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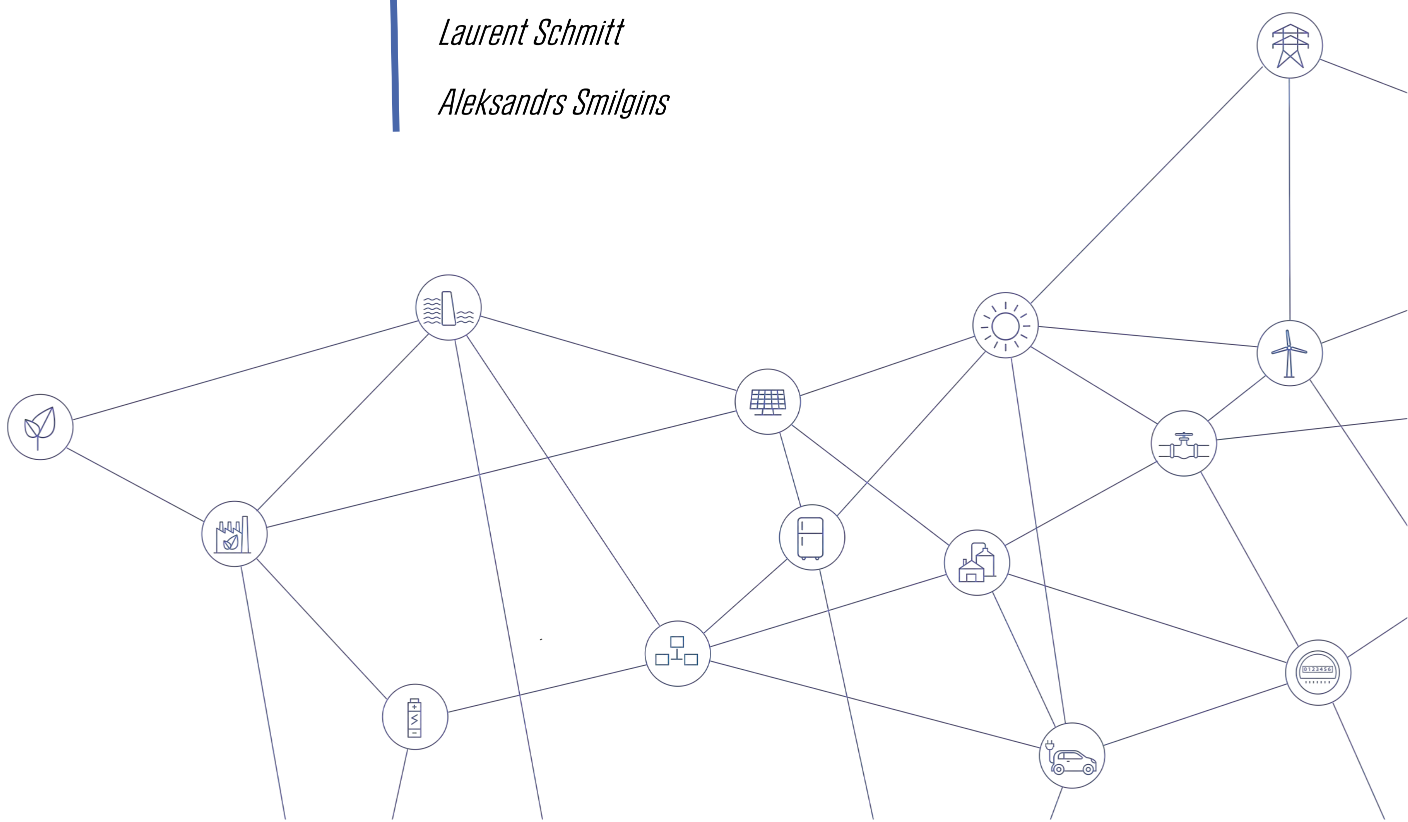

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Abstract

The digitalisation of the energy sector is giving rise to energy data spaces that aim to support secure, interoperable, and sovereign data sharing among stakeholders. While the focus has mainly been on technical aspects of data spaces, the economic dimensions, particularly the allocation of costs, are underexplored. This paper addresses this gap by examining principles and methods for cost allocation. We review ongoing European initiatives for energy data sharing and discuss how it can generate value while ensuring efficiency and fairness in cost allocation. We identify proportional and weighted proportional allocation rules as robust and implementable solutions. In addition, we briefly discuss governance options for fair access, data sovereignty, and economic sustainability, emphasising the complementary roles of public coordination and market mechanisms. We propose policy recommendations for a sustainable and equitable energy data ecosystem design in Europe: (i) the establishment of a single coordinating entity for a European energy data space, (ii) adoption of proportional cost allocation as default principle, (iii) distinguish between regulated and non-regulated exchanges, and (iv) incentivise early participation and data contribution.

Keywords: cost allocation; data spaces; economic sustainability; energy sector; European policy.

JEL classifications: C7, D4, L9, Q4.

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1. Introduction

In an increasingly data-driven world, the concept of data spaces has emerged as a foundational element for enabling secure, interoperable, and sovereign data sharing across sectors and organisations (Franklin et al., 2005). It fosters collaboration among actors while allowing preservation of data ownership. Within this context, energy data spaces are gaining prominence as key enablers of the digital energy transition (Berkhout et al., 2022). Energy data spaces can enhance efficiency, transparency, and innovation. They facilitate the exchange and integration of data among stakeholders, ranging from grid operations and consumption patterns to renewable generation and markets. However, while significant attention has been paid to the technical architecture of data spaces, economic considerations related to pricing and cost distribution have not yet been addressed. This paper aims at filling this gap by exploring the principles and challenges of cost allocation in energy data spaces, with a particular focus on the incentives for different participants.

Significant changes in energy infrastructure are expected globally. On the supply side, there is a growing emphasis on green energy, driven by the increasing adoption of global net-zero CO_2 emissions goals (DeAngelo et al., 2021). However, while the expansion of renewable energy brings environmental and economic benefits, its variable and intermittent nature poses challenges for system dispatchability and reliability. Price fluctuations caused by renewable generation may lead to periods of price spikes, as well as periods where prices drop to near-zero or even turn negative. Overall, increased reliance on renewables makes the supply side less flexible. Meanwhile, the demand side is undergoing significant changes. For instance, the widespread adoption of Electric Vehicles (EVs) is raising electricity consumption among both private and industrial consumers. At the same time, the demand side needs to become more flexible. Some private consumers can choose contracts with hourly pricing, allowing them to monitor real-time conditions and charge EVs during off-peak hours. Similarly, industrial users are becoming more flexible as factories become increasingly automatised. This enables production to be scheduled based on electricity costs at various times. Thus, while traditionally the electricity supply was designed to follow the demand, this is progressively changing. Supply is becoming more variable, while demand needs adaptability (see, among others, Sioshansi, 2020).

This new paradigm highlights flexibility as a feature of future energy systems. Technologies, such as smart meters and Artificial Intelligence (AI), have potential to optimise flexibility on both the demand and supply (IEA, 2025; IRENA, 2025). However, a baseline requirement is extensive data exchange, as (near) real-time data availability is essential for managing flexibility. This has led to the development of new data exchange systems in recent years at national and international levels (smartEn, 2023). Some examples at the national level include the Austrian Distribution System Operators (DSOs) and the Transmission System Operator (TSO) APG, who have operationalised the distributed data space for Austrian energy data exchange starting in 2012;[1] the Danish TSO *Energinet* who has introduced

[1] See https://www.eda.at/?lang=en

Datahub;[2] and the Spanish DSOs who developed *SIORD*[3]. At the international level, the EU has supported several projects aimed at enabling collaboration across countries on data exchange, including energy data spaces (EC, 2022). These projects aim to establish a trustworthy framework for leveraging EU energy data. Aligned with the EU's Clean Energy Package, they seek to reduce data integration costs and enhance the competitiveness of energy service companies in a unified European market.

While the design of data spaces addresses significant technical challenges, it is also essential to optimise their development and management from an economic and organisational perspective. Key questions include how the data space should be governed and by which entity. In the European context, a government body could play a role in guiding progress in a consistent and trusted direction for the continent. Additionally, proper cost allocation is crucial, as it ensures that users are treated fairly and that there is transparency around how resources are consumed, and who bears the associated costs. This serves to support the long-term sustainability of data spaces.

We focus on the economic design of energy data spaces, with emphasis on cost allocation and incentives for participants. From a cost perspective, a data space entails initial design and infrastructure costs, followed by operating expenditures, continuous system operation and maintenance, and staffing, among others. Since the initial development costs of energy data spaces are often grant-funded,[4] we focus on the operational costs to ensure long-term economic viability. Moreover, while initial participants of a large energy data space might be energy system operators, the ecosystem is not confined to the energy sector. Over time, cross-domain actors may benefit from access to energy data. In that context, it might be legitimate and efficient that a share of operational costs is allocated to external users, reflecting the broader public-good value of the data sharing infrastructure.

Finally, it is noteworthy that while a data space may be open source, this does not mean it should be entirely free of charge. Open-source technology allows certain layers of the code to be publicly accessible, modifiable, and distributable under open-source licenses. However, implementation and customisation can still incur costs.[5] For instance, EDDIE (European Distributed Data Infrastructure for Energy)[6] is an EU project that aims to introduce a decentralised, distributed, open-source energy data space, and one of its primary goals is to minimise implementation costs, although participants may still be required to pay fees to cover operational expenses.

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[2] https://energinet.dk/data-om-energi/datahub/

[3] https://www.edistribucion.com/en/innovacion-nuevas-tecnologias/GalvaniPlataformaSIORD.html

[4] Moreover, several foundational components of data spaces leverage existing digital infrastructure.

[5] For instance, Android is open source, yet manufacturers like Samsung and Xiaomi invest in developing their own OS adaptations. Similarly, while Linux itself is open-source, Linux-based systems like Red Hat Enterprise Linux and Ubuntu Pro offer paid enhancements such as improved stability, ease of use, and security updates.

[6] https://eddie.energy/

The remainder of the paper is organised as follows. Section 2 introduces the core features of energy data spaces and the main initiatives developed in the European context. Section 3 examines the objectives, principles, and axioms of cost allocation, presents several allocation methods, and applies selected methods to energy data spaces using a simplified example. Section 4 reviews current practice in data metering and cost sharing in selected European countries. Section 5 analyses regulatory and governance issues associated with energy data spaces. Section 6 concludes with policy recommendations.

2. Emerging models and value creation in energy data spaces

This section presents the main features and design principles of energy data spaces. It also reviews the ongoing European initiatives, identifies core benefits and business models, and discusses how these developments give rise to specific challenges for cost allocation and incentive design.

2.1 Features of energy data spaces

An energy data space is a framework that supports trusted and secure sharing of energy-related data within a collaborative ecosystem, where participants (including Transmission System Operators – TSOs, Distribution System Operators – DSOs, aggregators, service providers, and increasingly cross-sectoral actors) agree to exchange data in compliance with shared values, regulations, and fair treatment principles.[7]

At its core, an energy data space facilitates data interoperability and co-creation of value. Participants benefit from each other's data contributions, creating positive network effects: the more actors share data, the greater the collective value generated. As energy data are largely non-rival, different users can draw value from the same data simultaneously without depletion.

As such, data spaces exhibit characteristics of a digital public good. This means that individual participants produce spillover benefits for other participants, such as better forecasting, optimised grid management, or improved system flexibility, among others. However, this public-good nature poses challenges of fairness, sustainability, and potential underprovision. While all participants benefit from a functioning data space, some actors derive direct and substantial commercial gains (e.g., utilities or service providers), whereas others generate primarily systemic or societal value (e.g., reduced emissions, lower grid expansion costs). This asymmetry underscores the need for well-designed cost-allocation mechanisms that balance efficiency and equity.

Consider a large manufacturing company that, through energy data access, increases demand flexibility and optimises production, reducing electricity costs. This improvement generates broader societal gains, such as lower product prices (benefiting consumers),

[7] Definition adapted from the Data Spaces Support Centre (https://dssc.eu/).

higher company profits (resulting in increased tax revenue), optimised green energy use (reducing emissions), and/or reduced need for grid expansion (lowering system costs). These multi-layered effects illustrate the public-good nature of energy data spaces: while the company captures direct economic value, part of the resulting surplus accrues to society as a whole. This raises an important fairness question for cost allocation: how should required payments reflect both the private benefits to individual users and the wider systemic value created for others?

The "Blueprint of the Common European Energy Data Space" (Dognini et al., 2024) highlights this interconnectedness through five representative use cases:

- Collective self-consumption and optimised sharing for energy communities
- Residential home energy management integrating Distributed Energy Resources (DER) flexibility aggregation
- TSO-DSO coordination for flexibility
- Electromobility: roaming services, load forecasting, and schedule planning
- Renewables operations and maintenance optimisation, and grid integration

These examples demonstrate a high degree of interdependence among actors, making it difficult to evaluate the marginal impact of adding or removing participants. This also complicates centralised cost-sharing approaches. Energy data spaces support two categories of data exchange, with implications for governance and cost allocation:

- **Regulated Exchanges**. These primarily involve data sharing between core energy system actors (mainly TSOs and DSOs), sharing operational and metering data to support the efficient and secure operation of the system and essential market processes, such as settlement and customer billing. Because these exchanges deliver broad system-wide benefits, they are usually governed by public or regulated frameworks. In such cases, maximising participation is crucial, as the value of the data space increases with more users, and cost recovery mechanisms should focus on reducing entry barriers. Onboarding all TSOs and DSOs at the outset may be difficult, and instead, a few early adopters, likely more risk-tolerant and innovative, may lead the way. To encourage participation, the focus should be on ease of entry and cost minimisation for the early adopters, rather than monetisation of data.

  Non-regulated Exchanges. These exchanges encompass commercial or cross-sectoral interactions, where firms or organisations use energy data to provide innovative services or create new business models. For instance, mobility operators offering smart-charging solutions or financial institutions developing energy-linked products. These participants may come from outside the traditional energy domain. Additionally, these data exchanges may enable existing services to be offered in different countries.[8] Other examples include intermediaries providing flexibility assessments or prosumers sharing data with service providers. In these cases, users can decide whether to grant third-party access to their data (including companies outside the EU, provided they are EU-registered). It is therefore legitimate that part of the operational cost of the data space be allocated to such external users, reflecting the value they capture through access to and later use of energy-related data.

Due to these different features, if an energy data space facilitates both types of exchanges, they could be treated independently.

Finally, it is important to emphasise that while cost allocation often implies a centralised charging mechanism, this does not require centralising the data itself.[9] A centralised model offers several advantages over fragmented or competitive approaches:

- **Economies of Scale**. Like natural monopolies, data spaces involve high development costs but relatively low marginal operating costs. As user numbers grow, average costs per participant decline, making a single coordinated infrastructure more efficient than multiple competing systems.
- **Standardisation and Stability**. A unified system allows for technical standards to be established from the beginning. Competition could result in fragmented standards, which in turn complicates their adoption and raises the costs. Additionally, if a competing system is acquired, its standards may change, forcing users (e.g., TSOs or DSOs) to incur high transition costs. This uncertainty could delay participation. As the value of an energy data space is expected to grow with more users, such delays create the wrong incentives for its deployment.[10]
- **Accountability and Dependability**. A single coordinating entity can ensure consistent implementation across Member States, enabling participants to understand where and how digital energy services can be deployed. Therefore, the establishment of a Common European Energy Data Space (CEEDS) with clear Union-wide rules should encompass the matter by putting in place a reliable monitoring and overview in that sense. It should be possible to hold national data space facilitators accountable within that framework.

[8] EDDIE's website perfectly illustrates this with a cartoon showing an Austrian family sharing data with a hypothetical Spanish company, "Hola Energía," to access otherwise unavailable services.

[9] For instance, EDDIE introduces a distributed and decentralised framework in which data is not stored on central servers; instead, individual actors retain ownership and data is stored as closed to the source as possible as recommended in the European Strategy for data. However, it functions as a centralised entity that could charge fees to different participants.

[10] A historical example is the smartphone OS market after the iPhone's 2007 launch. Various competitors emerged: Nokia with Symbian, Microsoft with Windows Mobile, Blackberry with BlackBerry OS, and Google with Android. During this period, consumer uncertainty about future standards led to hesitation in adoption. See e.g., West and Wood (2013).

- **Data Sovereignty and Security**. Energy data is highly valuable and must be protected. Trust in the data space depends on each participant's confidence that sensitive or commercially valuable information will not be exploited without consent or oversight. Early competition could lead to large foreign entities (e.g., Amazon, Google, Microsoft, Meta, or even non-EU governments) dominating Europe's energy data space. This would limit EU control over citizens' data and could raise concerns about misuse or unauthorised commercialisation. Key actors, such as TSOs and DSOs understand this risk and may hesitate to share information with unregulated or foreign organisations. Moreover, private firms can more easily change data policies than EU-regulated entities, introducing further uncertainty and disincentivising early participation. Preserving data sovereignty is therefore both a technical and governance imperative.

In sum, even if a competitive approach were initially pursued, market dynamics would likely lead to consolidation. Establishing a single coordinating entity from the outset would help set standards, build trust, and ensure both efficiency and sovereignty, while allowing for decentralised data storage and control. This entity would also be responsible for charging costs to participants.

2.2 Overview of European energy data space initiatives

Several European initiatives are currently experimenting with the design and implementation of energy data spaces. These initiatives illustrate the diversity of possible architectures, governance structures, and business models. At the same time, they highlight the value that can be unlocked when data sharing becomes mainstream and systematic, secure, and transparent. Among the most significant efforts are five Horizon Europe "Innovation Action" projects specifically dedicated to developing and piloting energy data spaces:[11]

- **SYNERGIES**[12] is a marketplace-oriented data space where organisations (e.g., DSOs, TSOs, aggregators, retailers, local energy communities, and digital service providers) can exchange datasets and services through structured contracts. It supports hybrid storage (centralised cloud or distributed systems) and relies on blockchain-based smart contracts for transparency and automation. Compensation can be monetary, crypto-based, or barter through dataset exchanges, depending on the use case.

[11] These five Innovation Action projects were launched under the Horizon Europe Cluster 5 call HORIZON-CL5-2021-D3-01-12: Establish the grounds for a common European energy data space (https://ec.europa.eu/info/funding-tenders/opportunities/portal/screen/opportunities/topic-details/horizon-cl5-2021-d3-01-01).

[12] https://synergies-project.eu/

- **OMEGA-X**[13] is also a marketplace-based data space, built on the GAIA-X[14] federated architecture. Participants can be consumers or providers, organised at the community or company level. Contracts are structured as Data Product Usage Contracts, which are human- and machine-readable, tamper-proof, and verifiable. Its use cases cover renewable integration, flexibility, electromobility, and energy communities, with strong emphasis on interoperability across national and sectoral boundaries.

- **ENERSHARE**[15] adopts a reference architecture based on the 4+1 model.[16] It applies blockchain-based smart contracts to manage transactions and receipts between data providers and consumers. Its pilots span multiple countries and applications: predictive maintenance of wind farms in Spain, cross-sector flexibility services in Italy, planning and digital twin applications in Greece, and senior household monitoring in Portugal. These pilots demonstrate that access to data can enhance the operational efficiency, improve planning, and support consumer-oriented services.

- **Data Cellar**[17] focuses on enabling Local Energy Communities (LECs). It envisions a token-based compensation model for datasets, combined with distributed ledger technologies to handle flexibility and energy trading contracts. Its value propositions include improved energy efficiency, predictive maintenance, reduced transmission losses, and better customer engagement. Beyond community members and service providers, it explicitly targets municipalities, policy makers, and the research community, showing how data access can create spillovers beyond immediate market actors.

- **EDDIE**[18] is designed as a decentralised data space infrastructure, expected to be compliant with GAIA-X principles, where DSOs and TSOs provide access to near real-time and historical consumption and metering data through regional hubs and in-house devices. Rather than hosting data centrally, EDDIE facilitates interoperability and standardised access across countries, enabling companies to expand services cross-border. This highlights the role of energy data spaces in scaling up European digital markets.

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[13] https://omega-x.eu/

[14] https://gaia-x.eu/

[15] https://enershare.eu/

[16] The 4+1 View Model (Kruchten, 1995) describes system architecture from four technical perspectives (logical, process, development, and physical), supplemented by use-case scenarios that validate the design.

[17] https://datacellarproject.eu/

[18] https://eddie.energy/

In addition to the above projects, there are also other initiatives working towards the development of a CEEDS,[19] these projects include **Energy data-X**,[20] **Int:net** (Interoperability Network for the Energy Transition)[21] or the **INSIEME** (Integrated Network for Data Space and Interoperable Energy Management in Europe).[22]

2.3 Benefits, business models, and network effects

Across the five above-mentioned initiatives, there are several benefits expected to emerge.

- **Better transparency and knowledge sharing**. Data spaces reduce information asymmetry by giving smaller actors and consumers access to datasets previously held mainly by large utilities and system operators.
- **Lower transaction costs**. Standardised interfaces, smart contracts, and automated data integration reduce manual labour and harmonise processes across countries.
- **Increased competitiveness and reduced market entry barriers**. By decreasing integration costs, new service providers can enter more easily, fostering cross-border competition and innovation.
- **Broader innovation ecosystems**. Data availability enables new applications (e.g., AI-driven forecasting, digital twins, advanced flexibility services) and encourages experimentation in sandboxes or pilot projects.
- **Higher system efficiency and societal benefits**. Better forecasting, flexibility management, and predictive maintenance reduce grid expansion needs, support renewable integration, and ultimately lower emissions.

There are different business models that can emerge from the development of energy data spaces, e.g., marketplaces for direct data trading, tokenised exchange (e.g., reputation points or cryptocurrency) within communities, subscription-based access for standardised datasets, or bundled services where data is provided alongside analytics and decision-support tools. Moreover, the non-rival nature of data allows multiple layers of value creation from the same dataset, creating both opportunities and challenges for cost allocation.

It is important remember that network externalities are particularly strong, i.e., the more participants join, the greater the value of the data space. Early adopters benefit from privileged access, but full potential is realised only when many actors (especially regulated ones like TSOs and DSOs) participate. Conversely, adoption may be slowed by technological or institutional barriers, such as uneven national data infrastructures or consumer reluctance to adopt smart meters (where smart meters are not mandatory).

[19] https://energy.ec.europa.eu/publications/common-european-energy-data-space_en
[20] https://www.energydata-x.eu
[21] https://intnet.eu/
[22] https://insieme.energy/index.html

The energy data space initiatives presented in Section 2.2 underline that energy data spaces can generate benefits well beyond the direct users. Value is created at multiple levels: private (reduced costs, new services), system-wide (improved efficiency, lower investment needs), and societal (emission reductions, consumer empowerment). This reinforces the challenge of designing fair cost allocation mechanisms. While large firms may capture significant private benefits, part of the surplus accrues to society at large. The choice of cost-sharing rules must therefore balance fairness, efficiency, and incentives, ensuring sustainability without discouraging participation.

3. Cost allocation and pricing mechanisms

The long-term sustainability of energy data spaces depends on fair and transparent cost recovery. Beyond technical and governance design, it is essential to determine who pays, how much, and according to which principle. This section examines the main objectives and methods of cost allocation and pricing, focusing on how fairness, efficiency, and incentives can be balanced to ensure both participation and economic viability.

3.1 General aspects

Implementing an energy data space entails both establishment and operational costs. To ensure long-term sustainability, these costs must be recovered in a fair and transparent manner, often through usage-based contributions from participants. Understanding how these contributions are determined requires distinguishing, three interrelated concepts: cost allocation, pricing, and business models. *Cost allocation* defines how the underlying costs of a project, such as building and operating a system, are distributed among participants. *Pricing* refers to the rules (or tariffs) applied to users when they access goods or services (e.g., data). Pricing schemes can build directly on cost allocation (e.g., proportional pricing by usage), but they may also deliberately diverge, for instance, when certain users are subsidised to promote participation or inclusion. For instance, subsidised broadband access for rural households is one such case, which emphasises the idea of digital access as a public good (even if operating costs are not fully recovered). Similarly, in some projects early adopters may receive preferential rates to stimulate demand.[23] Thus, while pricing schemes may be linked to cost allocation, they can also reflect other choices by the provider of the goods or services, or by regulation. Finally, a *business model* represents the rationale of how an organisation creates, delivers, and captures value. Pricing mechanisms must therefore be designed not only to recover costs, but also to support the long-run economic sustainability of the business model or regulatory framework.

[23] When Tesla first rolled out its Supercharger network, new buyers of the Model S received unlimited free Supercharging for life. Today, however, the network is well developed, and receiving free charging with a new EV would be considered an exceptional privilege.

The design of pricing mechanisms has long been a central topic in economics. Classical models, such as those of Cournot (1838) and Bertrand (1883), examine how firms compete under different market structures, while theories of price discrimination (first-, second-, and third-degree) explore how users can be charged according to their willingness or ability to pay. In the energy sector, Conkling (2011) provides a comprehensive overview of different energy pricing principles. Other approaches, including auction mechanisms (Milgrom and Weber, 1982; Krishna, 2009), use competitive bidding to reveal users' preferences when costs or values are uncertain. For instance, Khezr and Menezes (2019) show how auctions can fund the expansion of natural monopoly infrastructure when multiple firms seek access. These examples highlight that pricing is not only a tool for cost recovery, but also a mechanism for shaping incentives and behaviour within the system.

On the other hand, there is extensive literature on cost allocation, which often focuses on identifying axioms and properties that make allocation rules acceptable (e.g., Young, 1985). Designing appropriate cost allocation rules is not merely a matter of technical calculation but also one of economic reasoning and ethical judgment. Even in everyday situations, fairness is not straightforward. For example, when splitting the cost of a Spotify subscription between friends living together, should the bill be divided equally, according to usage, or according to income? Questions of fairness arise even in very simple examples. It is therefore unsurprising that energy data spaces, with their many stakeholders and public good characteristics, pose an even greater challenge.

3.2 Cost allocation objectives

Whenever multiple actors benefit from a shared resource or infrastructure, the fundamental question arises: how should costs be distributed? Cost allocation is therefore not just an accounting exercise but a central problem of economic coordination and collective decision-making. Examples abound across sectors: governments share the expenses of cross-border infrastructure; firms divide R&D costs in joint ventures; municipalities apportion the costs of waste collection; and digital platforms allocate cloud or network expenses among users.

In all these cases, allocating costs is more than an accounting task. It is a matter of economic design, and collective decision-making. Allocation rules largely depend on context, but they must balance several (often conflicting) objectives: *efficiency* (ensuring that total costs are covered and resources are used optimally), *fairness* (ensuring that users are treated in a justifiable way), *incentive compatibility* (ensuring that participants behave honestly and remain engaged), and *stability* (ensuring that no participant or group has an incentive to withdraw from the collective arrangement). Other context-specific properties may play a role as well. Achieving all objectives simultaneously is rarely possible, which explains why cost allocation has been an important topic across different situations and sectors.

Everyday situations illustrate the challenge. When splitting a restaurant bill, a taxi fare, or a streaming subscription, different intuitive principles may apply; equal division, proportional division by usage, or differentiation by income or ability to pay. Each rule seems reasonable but yields different results, showing that *fairness* depends on context and interpretation. The same ambiguity arises at larger scales, for example when sharing the costs of pollution abatement among industries, coordinating climate adaptation investments among countries, or funding shared research facilities across universities.

Within this broader landscape, there are specific cases that pose distinctive allocation challenges. Natural monopolies (e.g., electricity grids, water networks, rail systems) exhibit high fixed costs and strong economies of scale, making it inefficient to duplicate them. Here, allocation concerns how the joint cost of maintaining the network is divided among users (e.g., freight and passenger trains, or electricity consumers). Likewise, cross-border or multi-organisational projects (e.g., international pipelines, cross-border interconnectors, or federated data infrastructures) require agreement among multiple decision-makers who may have divergent interests and, in some cases, incentives to free ride. Cost allocation in energy data spaces represents another specific challenge, as it combines features of shared digital infrastructure with public good characteristics, requiring mechanisms that ensure fairness, participation, and long-term sustainability.

3.3 General principles and axioms

The literature on cost allocation distinguishes between normative principles (broad economic and ethical objectives such as efficiency, fairness, stability, and incentive compatibility) and their formal expressions, known as axioms. Different axioms translate these abstract principles into precise mathematical or logical conditions that allocation rules may satisfy in a given context. They serve as analytical tools to evaluate whether a cost-sharing method is economically sound, fair, and sustainable. Some axioms are foundational, while others are refinements or more context specific. Foundational contributions by, e.g., Young (1985), Tijs and Driessen (1986), Moulin (1988), and Hougaard (2009), have developed these axiomatic frameworks, showing that while principles provide normative guidance, axioms define the concrete properties that operationalise them. Principles and axioms rarely align perfectly, and trade-offs are often evidenced in different context, i.e., methods that satisfy one property may violate another, highlighting the trade-offs inherent in fair division problems.

In the following subsections we summarise key axioms that are related to efficiency, fairness, stability, and incentive compatibility in cost allocation. We illustrate their importance with some examples from various domains and discuss their relevance in the context of energy data exchange spaces.

i. Efficiency (budget balance)

While efficiency plays a key role in many market design contexts, in cost allocation it simply means that the amounts allocated to all users should exactly sum to the total cost. In other words, the total cost must be fully covered, with neither deficit nor surplus. For example, in electricity grids, tariffs are calibrated so that total revenue matches the justified costs of system upgrades: there should be no deficits (which would make the project unviable) and no surpluses (which would unfairly burden users).

Although this is an essential property, it says nothing about *how* the costs should be distributed. Very unfair or extreme allocation rules, such as one user paying everything, would still satisfy efficiency as long as total cost recovery holds. This highlights an important point: a "perfect" allocation rule does not exist. Benefiting some users (by asking them to pay less) necessarily implies harming others (by asking them to pay more). Hence, if some users prefer allocation method A to B, others will prefer the opposite. In what follows, we assume any acceptable allocation method must satisfy *efficiency*.

ii. Stability-related axioms

These axioms concern whether users have incentives to remain in the system (or to leave it).

Individual rationality (Stand-alone test)

No user should pay more than their stand-alone cost if acting independently. This ensures stability, since no user will want to exit if their allocated share is not greater than the cost of acting alone. For example, in district heating networks, a household should not pay more for connection than the cost of installing an individual boiler or heat pump.

Stability (Coalitional stability)

Groups of users (coalitions) should not have an incentive to leave the collective arrangement. This extends individual rationality to groups: no coalition should be able to cover its own costs more cheaply outside the arrangement. In cooperative game theory, this is captured by the core: the set of allocations where no coalition can profit by deviating. For example, if we consider the case of joint transmission projects, utilities must find it preferable to cooperate under a shared cost allocation scheme rather than build separate lines.

In the context, each user compares the value of participation with the allocated cost (i.e., the participation fee). Operational costs are expected to be relatively small once the system is established, and the value of participation will normally exceed the fee. Therefore, while these stability properties are critical in general contexts, they are unlikely to be binding for energy data spaces. A user that benefits from the data space is unlikely to leave because of a slightly higher fee, and a group of users that all gain from participation will not withdraw due to imperfections in cost allocation. We therefore expect these properties to hold for most reasonable allocation methods in this context.

iii. Fairness-related axioms

Fairness is notoriously difficult to define, and consensus on what constitutes a fair rule is rare. This is precisely why multiple cost allocation methods exist: if there were universal agreement on fairness, one rule would suffice for all contexts. Nevertheless, one fairness axiom is broadly accepted.

Symmetry (Equal treatment of equals)

Identical users (under the chosen metric) should pay the same. Although the exact definition of fairness can be debated, the absence of this property would be widely perceived as unjust, as it implies that cost shares depend on arbitrary identities rather than relevant characteristics. For example, in an energy community, two households drawing the same amount of electricity from a shared battery should be charged equally.

In energy data spaces, this axiom is clearly desirable: two identical users paying different fees would be viewed as highly unfair.

iv. Incentive-related axioms

These axioms ensure that allocation rules do not create perverse incentives or allow manipulation.

Incentive compatibility (Strategy-proofness)

Users should not benefit from misreporting information. In other words, a cost allocation rule is incentive compatible when participants have no strategic advantage in providing false or misleading data about their usage, costs, or contributions. This property ensures that truthful behaviour is the best strategy for every participant. For example, in community battery projects, households should not be able to exaggerate their flexibility potential (such as overstating their ability to shift consumption), to obtain more favourable cost allocations. If users can manipulate reported information, the mechanism becomes vulnerable to gaming.

No advantageous splitting or merging

Users should not be able to manipulate allocations by splitting into multiple (artificial) entities or merging strategically. This ensures robustness against artificial restructuring of participation. For example, in electricity markets, a large industrial consumer should not be able to divide itself into smaller artificial consumers to qualify for cheaper tariff brackets.

Monotonicity

If a user increases their consumption level, their cost share should also increase. This guarantees that greater consumption or demand leads to a higher cost responsibility. For example, if we look at the case of shared solar projects, a household consuming more electricity from the shared system should not end up paying less than a smaller consumer.

In the context of energy data spaces, these incentive-related axioms are particularly important, since different users will provide and consume data. Regarding *Incentive compatibility*, it is not clear whether a user would be able to misreport any information, since data transfers are typically recorded automatically, leaving little or no room for manipulation. However, the last two axioms are clearly crucial. We are not interested in an allocation rule that could motivate users to split or merge strategically. Moreover, some users may naturally appear either as large single entities or as several smaller ones. For example, a national TSO might be organised into regional business units (e.g., north, south, offshore), or an aggregator might manage data from households in different regions. If an allocation rule satisfies *No advantageous splitting or merging*, the allocated cost remains the same whether the system perceives a large user or the same user divided into smaller units.

Monotonicity is also relevant. Small changes in user activity from one period to another should be reflected in the allocated cost. For example, higher data consumption should result in a higher fee, while lower data consumption should lead to a lower fee. This ensures that cost allocation remains consistent with actual behaviour and provides clear and predictable incentives for participants. However, the axiom only specifies the direction of the change, and it does not specify how much the cost should change. In other words, when activity increases, the corresponding fee should not decrease, but the exact relationship between the two may depend on the specific cost allocation method chosen.

v. Other axioms

There are also context-dependent properties that, while theoretically interesting, have limited practical relevance for energy data spaces. For instance, *Additivity* requires that if two independent cost-sharing problems are combined, the allocation for each agent equals the sum of their allocations in the separate problems. This condition is unlikely to hold for energy data spaces, as combining two such spaces may generate a total value greater than the sum of their individual values due to complementarities between datasets. *Consistency* requires that if one user leaves and their share is removed, the allocation rule applied to the remaining group yields the same relative results for those who stay. In energy data spaces, however, the departure or addition of a participant can alter both the overall value of the system and its cost structure. Hence, while these properties are important in some settings, they are unlikely to be critical for the operation of energy data spaces.

As such, in the following, we mainly focus on the axioms *Symmetry*, *No advantageous splitting or merging* and *Monotonicity*.

3.4 Examples of allocation methods

Several methods can be considered for distributing costs in energy data spaces. However, before presenting them, the initial question to address is what cost allocation should depend on, i.e., what information is available and measurable about users and their activities (in theoretical terms, this means defining how users are characterised). Different methods require different types of input data: some rely on clearly observable metrics (e.g., number of users, data volume, or transactions), while others depend on more complex or value-based assessments that may be difficult to quantify in practice. Understanding these informational requirements is therefore essential before selecting an appropriate allocation rule.

In energy data spaces, participants can play dual roles: they may consume data (by accessing or using information) and provide data (by contributing datasets to the system). The overall value of the data space arises from the interaction between these activities, i.e., each user's contribution enhances the usefulness of others' data, and the total value grows as more participants join. In principle, a fair cost allocation should reflect each participant's contribution to this overall value or the benefits they derive from participation.

However, this is rarely straightforward. Estimating the exact monetary value of specific datasets, whether provided or consumed, is typically infeasible. In theory, data value could be defined as the incremental economic benefit generated by access to or use of a dataset, such as improved efficiency, cost reduction, or new revenue streams. A DSO, for example, might estimate the financial benefit of reduced forecasting errors enabled by additional metering data, while a TSO could quantify avoided or deferred grid investments resulting from better congestion forecasting. Yet even in such cases, isolating the value of a particular dataset from other interacting factors remains highly uncertain.

The challenge becomes even greater when considering both data consumption and contribution. If allocation depends on consumption alone, should it be measured by data volume (e.g., gigabytes – GB)? Such an approach assumes each unit of data has identical value, which is rarely true. Conversely, if data contributions are considered, it is difficult to assess their quality or relevance objectively. For instance, if two DSOs use similar data but one provides richer and more accurate datasets, their respective contributions to system value differ, but quantifying that difference is complex. Moreover, if contributions were measured purely by volume, users might be motivated to upload low-value or redundant data, violating the principle of incentive compatibility. To avoid this, external governance or auditing mechanisms are needed to define what constitutes valid, high-quality data contributions.

Accordingly, the choice of a cost allocation method depends on the type and quality of information available about users. The following subsections present several allocation methods, ranging from simple, proxy-based approaches to value-oriented models, and discuss their relevance and applicability to energy data spaces.

i. Uniform (equal-split) allocation

Under uniform allocation, every participant pays the same fixed fee, regardless of usage. This approach is simple, transparent, and easy to administer, making it attractive when the costs of measuring individual contributions are high. However, it may discourage heavy contributors, who may feel they are subsidising lighter users, and it can incentivise overconsumption among those who use more than average. Because payments are unrelated to activity, it is unnecessary to estimate the value of data consumed or provided. For example, in local energy cooperatives, members may each pay the same annual membership fee to cover administrative costs, regardless of how much electricity they consume or generate. On the other hand, this simplicity can create wrong incentives: participants may withhold potentially useful data, or consume extra data, knowing their fee remains constant regardless of contribution. For instance, a DSO might refrain from sharing detailed grid operation data.

ii. Proportional allocation

Although uniform allocation is simple and transparent, it ignores the heterogeneity in value creation and resource use associated with different data types and participants. When cost allocation depends on user characteristics, it becomes necessary to define how activity is measured and how data consumption and provision are jointly evaluated. Suppose that each user’s overall activity can be represented by a single quantitative indicator, such as total GB of data consumed, the net balance between data imported and provided, or another standardised metric reflecting both data quality and frequency of use. Once such an indicator is established, a natural approach is to allocate costs in proportion to this measurable activity.

Under proportional allocation, users pay in proportion to their level of engagement or usage. Despite its simplicity, the rule possesses remarkably strong theoretical properties and has been extensively analysed across different contexts (see, e.g., Moulin, 1987; Chun, 1988; Skaperdas, 1996; Hougaard, 2007; Hougaard et al., 2017; Szwagrzak and Østerdal, 2025). These references show that even though proportional allocation is very straightforward to apply (once the metric is defined), it has been rigorously tested and proven to satisfy different desirable axioms in diverse settings, from resource division to contest theory. In particular, it is the only allocation rule that satisfies the No Advantageous Splitting or Merging property, making it robust to strategic manipulation.

Its transparency and intuitive fairness make proportional allocation appealing, especially when user activity can be measured objectively. For example, in electricity distribution, tariffs often charge consumers proportionally to their kilowatt-hour (kWh) consumption, ensuring that heavier users bear a larger share of costs. Likewise, in data platforms, fees are commonly based on the number of queries or downloads executed by each participant.

iii. Weighted proportional allocation

In this variant, total costs are distributed proportionally to users’ activity levels, but adjusted by weights may capture additional, context-specific factors beyond raw usage. These weights allow cost allocation to reflect heterogeneity among participants, such as differences in timing, contribution, or institutional role.

Relevant weighting dimensions may include:

- Time of participation where early adopters pay less to encourage initial network growth
- Quality or quantity of data contributed rewarding users who enhance the collective value of the data space
- Organisational size and (financial) capacity, e.g., recognising differences between large system operators and smaller service providers

- Different user types, distinguishing between regulated entities (e.g., TSOs, DSOs) and non-regulated or cross-sectoral actors

Unlike the proportional rule, the weighted proportional approach may be dynamic, i.e., weights can evolve over time to incentivise behaviours aligned with the data space's strategic objectives. For instance, a European energy data space is likely to involve initially a limited number of progressive DSOs and TSOs, i.e., a "coalition of the willing," before scaling to broader participation. This early phase offers an opportunity to experiment with cost allocation models where weights may favour participation and data contribution over strict cost recovery. As participation broadens and the data space matures, the weighting structure can gradually converge toward a more neutral proportional rule emphasising focus on raw activity levels. The few DSOs and TSOs that were among the early adopters may also be promised to be awarded with lower weights in the future than other users with the same activity levels. Illustrative analogies exist in other domains. In community solar projects, early adopters often pay reduced fees to reflect their higher initial risk and role in enabling scale. Similarly, in data-sharing platforms, participants providing large or high-quality datasets may receive discounted access fees compared to those primarily consuming data. In both cases, a weighting mechanism can help align private incentives with collective benefits.

Moreover, the weighting scheme in this allocation rule can be further refined to link data contributions and data consumption of different users. For example, weights could depend on the ratio of data provided to data consumed, adjusted for quality and relevance. Such formulations help avoid free-riding behaviour and ensure that actors contributing with valuable data are rewarded, while heavy consumers of shared data bear a fairer share of the costs.

iv. Cooperative game-theoretic approaches

Both proportional approaches rely on measurable individual activity indicators, but neither captures externalities, i. e., cases where one user's participation increases value for others. This limitation is particularly important in data-intensive systems, where value often arises from combining heterogeneous datasets. For example, when a person drives a car, the navigation system relies on both digital map data and real-time GPS signals. Without either of them, the whole system would not function. In this simple example each dataset has limited value on its own, yet together they generate substantial utility. Hence, the total value emerges from interaction and interdependence rather than isolated contributions. Such interdependence can be formally analysed using cooperative game theory, particularly within the framework of Transferable Utility (TU) games (see, e.g., von Neumann and Morgenstern, 1944; Peleg and Sudhölter, 2007; Hougaard, 2009).

Cooperative game-theoretic methods examine how costs or benefits evolve as agents form coalitions, providing a structured way to account for interdependencies. Several allocation rules exist within this framework. The *Shapley Value* (Shapley, 1953), for instance, allocates costs based on each participant's average marginal contribution across all possible coalitions; the *Nucleolus* (Schmeidler, 1969) seeks allocations that minimise dissatisfaction and promote stability; egalitarian approaches aim to assign shares that are as equal as possible under some constraints, emphasising equality over contribution or marginal value (see, e.g., Dutta, 1989; Hougaard and Smilgins, 2016). These approaches can be relevant in energy data spaces, where value creation depends on joint participation. However, there is a major challenge: the number of possible coalitions among n users is $2^n - 1$, i.e., it grows exponentially. For example, with three users there are seven possible coalitions, but with twenty users there are more than one million. As a result, exact computation of allocation rules like the Shapley Value may become infeasible for large systems.

v. Auction- and Bargaining-Based Approaches

It is noteworthy that, instead of a specific cost allocation rule, it may be possible to delegate the task to the market, while defining an appropriate framework and set of guiding rules. In auction-based mechanisms, participants bid for access, and prices are determined endogenously through an auction. These methods, grounded in market and mechanism design theory, encourage efficient resource allocation and often elicit truthful revelation of willingness to pay. In Khezr and Menezes (2019) propose auctions as a fair mechanism for multiple firms to jointly fund new infrastructure facilities. Auctions are suitable where excluding some participants is acceptable, and this may only apply to some data spaces.

Beyond formal allocation rules, costs can also be distributed through negotiation and bargaining among participants. In such cases, allocations depend on bargaining power, regulatory frameworks, and mutual dependencies. For example, when the EU implemented its “Roam Like at Home” policy in 2017 under the Roaming Regulation (Regulation No. 531/2012, as amended),[24] telecom operators had to abolish retail roaming charges across member states. Since network usage varied widely (with southern tourist destinations hosting more inbound traffic), operators negotiated bilateral agreements within regulated wholesale price caps. This bargaining-based approach offered flexibility while ensuring that no operator was disproportionately disadvantaged.

Such approaches can place a burden on users, which may be undesirable in practice. Moreover, relying entirely on market or bargaining mechanisms can lead to situations where core axioms are violated. For example, two identical users might pay different fees depending on their bargaining (violating *Symmetry*), or an auction could generate either more or less revenue than the total system cost (violating *Efficiency*).

vi. Hybrid approaches

In practice, hybrid approaches can combine features of the above methods. Examples include: Two-part tariffs, combining a fixed fee (uniform component) with a variable fee (proportional to activity); using cooperative game theory to allocate total cost among broad

[24] https://eur-lex.europa.eu/eli/reg/2012/531/oj

user groups, followed by proportional allocation within each group; defining clear cost allocation methods for regulated data exchanges, while leaving non-regulated or commercial exchanges open to bargaining or market mechanisms.

Finally, it is important to recognise that cost allocation does not need to be static. In the early development phase, the primary goal may be to promote participation and establish trust, which justifies subsidised or weighted proportional rules favouring early adopters. Once the network matures and participation becomes widespread, cost allocation can gradually transition toward standard proportional schemes focused on efficiency and long-term sustainability.

3.5 Example of cost allocation methods

Consider a toy numerical example of an energy data-sharing infrastructure with four users, labelled A, B, C, and D, which costs in total €120 to operate during a given period.

Under uniform allocation, the total cost is divided equally, so each user pays €30. While this method is straightforward, it ignores all information about user behaviour or activity. The allocation therefore becomes (30, 30, 30, 30) across the four users. The *Monotonicity* axiom would be violated, as changes in user activity have no effect on the allocated share. Furthermore, *No advantageous merging* is not satisfied: for instance, if A and B decide to merge and act as a single organisation, the system now has three users (AB, C, and D). When the costs are divided equally, each user pays €40. As such, A and B together now pay only €40 instead of €60 (a one-third reduction without changing how much data they actually process).

Next, assume that we want to base the cost allocation on activity levels, under the principle that higher activity implies a larger allocated share of the cost. Suppose the four users have the following activity levels under a chosen metric (here measured in GB):

- User A: 10 GB
- User B: 20 GB
- User C: 30 GB
- User D: 40 GB

In a proportional scheme, costs are distributed according to each user's share of total usage. The total data consumption is 100 GB, and users A, B, C and D would pay respectively €12, €24, €36, and €48, summing to €120. This implies a unit cost of €1.20 per GB, which is very easy to explain to the participants. This scheme remains straightforward but now incorporates user activity, assuming there is a coherent way to measure it. *Monotonicity* is satisfied, since increasing activity leads to a higher allocated share for any user. Moreover, *No advantageous splitting or merging* is satisfied only by the proportional rule: if A and B merge, they pay €36 (= 30/100 × 120), which equals their total cost without merging. Similarly, splitting would not affect the total cost allocation.

Next, one might wish to incentivise early participation in the data space, and the weighted proportional rule could be applied. Suppose user C joined significantly earlier than the others and played a crucial role in helping to establish the data space, e.g., by contributing initial datasets, testing the platform, or bearing early development risks. To acknowledge this foundational role, C receives a preferential weight that reduces their effective contribution for cost-sharing purposes. Assume the weights of the four users are (1, 1, 0.5, 1), such that user C is rewarded for early entry. The weighted proportional rule yields: ($\frac{1*10}{z} * 130, \frac{1*20}{z} * 130, \frac{0.5*30}{z} * 130, \frac{1*40}{z} * 130$) with z =1*10+1*20+0.5*30+1*40.

This results in allocations of approximately (€14.1, €28.2, €21.2, €56.5).

Compared to the standard proportional rule, user C's allocated cost decreases from €36 to €21.2. This reduction occurs because C's lower weight functions as a discount reflecting their early and strategically important participation, with the remaining cost redistributed among the other three users.

So far, cost allocations were based on observable activity levels (GB of data). However, in many data spaces the main source of value does not stem from individual usage, but from the interactions and synergies created when different users combine their data. To capture these interdependencies, we now move from activity levels to a value-based representation of the system using a cooperative value function. For four users, assume the values of all possible coalitions are given as presented in Table 1.

For example, users A and B individually create values of 200 and 300, but together produce 800, indicating a synergy effect. When all four users participate, the total value of the data space is 1,500, exceeding the sum of their individual contributions. The table captures the interdependence among users, but as noted earlier, the problem grows rapidly with the number of participants. Even with only four users, there are 15 (=2^4 – 1) non-empty coalitions.

Using the Shapley value (Shapley, 1953), the total value can be allocated among users as (375, 475, 550, 100) summing to 1,500. These numbers represent each user's allocated share of the total system value (when everyone participates) derived from the Shapley value, the unique solution concept satisfying a specific set of axioms. One of these axioms, the dummy player axiom, is illustrated in this example. User D adds exactly 100 to any coalition, regardless of its composition. Under the definition, such a user is a dummy player, and the Shapley value correctly assigns D exactly 100.

However, the Shapley value is known not always to lie in the core. The core consists of allocations that no coalition would want to deviate from because they can guarantee themselves at least their coalition value by acting independently. An allocation outside the core therefore fails to satisfy some coalition's stability constraint: at least one group of users could obtain a higher total value by breaking away from the grand coalition. Although the Shapley value is fair in an axiomatic sense, it does not necessarily ensure such coalition stability.

Table 1. Examples of coalition values among the four participants

Coalition	Value
∅	0
{A}	200
{B}	300
{C}	400
{D}	100
{A,B}	800
{A,C}	850
{A,D}	300
{B,C}	950
{B,D}	400
{C,D}	500
{A,B,C}	1,400
{A,B,D}	900
{A,C,D}	950
{B,C,D}	1,050
{A,B,C,D}	1,500

To translate these values into a cost allocation, several approaches are possible. One simple illustrative method is to treat higher Shapley values as indicators of greater contribution and therefore assign lower costs to such users. For example, subtracting each user's Shapley value from the total system value (1,500) and allocating the total cost proportionally to these residuals yields an approximate cost allocation of (€30, €27.3, €25.3, €37.3) summing to €120.

Table 2 compares cost allocation methods that could be applied to our example and assesses the extent to which each method fulfils the main axioms presented in the previous section.

Table 2. Comparison of allocation methods according to key axioms

Cost Allocation Method	Symmetry (Equal treatment of equals)	No Advantageous Splitting / Merging	Monotonicity
Uniform (Equal-Split)	Yes	No	No
Proportional	Yes	Yes	Yes
Weighted Proportional	Depends (holds only if identical users have equal weights)	Depends (on how the weights are defined when users split or merge)	Yes
Shapley Value	Yes	No	Yes

4. Data metering and cost sharing in some European countries

As discussed in Section 2, several R&D projects are currently deploying energy data spaces across different European countries. The costs associated with such deployments are primarily covered by research grants, typically funded by the European Commission under the Horizon Programme or the Digital Europe Programme. Access to data spaces and the related services is then normally free, without any explicit allocation of costs to the users of the data spaces. At the national level, several energy data sharing infrastructures have emerged or are emerging, supporting trusted and secure sharing of energy-related data within a collaborative ecosystem, where participants agree to exchange data in compliance with shared values, regulations, and fair treatment principles. This is the case of the use of infrastructure for sharing of metering and consumption data. Directive (EU) 944/2019 prescribes that each Member State "shall organise the management of data to ensure secure and efficient data access and exchange, as well as data protection and security" (art. 23(2)). However, no specific, harmonised Data Management Model (DMM) is provided by the Directive. Different models have been implemented, and the data sharing infrastructures have been organised in alternative ways (Beckstedde and Rossetto, 2025).

In this section, we report some of the national experiences with the establishment of these data-sharing infrastructures, highlighting the main cost drivers and the way costs have been allocated to the various actors involved in order to ensure their recovery. By doing this, we aim to complement the theoretical analysis performed in Sections 2 and 3 with practical experience and suggest scope for further research.

4.1 Cost level and structure of energy consumer data sharing infrastructure

Assessing the level and structure of the costs associated with the establishment and operation of an infrastructure for the sharing of consumer data is not trivial for two reasons, somewhat interrelated. First, there is limited information publicly available on the costs associated with the management of data. Second, as mentioned above, different countries have adopted different DMMs, which allocate the various roles to different entities. The same entities can then deliver different sets of tasks in the various countries, making any assessment more complicated. Any simplistic comparison of the balance sheet of similar entities across countries must be dealt with care. To the best of our knowledge, there is currently no comprehensive collection of data about data management costs in Europe. For some countries, such as Norway, more information is easily available, typically in the local language, but for most of them this is not the case.[25]

However, based on a series of interviews with experts directly involved in the establishment and operation of data sharing infrastructure in several European countries, it is possible to provide some general indications on the level and structure of the costs associated with data sharing.[26]

With regard to the level of costs, interviewed experts suggests that costs related to data management are in the order of a few tens of millions of euros per year for a typical European country. This amount is mostly due to the development of the infrastructure and does not include the deployment of smart meters. The cost of operating the infrastructure is a small fraction of the overall costs (a few million euros per year). This suggests that data management, although non negligible, represents only a tiny share of the total costs of the energy system in Europe.

Regarding the structure of costs, interviewed experts confirm that development costs are driven mostly by: i) the effort to find an agreement on the processes, the communication standards, and the system interfaces with all the relevant actors; and ii) the implementation of the IT solutions that technically support the DMM chosen. Every time there is a decision to implement a new process or functionality, experts representing the various stakeholders impacted by data management (e.g., system operators, energy suppliers, representatives of consumers, technology vendors) are typically mobilised in technical working groups, whose cost is clearly distributed among the stakeholders. IT solutions are normally purchased by external providers and tend to be custom-built. The use of standardised IT solutions can to some extent reduce this source of costs.

Operational costs are driven mostly by: i) personnel costs; and ii) software licences. The maintenance of the IT infrastructure and data storage are also relevant. The increase in the

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[25] Detailed information about the costs of the Norwegian data hub (Elhub) is provided every three years in a report presenting the results of the cost-effectiveness audit to which the data hub is subject. The report provides data also for Denmark and Finland, which have adopted similar data management models. https://publikasjoner.nve.no/rme_eksternrapport/2025/rme_eksternrapport2025_07.pdf (Vista Analyse og Vali, 2025).

[26] The information in Section 4.1 is mainly derived from a series of expert interviews conducted in January-February 2025 in the context of the EDDIE project (https://eddie.energy/). See Chapter 5 of the forthcoming deliverable 7.2 of that project for more details on the research methodology.

volume of consumer data associated with the move to hourly or 15-minute metering or the obligation to retain the data for longer periods tend to increase the cost of data storage. Cloud-based solutions are expected to limit this increase, while some experts argue that relying on cloud-based solutions can pose problems in terms of data protection and sovereignty. Auditing the proper behaviour of third parties who have access to the data sharing infrastructure can also be a source of significant costs for some DMMs.

Although further and more systematic research would be beneficial to confirm these general indications, it is possible to conclude, based on them, that the costs associated with an energy consumer data sharing infrastructure are largely fixed (i.e., independent from the amount of data shared). Moreover, it seems that the complexity of the ecosystem within which data are shared has a clear impact on development costs. The more fragmented is the environment, the more effort must be implemented to reach an agreement on new processes and functionalities, and the more expensive technical implementation is likely to be. This is not to say that centralised solutions are necessarily superior, but only that it is important to strive for interoperable and possibly standardised solutions as much as possible.

4.2 Cost allocation in some European countries

Although ultimately the final customer pays, the costs of managing metering and consumption data can be allocated to different actors and recovered in different ways. Different choices in cost allocation can be justified in terms of several factors, including the specific DMM of a country. To our knowledge, there is currently no systematic collection of this information at the European level. However, interviews with experts and desk research suggest that data sharing cost allocation takes different forms in European countries.

We illustrate the cost allocation methods in six European countries that implement different management models for metering and consumption data. Italy and Norway have implemented centralised DMMs. Spain and the Netherlands are characterised by a hybrid DMM, while Austria and Belgium have a more decentralised model.[27] In Italy and Norway, a national data hub collects the metering and consumption data from the DSOs, storing them, managing access to data, and performing a series of market processes. Consumers, suppliers, and other eligible parties can access customer data on such data hubs.

In the case of Italy, the data hub, called 'Sistema Informative Integrato' (SII), is managed by Acquirente Unico (AU), a public company owned entirely by Gestore dei Servizi Energetici (GSE), which is owned by the Italian state through the Ministry of Economy and Finance.[28] The SII has an account separate from that of the other activities performed by the AU. Every year the SII budget is forwarded to the Italian national regulatory authority (ARERA), which

[27] The role of EDA in Austria and Atrias in Belgium suggests that the Austrian and Belgian DMMs present some elements of centralisation and are different from the so far fully decentralised models observed in France or Germany. See Beckstedde and Rossetto (2025) for a taxonomy of data management models.

[28] See https://www.acquirenteunico.it/organizzazione.

determines the fee to be paid by every balance responsible party and by every actor delivering the service of "maggior tutela" to recover the cost of the SII.[29] The fee is equal to EUR 0.045 per withdrawal point/month in October 2024.[30] More recently, ARERA launched a public consultation about the possibility of extending the application of the fee to the commercial counterparties, who are not balance responsible parties or actors delivering the service of "maggior tutela", that are registered on the SII and benefit from its services. As the number of commercial counterparties has grown over recent years, ARERA has signalled the intention to allocate to them half of the costs of the SII related to electricity, thereby achieving a fairer and more appropriate cost allocation.[31]

In Norway, the data hub, called 'Elhub', is managed by Elhub AS, a subsidiary owned by Statnett SF, the Norwegian TSO, which is owned by the Norwegian state through the Ministry of Energy.[32] Every three years, Elhub is subject to an external audit of its historical and prospective costs. The Norwegian national regulatory authority (NVE/RME) approves the fee model that Elhub is allowed to charge network operators (DSOs), power suppliers, and service providers (third parties). A proposal of the fee model is submitted by Statnett SF after a consultation with the industry. The decision by NVE/RME, covering 2023-2025, specifies that any Elhub user, i.e., network operators, power suppliers and service providers (third parties), pays a fixed fee of NOK 57,000 per year. This fixed fee reflects the costs borne by Elhub to perform basic services and provide customer service for Elhub users. These costs are largely unaffected by the number of Elhub users, the number of metering points or the size of the companies.[33] In addition to this fixed fee, network operators and power suppliers pay a fee per metering point under their control. The aim of this metering point-dependent fee is to distribute residual costs evenly across all metering points. The metering point-dependent fee is NOK 79.39 per year for the network operators and NOK 19.85 per year for power suppliers. Service providers are exempted from the payment of the metering point-dependent fee: this is justified by the fact that such arrangement promotes energy efficiency, energy advice and innovation, leading to a more efficient retail market, in line with

[29] The fee is also paid by every user of the natural gas distribution service.

[30] See ARERA decision 22 October 2024, 428/2024/R/COM. The structure of the fee has been decided on the consideration that costs are mostly related to the participation of each withdrawal point in the liberalised energy market, rather than the energy volume associated with each withdrawal point. Moreover, this fee structure does not penalise smaller actors.

[31] See ARERA consultation document 15 April 2025, 173/2025/R/COM. Following the conclusion of the public consultation, ARERA has confirmed the decision to split the fee fifty-fifty between the balance responsible party and the commercial counterparty. Actors delivering the service of "maggior tutela" pay the fee in full. In the natural gas sector, the split of the fee is a bit different: 10% for the "utenti del bilanciamento", 40% for the "utenti del dispacciamento" and 50% for the "controparti commerciali". This distribution of the fee will take place from April 2026. See ARERA decision 18 June 2025, 262/2025/A, available at: https://www.arera.it/fileadmin/allegati/docs/25/262-2025-A.pdf.

[32] See https://elhub.no/. Statnett SF has a license as settlement authority in Norway.

[33] A reduced fixed fee of NOK 25,000 per year is paid by system suppliers. This reduced fee reflects the costs that Elhub bears to offer system suppliers access to test environments and associated services in Elhub.

the goals of regulation.[34] On top of these regulated fees, which represent the bulk of Elhub revenues, the data hub is allowed to charge also municipalities, research centres and other parties that ask for access to data for other purposes, such as scientific research. These charges are not regulated.

Now consider two countries that implement some form of hybrid DMM. In Spain and the Netherlands, there is no national data hub. Metering and consumption data are normally stored at the DSO level. However, the function of permission administrator and data access providers have been centralised in recent years. Datadis performs that role in Spain, while MFF/BAS does it in the Netherlands.

In the case of Spain, Datadis provides final customers and authorised third parties, such as energy service providers, with secure, centralised access to the metering and consumption data across all Spanish electricity distribution companies.[35] Datadis is a 'Comunidad de Bienes' created by the main DSOs and operated by Aelēc, the Spanish Association of Electric Energy Companies. DSOs initially not involved in the creation of Datadis, typically controlling only a small share of the Spanish distribution sector, have been later invited to join Datadis. Final customers and authorised third parties can access Datadis free of charge. DSOs cover the costs of developing and maintaining Datadis in proportion to their regulated income.[36] DSOs can include their contribution to Datadis in their regulated costs and recover it via network tariffs.

In the Netherlands, interested parties can become part of Marktfaciliteringsforum (MFF), an association whose members jointly make agreements about the exchange of energy data. MFF is practically supported by Het Normo, previously known as Beheerder Afspraken Stelsel (BAS), a separate and independent legal entity with the Dutch TSOs and DSOs as its shareholders.[37] Het Normo is in charge of the implementation and monitoring of the agreements made within the MFF, and administers the Energy Data Exchange Framework (EDEF).[38] Participation in the MFF is free of charge and open to all stakeholders. Dutch system operators are mandated by law to enable energy data exchange and cover the costs of Het Normo. Electricity and gas TSOs and DSOs share these costs as follows: Tennet and Gasunie, the electric and gas TSOs respectively, cover 50% of the costs of Het Normo (25% each), while the Dutch DSOs cover the remaining 50% (each DSO contributes in proportion to the number of users connected to its network). The expenses incurred by the system operators are then recovered via network charges.

Austria and Belgium have a more decentralised DMM in place. In these countries there is no data hub nor a specific platform for the centralised management of access and consent to

[34] See NVE/RME decision 19 December 2022, available at: https://www.nve.no/media/15019/202218127-6-rme-godkjenner-statnett-sf-sitt-forslag-til-gebyrmodell-for-elhub.pdf.

[35] See https://datadis.es/home.

[36] Small DSOs, initially not involved in the setup of Datadis, contribute, pro quota, only to maintenance costs.

[37] See https://hetnormo.nl/.

[38] See https://www.mffbas.nl/en/. A summary overview of MFF/BAS can be found in Hermans (2024).

data access. However, different actors have developed a standardised data exchange framework, which includes communication protocols, data formats, and processes to support the access and exchange of data.

In Austria, DSOs and TSOs established Energiewirschaftlicher Datenaustausch (EDA) in 2012 via their association 'Österreichs Energie' to support all market participants with secure and efficient communication and standardised information exchange.[39] EDA enables data exchange via three different connection types, which aim to satisfy different needs. Data, which remain stored at the level of DSO, can be shared either via the EDA portal (web-based solution), via email, or via a communication endpoint. Electricity and gas system operators cover most of the costs of EDA.[40] However, some of the costs are recovered via fees which are applied to energy service providers, and energy communities. Depending on the market role selected, different fees apply: the use of the EDA portal is free for everybody up to 50 metering points, while the use of email connectivity or communication end-point, which support the exchange of a higher volume of data, is charged, depending on the underlying role which is using the related connection type.[41] This fee structure purposely facilitates market communication for small market participants, who are subsidised by the fees paid by larger participants. However, as the establishment of a data space at the national level is increasingly mission-critical, and more diverse in terms of functionalities supported and participants, pricing structure is most probably going to be adapted to cope with this evolution. The need for such step-by-step adaption of cost allocation schemes may also be addressed within the CEEDS.

In the case of Belgium, electricity and gas DSOs play the role of data manager and, in 2011, have jointly established Atrias to support them.[42] Data exchange occurs on the MIG 6 communication protocol. Atrias acts as an IT partner of the DSOs, executing some functions on their behalf. In particular, Atrias is involved in the communication of data between all market parties, in the management of the access register, and in settlement calculation. Atrias is not involved in data storage (this role is performed directly by the DSOs). Since 2021, the Flemish regulator (VREG) has introduced a data management tariff that is expected to cover all the costs borne by the DSOs.[43] This data management tariff is part of the periodic network charges that final customers pay. It is fixed per metering point. In 2025, the tariff was, for final customers connected to the low-voltage network, equal to EUR 18.56/year (including VAT), irrespective of the type of meter.[44] Flexibility service providers

[39] See https://www.eda.at/.

[40] A pricing model is used that fairly distributes costs between the electricity and gas sectors; however, this pricing model is not publicly accessible.

[41] A list of prices is provided here: https://www.eda.at/pdf/anlage5preisblatten.pdf.

[42] See https://www.atrias.be/.

[43] See https://www.vlaamsenutsregulator.be/nl/veelgestelde-vragen/wat-het-tarief-databeheer-en-waarom-het-hoger-dan-het-vroegere-meet-en-teltarief.

[44] In 2024, the data management tariff was more differentiated: the basic tariff was EUR 13.95/year (including VAT), but customers with a digital meter who opted for quarterly readings in their contract (e.g., because they had a dynamic price contract with their supplier) had to pay an additional EUR 1.19 per year.

pay a fixed fee per year to contribute to the data management function, but the amount is minor (roughly 200 euros per year) and covers only the administrative costs.

5. Regulation and Governance

As we have seen in Section 4, different cost allocation practices are implemented throughout Europe in order to recover the costs associated with energy data sharing infrastructures. This can be the consequence of the different DMMs adopted and the specific cost structures of the various entities involved. It is also likely to be the consequence of specific arrangements taken in the past at the national level. European legislation currently does not aim at reducing this variability, as it only defines a few general principles that cost allocation should follow, leaving ample leeway to the Member States in designing how the costs of supporting data sharing are covered.

In this section, we explore regulation and governance aspects of energy data cost allocation, by highlighting the minimum legal requirements introduced by EU legislation, and then reflect on the implications that data sharing governance has on the matter.

5.1 Minimum legal requirements for cost allocation in EU legislation

European sectoral legislation provides some details with regard to how the costs associated with energy consumer data management should be allocated. Article 23 of Directive (EU) 2019/944 devotes a paragraph to the matter, where three principles are stated. The paragraph is as follows:

I. "No additional costs shall be charged to final customers for access to their data or for a request to make their data available;

II. Member States shall be responsible for setting the relevant charges for access to data by eligible parties.

III. Member States or, where a Member State has so provided, the designated competent authorities shall ensure that any charges imposed by regulated entities that provide data services are reasonable and duly justified" (art. 23 (5)).

Hence, the Directive maintains that, at least for the management of the data relevant to Article 23,[45] costs should not be directly allocated to final customers or at least not allocated on the basis of their request to access their data or for a request to make their data available. Apparently, this leaves the possibility to either charge final customers on the basis of a fixed charge independent from the direct use of the data sharing infrastructure or to charge other

[45] Article 23 (1) specifies that "For the purpose of this Directive, data shall be understood to include metering and consumption data as well as data required for customer switching, demand response and other services."

actors of the system that access those data, the so-called eligible parties.[46] However, the Directive then does not provide much details on how eligible parties can or must be charged. It simply specifies that Member States are responsible for setting the charges and that, in case the charges are imposed by regulated entities, such as, for example, a national mandatory data hub, those charges must be reasonable and duly justified.

Although a proper investigation of the appropriate interpretation of these provisions is beyond the scope of this paper, it seems that such provisions rule out the use of cost allocation methods based on cooperative game-theoretic or auction-base approaches. A purely uniform allocation of costs is likely to be equally incompatible with the Directive, as it does not appear to be neither reasonable nor duly justified to charge the same cost to everybody, independently of the use of the data sharing infrastructure and any cost-responsibility. The use of a proportional cost allocation method seems to be the only approach compatible with the Directive. However, in the absence of any additional detail provided by the same Directive, a question remains: proportional to what?

5.2 Governance

The analysis of the costs associated with the establishment of energy data sharing infrastructure in Section 4.1 shows that an important cost driver is represented by the need to align the interfaces and the processes among the various actors involved in data management. Having all the actors on board is important to ensure an effective and efficient implementation of the chosen data exchange framework. However, this can be far from simple, given the diversity in capabilities and interests that can characterise them. Trust in the other actors is essential to promote cooperation and possibly accept to embrace changes in the status quo that generate costs or reduce the role of gate keepers in data management. A cost allocation perceived as fair and transparent can play an important role in generating trust, thereby facilitating the establishment of an efficient and effective data sharing infrastructure. Again, proportionality in the cost allocation method seems to be way forward.

The trust and willingness to cooperate for the establishment of a data sharing infrastructure may initially emerge only within a small group of forward-looking actors. Other actors, either regulated ones or commercial, can be initially less inclined to be involved, for instance due to a conservative management or a not so clear business case. Given the network effects that a data sharing infrastructure can generate, as mentioned in Section 2, it is important that the chosen cost allocation method and the adopted governance framework facilitate the participation of new actors over time. An expansion of participation can in fact increase the value generated and redistribute the burden on the actors that already contribute to cost recovery.

Eventually, it is possible to imagine that a different cost allocation method is adopted in the early stages of the energy data sharing infrastructure and when the infrastructure is fully in

[46] Energy suppliers and other energy service providers can be eligible parties. See Nicolai and Münchmeyer (2025) for a discussion of the definition of eligible parties in the context of energy service interoperability.

place and network effects have become significant due to the large number of actors already using it. Such an evolution in cost allocation can potentially facilitate the rapid uptake of the infrastructure and ensure dynamic efficiency. Therefore, the governance framework adopted should allow for adaptive cost allocation, with periodic reviews to realign charges with participation levels, data value, and system maturity.

6. Conclusions and policy recommendations

This paper explores the economic foundations of cost allocation in energy data spaces, emphasising the need for fair, transparent, and sustainable mechanisms to support their operation. As data exchange becomes increasingly central to the digital energy transition, defining who pays for what, and according to which principle, will determine both participation incentives and system's long-term viability.

Based on the discussions of this paper, four key conclusions and policy recommendations emerge:

i. *The establishment of a single coordinating entity for the European energy data space*. Early competition between data space developers could fragment standards, reduce interoperability, and lead to dominance by large non-European digital platforms and undermine trust and data sovereignty. Data spaces exhibit economies of scale and natural-monopoly characteristics, making a coordinated framework more efficient. A unified entity can ensure stability, standardisation, and efficient governance. A centralised governance structure would ensure coherence across national initiatives, promote data interoperability, and maintain trust among stakeholders. Such an entity should guarantee neutrality, stability, and alignment with existing regulations.

ii. *The adoption of proportional cost allocation as the default method*.
The proportional allocation as a cost sharing mechanism satisfies both *Monotonicity* and *No advantageous splitting or merging*, which are crucial fairness and incentive-compatibility for data spaces. The method is simple, transparent, and robust against strategic behaviour, unlike uniform or game-theoretic rules. It aligns best with the efficiency and fairness conditions. It is easy to implement, and ensures that costs are shared fairly in proportion to measurable participation or activity levels. This method has the advantage of potentially promote trust among the participants, a condition essential to ensure an effective and efficient governance of the same.

iii. *Differentiate between regulated and non-regulated data exchanges*.
Regulated exchanges, such as TSO-DSO operational data flows, create broad system-wide benefits, which calls for governance and cost-recovery mechanisms consistent with their public good nature. In contrast, non-regulated exchanges

enable commercial or cross-sectoral services and can rely on market-based pricing or weighted proportional mechanisms reflecting user activity and data contribution. As these two categories differ fundamentally in purpose, incentives, and beneficiaries, they can be treated separately in a cost allocation exercise.

iv. *Incentivise early participation and data contribution*.
Strong network effects in energy data spaces, where the value of the system increases with the number and diversity of participants, make early adoption critical for achieving scale. A weighted proportional allocation can incorporate rewards to early adopters or actors who contribute valuable data by assigning them lower weights or preferential terms, while satisfying the fairness and efficiency principles. Such incentives should help overcome initial reluctance to join the data space, support trust-building, and accelerate the growth of the data space ecosystem.

In summary, energy data spaces require more than technical interoperability. Their success calls for sound economic design. These recommendations help build a governance and cost allocation framework that support both the scalability and the long-term sustainability of the European energy data ecosystem.

References

Beckstedde, Ellen, and Nicolò Rossetto. 2025. "Energy consumer data management models: a richer taxonomy and four reflections from the European experience." EUI; RSC; *Policy Brief*; 2025/10; Florence School of Regulation. https://doi.org/10.2870/2683794.

Berkhout, Volker, Carsten Frey, Philipp Hertweck, David Nestle, and Manuel Wickert. 2022. "Energy Data Space." In *Designing Data Spaces*, 329–341. Springer. https://doi.org/10.1007/978-3-030-93975-5_20.

Bertrand, Joseph. 1883. "Théorie Mathématique de La Richesse Sociale." *Journal Des Savants*, 499–508.

Chun, Youngsub. 1988. "The Proportional Solution for Rights Problems." *Mathematical Social Sciences* 15 (3): 231–246.

Cournot, Antoine Augustin. 1838. *Researches into the Mathematical Principles of the Theory of Wealth*. Hachette.

Conkling, Roger L. 2011. Energy pricing: economics and principles. *Springer Science & Business Media*.

DeAngelo, J., Azevedo, I., Bistline, J., Clarke, L., Luderer, G., Byers, E. and David, S.J. 2021. "Energy systems in scenarios at net-zero CO_2 emissions." *Nature Communications* 12, 6096. https://doi.org/10.1038/s41467-021-26356-y.

Dognini, Alberto, Antonello Monti, Antonio Kung, Arturo Medela, Charukeshi Mayuresh, Christoph Schaffer, Daniele Stampatori, et al. 2024. "Blueprint of the Common European Energy Data Space." https://doi.org/10.5281/zenodo.10789975.

Dutta, Bhaskar, and Debraj Ray. 1989. "A Concept of Egalitarianism Under Participation Constraints." *Econometrica* 57 (3): 615–635.

EC. 2022. "Commission Staff Working Document Accompanying the document Communication from the Commission to the Parliament, the Council, the European Economic and Social Committee and the Committee of the regions Digitalising the energy system – EU action plan." Strasbourg, 18.10.2022, SWD(2022) 341 final.

Franklin, M., Halevy, A. and Maier, D. 2005. "From Databases to Dataspaces: A New Abstraction for Information Management." *ACM Sigmod Record*, 34(4), 27–33. https://doi.org/10.1145/1107499.1107502.

Hermans, Peter. 2024. "The Perfect Storm: Where the Energy Transition Meets the Digital Transformation." in Doleski, Oliver, and Monika Freunek (edited by), *Handbook of*

Electrical Power Systems Energy Technology and Management in Dialogue, 509-527. doi/10.1515/9783111264271-026/html.

Hougaard, Jens Leth. 2009. *An Introduction to Allocation Rules*. Springer.

Hougaard, Jens Leth, Dorte Kronborg, and Aleksandrs Smilgins. 2017. "Fair Division of Costs in Green Energy Markets." *Energy* 139: 220–230.

Hougaard, Jens Leth, and Herve Moulin. 2014. "Sharing the Cost of Redundant Items." *Games and Economic Behavior* 87: 339–352.

Hougaard, Jens Leth, and Aleksandrs Smilgins. 2016. "Risk Capital Allocation with Autonomous Subunits: The Lorenz Set." *Insurance: Mathematics and Economics* 67: 151–57. https://doi.org/10.1016/j.insmatheco.2015.12.002.

IEA. 2025. *Energy and AI*. International Energy Agency. Paris.

IRENA. 2025. *Digitalisation and AI for power system transformation. Perspectives for the G7*. International Renewable Energy Agency. Abu Dhabi.

Khezr, P., and F. M. Menezes. 2019. "Funding Natural Monopoly Infrastructure Expansion: Auctions Versus Regulated Uniform Access Prices." *Journal of Regulatory Economics* 55(2): 193–213.

Krishna, Vijay. 2009. *Auction Theory*. 2nd ed. Burlington, MA: Academic Press/Elsevier. https://doi.org/10.1016/B978-0-12-374507-1.X5026-7.

Kruchten, Philippe. 1995. "Architectural Blueprints—The "4+1" View Model of Software Architecture." IEEE Software 12(6): 42–50. https://doi.org/10.1109/52.469759.

Milgrom, P., & Weber, R. J. (1982). "A theory of auctions and competitive bidding." *Econometrica*, 50(5), 1089–1122.

Moulin, Hervé. 1987. "Equal or Proportional Division of a Surplus, and Other Methods." International Journal of Game Theory 16(3): 161–186.

Moulin, Hervé. 1988. Axioms of Cooperative Decision Making. Cambridge University Press.

Nicolai, S., and M. Münchmeyer. 2025. "The EU Data Act and electricity consumer participation in demand response and flexibility services." *Journal of Energy & Natural Resources Law*. https://doi.org/10.1080/02646811.2025.2485725.

Peleg, Bezalel, and Peter Sudhölter. 2007. "Introduction to the Theory of Cooperative Games". 2nd ed. *Springer*.

Schmeidler, David. 1969. "The Nucleolus of a Characteristic Function Game." *SIAM Journal on Applied Mathematics* 17 (6): 1163–1170.

Szwagrzak, Karol, and Lars Peter Østerdal. 2025. "Rationalizing Sharing Rules." Games and Economic Behavior 154: 97-118.

Shapley, Lloyd Stowell. 1953. “A Value for n-Person Games.” In *Contributions to the Theory of Games II*, edited by Harold W. Kuhn and Albert W. Tucker, 28:307–17. Princeton University Press.

Sioshansi, Fereidoon. 2020. “Variable generation, flexible demand”. Academic Press.

Skaperdas, Stergios. 1996. “Contest Success Functions.” *Economic Theory* 7 (2): 283–290.

SmartEn. 2023. “Data sharing from system operators.” *smartEn Spotlight*. February, available at: https://smarten.eu/reports/report-l-spotlight-on-data-sharing-from-system-operators/.

Tijs, Stef H., and Theo S. H. Driessen. 1986. “Game Theoretical Solutions and Cost Allocation Problems.” *Management Science* 32 (8): 1015–1028.

Vista Analyse og Vali. 2025. “Ekstern revisjon av kostnadseffektivitet i Elhub.” Ekstern Rapport nr. 7/2025, RME, available at: https://publikasjoner.nve.no/rme_eksternrapport/2025/rme_eksternrapport2025_07.pdf

Von Neumann, J., and Morgenstern, O. (1947). “Theory of games and economic behavior” (2nd rev. ed.). *Princeton University Press*.

West, Joel and Wood, David. 2013. “Evolving an Open Ecosystem: The Rise and Fall of the Symbian Platform”. Advances in Strategic Management 30:27-67.

Wilson, R. 1969. “Competitive bidding with asymmetric information.” Management Science, 15(7), 446–448.

Young, H. Peyton. 1985. *Cost Allocation: Methods, Principles, Applications*. Amsterdam: North-Holland.

Young, H. Peyton. 1985. “Monotonic Solutions of Cooperative Games.” International Journal of Game Theory 14(2): 65–72.