specific sources to attribute characteristics such as carbon emissions or renewable energy share. A prominent application is tracing the carbon emissions associated with electricity production and consumption, i.e., carbon footprinting, as demonstrated by researchers such as J. Hu *et al.*, (2024) and practitioners such as Eleks (2025). For carbon footprinting, carbon emissions are conceptualized as a virtual flow tied to power flow, allowing for the accurate assignment of carbon emission factors to individual grid nodes (Qing and Xiang, 2024; P. Wang *et al.*, 2023). By doing so, PFT can provide an alternative to, for example, market-clearing based marginal carbon emission metrics (Z. Lu *et al.*, 2024). PFT methods can also be used to predict future carbon emissions based on historical data (see, for example, (Liang *et al.*, 2023)). PFT also facilitates the tracing of renewable energy contributions for green power trading and grid integration (Aarhus University, 2023). In this context, PFT supports the maximization of physical energy flows between renewable generators and specific loads, such as electrolyzers for green hydrogen production, while also upholding the principle of "additionality." This ensures that RES-based production does not displace other uses of renewable energy sources (Dudkina *et al.*, 2022; Dudkina *et al.*, 2024).

Topology Model

PFT methods differ significantly based on the topology model used to represent the power system network, which is used to compute the underlying power flow solution on which PFT operates. A method can use an Alternating Current (AC) model, a simplified Direct Current (DC) model, or a hybrid approach that incorporates both.

AC-based methods are grounded in utilizing the results of AC power flow equations. Methods based on circuit theory often fall into this category and leverage network matrices, such as the admittance (Y) (e.g., Y. C. Chen and Dhople (2020)) or impedance (Z) (e.g., C. Wang *et al.*, (2022)) matrix, to trace complex power. But also methods based on the proportional sharing principle, such as graph-based methods, can be used for complex power flow tracing (e.g., F. Ma *et al.*, (2023)).

DC-based methods rely on (simplified) DC power flow models. These models represent a simplification of a full power flow looking only at active power flows (Purchala *et al.*, 2005) and do not consider losses by default. PFT that only considers active power has primarily been applied to transmission networks, where reactive power often plays a lesser role. For example, Zhang *et al.*, (2023) use active PFT for interzonal carbon emission flows, focusing on transmission networks. Similarly, Yang *et al.*, (2023) and Ren *et al.*, (2023) only consider active power flows for allocating carbon emissions associated with transmission losses. Reactive power is, however, essential for maintaining voltage at all buses within their limits and enhancing active energy transfer capability by supplying reactive demands (Enshaee and Yousefi, 2019). Consequently, as power systems have evolved and the focus has shifted toward networks with increasing penetration of DERs where voltage regulation is a significant concern, reactive power tracing has gained importance (see, for example, Jiang and Zhang (2021)).

Our *hybrid* characteristic encompasses methods that solve power flow problems with an AC model in a part of the system, whereas with the DC model in other parts (Kim and Overbye, 2011). This may provide a balance between the computational efficiency of DC-based methods and the accuracy of AC-based methods. It is also possible to initially begin with an AC-model and then add, for example, losses ex-post, as exemplified by Vlaisavljevic *et al.*, (2019).

Level of Analysis

Our level of analysis dimension categorizes PFT approaches based on the type of grid they analyze. This distinction is fundamental because operational characteristics, data availability, and tracing needs differ significantly between transmission grids, distribution grids, and microgrids. Although some tracing methods are theoretically agnostic to scale, practical implementations often reflect differences in feasibility and accuracy. For example, the consideration of reactive power generally plays a more important role in distribution than transmission grids (cf. above).

PFT applications in *transmission grids* focus on (ultra) high-voltage systems typically operated by transmission system operators. These grids serve as the backbone of national and regional electricity systems, and PFT is often used for large-scale loss allocation, emission attribution, or interzonal flow decomposition. For example, Deacon *et al.*, (2021) analyze zonal carbon content in Great Britain's high-voltage transmission system using a graph-based tracing method, emphasizing the importance of flow attribution at the transmission level for informing locational emission signals and policy mechanisms, such as carbon border adjustments. Similarly, M. Yu *et al.*, (2023) examine power transfer between Chinese provinces through a tracing model applied to the transmission grid. Schäfer *et al.*, (2019) focus on transmission grids to identify patterns in the time series of imports/exports and physical cross-border flows in the European electricity markets.

Tracing at the distribution grid level addresses medium- and low-voltage networks, which have a greater presence of renewable integration, P2P energy trading, and flexible loads. These grids are more decentralized and often data-constrained, necessitating methods that can handle, for example, incomplete information and bidirectional power flows. Hofmann and Schlott (2022) propose a framework for quantifying flexibility contributions in distribution networks using a tracing method based on linear equations. Fei and Moses (2019) present a decentralized PFT mechanism for distribution networks, in which data is shared in a privacy-preserving manner, which is also a bigger concern there than in transmission grids, as fine-grained distribution-level data may allow for conclusions about individual consumers' behaviors. D. Wang *et al.*, (2024) also focus on the distribution grid in their approach to identify key nodes in the network for improving the reliability and economy of network monitoring, and accelerating the realization of transparency, observability, and measurability.

Microgrid-level tracing deals with localized systems that operate autonomously or with minimal coordination with the main grid. These systems are ideal for experimenting with novel tracing methods due to their scale, self-sufficiency, and asset heterogeneity. Budi *et al.*, (2020) implement a P2P energy trading system in a microgrid setting, using PFT to determine transactional losses and support fair billing. Their work illustrates that tracing serves crucial economic and operational purposes even in minimal grid environments. Similarly, Pease *et al.*, (2023) explore the use of PFT in a solar-powered community microgrid.

5 Discussion

Our results imply that PFT is, from a technical and methodological point of view, a rather mature field with almost 30 years of research and various contributions from academic and industry sides, offering a diverse toolbox for various application areas (cf. Section 4). Recent approaches that scale to large networks, for example Shen *et al.*, (2025) with regard to quantification of nodal carbon emissions, further support this methodological maturity while highlighting remaining data frictions for fine-granular calculation. Hence, from our view, the primary barrier to the wider adoption of PFT is no longer related to the methods themselves, but rather the availability, granularity, and quality of the required data to perform PFT. This shift necessitates an IS-focused research agenda that prioritizes data infrastructure and governance frameworks to fully exploit the potential of PFT. To provide such a research agenda, we take a data and IS perspective and, by focusing on the compelling example of carbon emissions tracing for enabling carbon-adaptive decisions on the demand side, discuss how digital technologies may be leveraged to enhance the measuring, reporting, and verification processes related to PFT and illustrate future research avenues.

A recurring constraint across the surveyed literature is the challenge of accessing or generating data granular enough to effectively implement PFT approaches in practice. Deacon *et al.*, (2021) and Ströher and Strüker (2024) highlight that methods often prove inapplicable in distribution networks, as reliable, fine-grained grid data remain unavailable even to Distribution System Operators (DSOs), due to faults, maintenance work, or network reconfigurations. Similarly, Qing and Xiang (2024) emphasize that real-time PFT applications in dynamic operational contexts like local flexibility markets or P2P trading are hindered by the lack of temporally fine-grained data. Unlike the high temporal resolution typically assumed in academic literature (where Tranberg *et al.*, (2019) note that PFT methods are almost exclusively applied to simulation data), most utilities rely on hourly or 15-minute interval data that are often delayed. Electricity Maps (2025a) exemplify this challenge, as they aggregate data from diverse sources (e.g., system operators, energy utilities, and government entities) but must supplement these with estimates when data lacks sufficient granularity or arrives delayed. This temporal disparity undermines PFT's ability to support accurate carbon emissions tracing and carbon-adaptive decision-making.

Digital technologies can help address this issue by digitalizing different aspects of the measuring, reporting, and verification of electricity data, for example with regard to embedded carbon emissions (Körner *et al.*, 2025). Eleks (2024), for instance, use satellite imagery and object detection models for power grid mapping, complemented by Large Language Models (LLMs) to extract supplementary data from internet sources. This data can then be used to receive a more fine-granular carbon footprint for electricity (Eleks, 2025). Deacon *et al.*, (2021) propose deploying additional smart metering devices to obtain actual measurements rather than estimates. However, they highlight that more metering points do not only increase costs but also risks of unmanageable data volumes. Digital technologies also offer approaches to increase efficiency to cope with larger data volumes: Qing and Xiang (2024) develop a machine learning-enhanced mixed-integer linear programming approach to enable sparser allocation calculations for carbon emission tracing via PFT. For receiving verified data, Sun *et al.*, (2023) propose a blockchain-based PFT infrastructure that enhances tamper-resistance and transparency, while offloading computations to cloud providers to resolve nodal computation limitations. X. Yu (2022) combines PFT with a neural network to provide an analytics tool that gives insights for an optimized network configuration for smart grids.

These examples illustrate the potential of digital technologies in supporting PFT. In particular with regard to carbon data, digital technologies have already been shown not only to improve efficiency and accuracy in various ways, but also to support effective data sharing (Ströher *et al.*, 2025). However, in contrast to literature on PFT methods themselves, the integration of digital technologies to support PFT, especially taking a data perspective, is not yet extensively covered in academic and gray literature. Hence, we advocate for further research in this area and provide a research agenda with exemplary research questions related to carbon emissions tracing in Table II.

#	**Focus**	**Exemplary Research Question**
1	Data Availability	How can digital technologies provide real-time grid topology and injection data to enable dynamic PFT for fine-grained Scope 2 emissions reporting?
2	Data Quality	How may Artificial Intelligence (AI) be leveraged to detect and correct inconsistencies in grid data to improve data quality for carbon accounting?
3	Data Privacy	How to enable privacy-preserving PFT, allowing prosumers to act carbon-adaptive without fully disclosing production & consumption data?
4	Data Sharing	How can system operators be incentivized to systematically collect and share fine-grained grid data for PFT-driven carbon emissions tracing?
5	Trust & Transparency	How to foster trust in fine-grained carbon emissions data based on PFT calculations?
6	Data Verifiability	How to develop a framework that enables independent verification of PFT input data as well as results?

Table II: Research Agenda on Power Flow Tracing from a Data Perspective

6 Conclusion

In this paper, we provide a structured understanding of PFT by synthesizing academic and gray literature through a MLR and developing a taxonomy comprising six dimensions and 20 characteristics (cf. Figure 3). Through this approach, we unify previously fragmented terminology by organizing PFT methods within an IS-oriented artifact that directly addresses the needs of decision-makers in the energy sector such as grid operators. Our taxonomy offers classification dimensions that enable such decision-makers to understand key differentiation characteristics when choosing or designing a PFT approach. Additionally, we identify research gaps, most notably the shift from methodological refinement toward addressing data aspects like availability, granularity, and quality as the primary barriers to broader PFT adoption.

This paper illustrates that proportional sharing methods, particularly linear equation-based approaches, remain the dominant paradigm in both academic and industry contexts, largely due to their computational efficiency and adaptability to a wide range of applications. The tracing of electricity origin, motivated by sustainability efforts, emerges as the most extensively discussed application area.

Our systematization of PFT methods has practical implications for policymakers and grid operators, enabling them to identify suitable methods for specific regulatory, technical, or operational contexts. Our taxonomy supports and enhances decision-making for choosing or designing PFT methods across applications such as dynamic pricing, congestion management, and carbon emissions tracing.

We acknowledge several limitations. Our taxonomy reflects literature published from January 2019 to April 2025 and may not capture proprietary industrial implementations. Furthermore, despite relying on predefined criteria (cf. Section 3), the assignment of categories required subjective judgment. As such, our taxonomy does not exhaustively represent all conceivable methods but aims to reflect the diversity of approaches currently discussed in academic and industrial discourse. It supports comparative analysis, highlighting differences and trade-offs among design choices. Empirically validating the taxonomy-guided method selection process through pilot applications in operational grid environments would further substantiate its practical utility.

By bridging accurate methods with practical implementation needs, PFT may evolve from a primarily theoretical tool into a core component of sustainable energy systems. Achieving this transition will require interdisciplinary collaboration to ensure transparency, equity, and scalability in the digitalized electricity sector. Drawing from the research agenda proposed in Table II, we recommend using data as a vantage point for addressing PFT research questions. While we heavily focus on methods and application areas in this paper, future research from other disciplines, focusing for example on policies and economics, can significantly contribute to a plethora of research avenues such as proposing incentives to share data necessary for PFT or identifying regulatory barriers for collecting these data.

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Appendix A: Taxonomy Development Process