

## Review

# Machine Learning and Blockchain in Peer-to-Peer Energy Trading: A Cross-Layer Review of Functional Roles, Market Operation, Trust, and Privacy

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## Abstract

Peer-to-peer (P2P) energy trading combines local energy resources, market coordination, data-driven decisions, and transaction management. This review examines how machine learning (ML) and blockchain are used across these functions and separates market and ledger processes from physical electricity delivery. A structured review procedure was applied to a corpus of 52 peer-reviewed journal articles, including the core P2P energy-trading evidence and a limited number of closely related contextual studies, supplemented by 10 non-journal or foundational sources, using defined search families, screening criteria, and qualitative synthesis. The literature is organized by the functional role of ML and compared across architecture, market operation, trust, consensus, privacy, and implementation. The consensus discussion considers practical Byzantine fault tolerance, Istanbul Byzantine fault tolerance, proof-of-authority, and application-oriented Byzantine-fault-tolerance variants, while the privacy discussion distinguishes federated learning, differential privacy, zero-knowledge proofs, and secure multiparty computation. Two deterministic MATLAB examples are included only for illustration. In the five-prosumer forecasting example, regression reduced mean absolute error (MAE) from 0.4240 to 0.2219 kWh and the hourly grid-import mismatch from 30.3529 to 7.9029 kWh. In the 10-peer workflow, five trades settled 7.7587 kWh, corresponding to 59.35% of the horizon-level surplus–deficit denominator defined in the simulation. These examples do not validate feeder feasibility, consensus performance, cryptographic security, or deployment readiness.

**Keywords:** peer-to-peer energy trading; blockchain; machine learning; distributed energy resources; consensus; privacy-preserving computation



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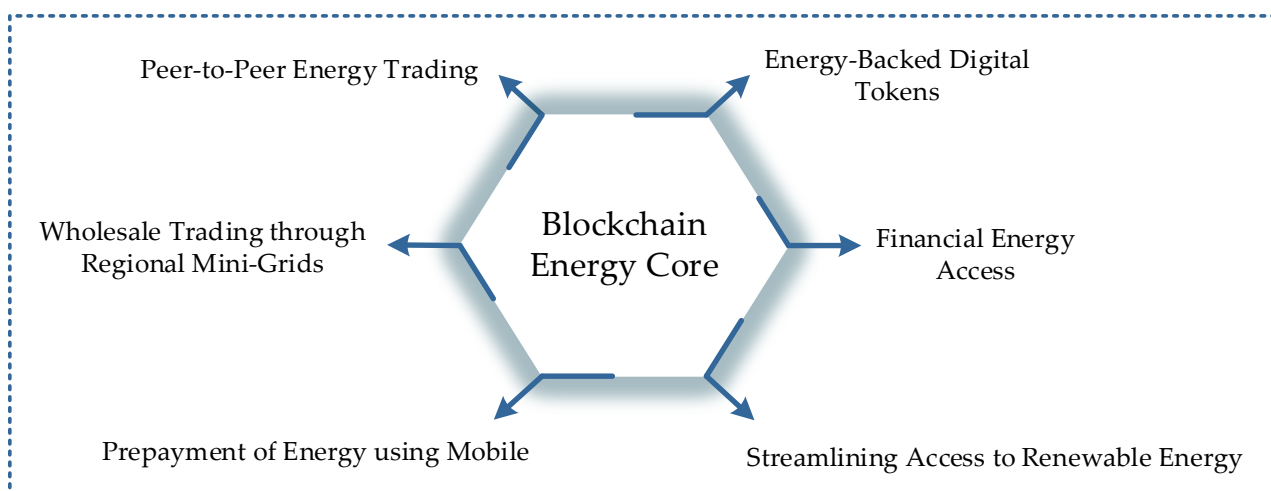
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## 1. Introduction

### 1.1. Background

The increasing deployment of distributed energy resources (DERs) such as rooftop solar panels, small wind turbines, and battery storage systems has shifted the structure of power systems from a centralized model toward a more decentralized one [1,2]. In this

context, P2P energy trading has emerged as a practical alternative. It allows prosumers, defined as entities that both produce and consume electricity, to exchange energy or energy-related products through local or distributed market arrangements [3]. Such arrangements may still involve a market platform, aggregator, distribution-system operator, or other coordinating entity. However, implementing P2P energy markets in practice involves two recurring challenges. The first challenge is ensuring trust, transparency, and security among participants who do not know each other. The second challenge is coordinating the market in real time, including price determination, load forecasting, and transaction settlement, especially when a large number of prosumers are active. Blockchain technology addresses the first challenge. As shown in Figure 1, six use cases of blockchain in the energy sector are connected to a common Blockchain Energy Core. These use cases include Peer-to-Peer Energy Trading, Energy-Backed Digital Tokens, Wholesale Trading through Regional Mini Grids, Financial Energy Access, Prepayment of Energy using Mobile, and Streamlining Access to Renewable Energy. The Blockchain Energy Core acts as a decentralized and immutable ledger. It records all transactions related to energy generation, consumption, and settlement without needing a trusted third party. Nevertheless, blockchain alone does not solve the second challenge. The need for efficient market clearing, adaptive pricing, load prediction, and anomaly detection in a dynamic environment requires additional intelligence. ML provides this support. Methods such as deep reinforcement learning (DRL) for bidding strategies and federated learning for privacy-preserving load forecasting can support decentralized P2P market operation. Blockchain and ML serve different but related functions: blockchain can support shared and traceable transaction records, while ML can support forecasting and decision tasks under changing operating conditions [4].



**Figure 1.** Blockchain applications in the energy sector [5].

### 1.2. Key Concepts and Terminology

Several terms used in the P2P energy-trading literature describe related but distinct concepts. DERs refer here to small-scale generation, energy-storage, and flexible-demand resources connected at or near the distribution level [6]. A prosumer is a participant that can both consume and supply electricity depending on its local energy balance.

Transactive energy is used as a broader concept describing the coordination of energy-related decisions through economic and control signals, whereas P2P energy trading refers more specifically to arrangements in which participants exchange energy or energy-related products through a local or distributed market mechanism [7]. The degree of decentralization may differ among implementations, and P2P trading does not necessarily

exclude the involvement of a market platform, distribution-system operator, aggregator, or other coordinating entity.

Blockchain-based energy trading refers to the use of distributed-ledger functions for activities such as transaction validation, shared record keeping, participant authentication, and settlement. In such systems, a smart contract represents predefined transaction or market rules in executable form and can be activated when specified conditions are met. Smart-contract settlement therefore refers to the execution and recording of agreed transaction conditions and is distinct from the physical delivery of electricity through the distribution network [8].

In this review, these terms are distinguished because the physical power system, market mechanism, data-driven decision layer, and blockchain-supported transaction layer have different functions. The same terminology is used throughout the architectural, methodological, and simulation discussions.

### 1.3. Review Methodology

This review uses a structured literature-review procedure to make the search, selection, and synthesis steps traceable. It is not presented as a Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) systematic review or as a quantitative meta-analysis. The scope covers P2P, local, community-based, and transactive energy trading, with attention to blockchain-supported transaction and trust management; ML-based forecasting and decision support; and market, optimization, privacy, and physical-grid considerations.

The literature was examined through ScienceDirect, Institute of Electrical and Electronics Engineers (IEEE) Xplore, Wiley Online Library/Institution of Engineering and Technology (IET), Multidisciplinary Digital Publishing Institute (MDPI), Association for Computing Machinery (ACM) Digital Library, Taylor & Francis Online, and Frontiers. These sources were used as literature-search platforms because they cover the journal and publisher outlets represented in the final evidence base. The search and reference audit were updated on 11 August 2026. The principal peer-reviewed publication window was 2021–2026. Earlier sources were retained only when they were needed for foundational consensus protocols, terminology, or implementation context. Backward reference tracing from relevant reviews and research articles was also used to identify sources directly related to the review scope.

Three complementary search families were used. The first combined P2P-energy-trading terminology with blockchain terms: (“peer-to-peer energy trading” OR “P2P energy trading” OR “local energy trading” OR “transactive energy”) AND (blockchain OR “distributed ledger” OR “smart contract”). The second combined energy-trading terms with ML terms: (“peer-to-peer energy trading” OR “P2P energy trading” OR “local energy market” OR “transactive energy”) AND (“machine learning” OR “deep learning” OR “reinforcement learning” OR “federated learning” OR forecasting). The third targeted market and system studies: (“peer-to-peer energy trading” OR “P2P energy trading” OR “local energy trading”) AND (optimization OR “market design” OR privacy OR security OR “physical grid” OR “distribution network”). The expressions were adapted to the search syntax of each source without changing their conceptual scope.

Studies were retained in the core analytical synthesis when they directly addressed P2P, local, community-based, or transactive energy trading and examined at least one review dimension relevant to this paper, including blockchain and smart contracts, consensus and trust, privacy, ML-based forecasting or decision-making, market design, optimization, or physical-network operation. A limited number of peer-reviewed studies from closely related domains were additionally retained for background definitions, enabling technologies, methodological context, or implementation-related discussion. These contextual

studies were not used as the primary basis for establishing the research-gap or positioning claims of the review. Eligible studies were required to provide sufficient methodological, architectural, computational, or application information for the intended qualitative analysis. Only English-language publications were considered.

Studies were excluded when they focused only on cryptocurrency or non-energy P2P finance; discussed blockchain or ML in smart grids without a direct energy-trading link; duplicated another publication; or did not provide enough technical information for the intended comparison. Non-journal sources, including institutional and market reports, book-based material, a thesis, conference or preprint material, and a protocol specification, were retained only for contextual, implementation, or foundational information and were not treated as the principal evidence for the research-gap comparison.

Screening was conducted in two stages. Titles and abstracts were first checked against the stated scope. Potentially relevant records were then assessed at full-text level for their technical role, market context, method, validation approach, and relevance to P2P energy trading. The final manuscript contains 62 unique references. Of these, 52 are peer-reviewed journal articles forming the journal-based evidence corpus, which comprises the core P2P energy-trading studies together with a limited number of closely related peer-reviewed sources retained for contextual purposes. The remaining 10 references are supplementary or non-journal sources used for contextual, implementation, or foundational information.

For each included study, information was extracted using a common analytical structure covering research focus, blockchain function, consensus or trust mechanism where applicable, ML role and technique, market or decision mechanism, physical-grid representation, data source, validation approach, reported indicators, and stated limitations. Reviews were used mainly to establish thematic coverage and positioning, while original research articles were used to examine implementation and methodological details. Because the studies differ in objectives, system scale, datasets, algorithms, and reported indicators, a quantitative meta-analysis was not used; the evidence was synthesized through structured qualitative comparison and functional categorization.

Generative artificial intelligence (AI) was used during manuscript revision for language and structural editing and to assist with drafting reviewer-requested revisions. Details are provided in the Acknowledgments. The authors retained responsibility for source selection, numerical verification, and final interpretation, and generative AI output was not treated as scientific evidence.

For clarity, the main elements of the adopted review procedure are summarized in Table 1. The table consolidates the scope of the review, literature sources, publication period, search structure, eligibility criteria, screening procedure, composition of the evidence base, and synthesis strategy. This summary is provided to make the study-selection process readily traceable and to distinguish the principal peer-reviewed evidence used for the analytical synthesis from supplementary sources retained for contextual purposes.

**Table 1.** Review protocol and composition of the evidence base.

| Review Component                    | Adopted Procedure                                                                                                                                          |
|-------------------------------------|------------------------------------------------------------------------------------------------------------------------------------------------------------|
| Review scope                        | P2P, local, community-based, and transactive energy trading with emphasis on blockchain, ML, market/optimization, privacy/trust, and physical-grid aspects |
| Literature sources/search platforms | ScienceDirect; IEEE Xplore; Wiley Online Library/IET; MDPI; ACM Digital Library; Taylor & Francis Online; Frontiers                                        |
| Principal publication period        | 2021–2026                                                                                                                                                  |
| Last literature update              | 11 August 2026                                                                                                                                             |

Table 1. *Cont.*

| Review Component                                   | Adopted Procedure                                                                                                                                                                                                            |
|----------------------------------------------------|------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| Language                                           | English                                                                                                                                                                                                                      |
| Search structure                                   | Three complementary search families covering blockchain/trust, ML/intelligence, and market/grid studies, supplemented by backward reference tracing                                                                          |
| Screening procedure                                | Title/abstract screening followed by full-text relevance assessment                                                                                                                                                          |
| Main inclusion criterion                           | Direct relevance to P2P/local/community-based/transactive energy trading for the core analytical synthesis; closely related peer-reviewed studies were selectively retained for contextual or enabling-technology discussion |
| Main exclusion criterion                           | Non-energy P2P finance; generic blockchain/ML applications without a direct energy-trading link; duplicates; technically insufficient studies                                                                                |
| Peer-reviewed journal corpus                       | 52 peer-reviewed journal articles                                                                                                                                                                                            |
| Supplementary/non-journal sources                  | 10                                                                                                                                                                                                                           |
| Total unique references in the reviewed manuscript | 62                                                                                                                                                                                                                           |
| Evidence synthesis                                 | Structured qualitative comparison and functional categorization                                                                                                                                                              |

The publication-source distribution of the 52 peer-reviewed journal articles was also examined as a descriptive check on the evidence base. Elsevier journals account for 36 articles (69.2%), followed by IEEE with six (11.5%), MDPI with four (7.7%), and Wiley/IET with two (3.8%). ACM, Taylor & Francis, Frontiers, and one other journal publisher contribute one article each (1.9% each). No Springer journal article is represented in the final 52-article journal corpus. These counts are descriptive only and are not used to weight study quality.

#### 1.4. Thematic Synthesis of Previous Studies

The existing review literature indicates that the main components of P2P energy trading have already been examined from several perspectives, but with different organizing priorities. A first stream comprises broad market- and system-oriented reviews that organize the field around market structures, operational layers, trading platforms, optimization methods, information and communication technology (ICT) infrastructure, physical-network constraints, and implementation challenges [9–16]. For example, [11] provides a synthesis of market structures, centralized and distributed optimization, game-theoretic approaches, deep reinforcement learning, blockchain-based optimization, and network constraints, whereas [15] examines market architectures, bidding and auction mechanisms, game theory, mathematical optimization, and ML-based solution methods. Systematic market-model studies such as [13] further emphasize governance, market topology, physical constraints, scalability, information security, and participant privacy. Collectively, these reviews provide a broad market- and system-level foundation; however, ML is generally treated as one enabling or solution family among several rather than being used as the primary functional basis for organizing the P2P trading process.

A second stream is blockchain-centered [17–21]. These reviews examine blockchain as an infrastructure for decentralized transaction management and discuss different combinations of smart contracts, consensus mechanisms, privacy, security, interoperability, transaction architectures, and regulatory or implementation issues. The emphasis varies considerably within this stream. Reference [19], for example, connects market economics, network-capacity considerations, and policy/regulation through a blockchain-supported

trading model, whereas [20] concentrates specifically on consensus mechanisms, their communication and computational characteristics, and their suitability for electricity-trading applications. The recent systematic review in [21] similarly focuses on the opportunities, limitations, trust, privacy, traceability, and strategic challenges of blockchain-based transactive energy systems. These studies provide detailed coverage of the trust and transaction layer, but ML-based market intelligence is not their principal organizing perspective.

A third group of reviews addresses narrower but important dimensions of decentralized energy trading. Multi-energy trading and the integration of electricity, hydrogen, and heat are examined in [22]; business models and actor relationships are systematically analyzed in [23]; the role of distributed energy storage is the central concern of [24]; terminology and the distinguishing characteristics of P2P, transactive energy, and community self-consumption are investigated in [25]; real-world project and business-model experience is synthesized in [26]; and potential distributional and social impacts are explored in [27]. These studies broaden the evidence base beyond algorithmic market operation by incorporating multi-energy, business, social, and implementation perspectives. At the same time, their intentionally specialized scopes mean that they do not attempt to jointly organize ML functions, blockchain-supported trust and settlement, and the complete operational sequence of P2P transactions.

ML-oriented elements are therefore not absent from the prior review literature, but they are distributed across different analytical contexts. Reference [11] treats deep reinforcement learning within the broader optimization landscape, and [15] considers ML together with game theory and mathematical optimization as alternative solution approaches for P2P market operation. More specifically, [28] provides a survey of forecasting and scheduling strategies for smart-home P2P energy networks and supplements the review with a simulation-based analysis. Accordingly, the motivation for the present review is not that ML, blockchain, optimization, market design, or simulation have been overlooked individually. Rather, the remaining opportunity lies in organizing these dimensions according to their functional interaction across the P2P trading lifecycle and clarifying how learning-based intelligence, market decision-making, blockchain-supported trust and settlement, and physical and Internet of Things (IoT) infrastructure relate to one another within the same analytical structure.

Across these strands, three patterns recur. First, P2P research has moved beyond bilateral electricity exchange toward community, multi-energy, and digitally coordinated market settings. Second, optimization and learning methods are increasingly considered alongside blockchain-supported transaction and settlement processes rather than as isolated tools. Third, recent studies give more attention to physical-network constraints, privacy, governance, and deployment conditions. The literature does not converge on a single degree of decentralization: some schemes retain an aggregator, market operator, or off-chain optimizer, whereas others distribute more of the decision process. A related trade-off is that additional ML, optimization, privacy, or Byzantine-fault-tolerance functions can improve a specific technical objective while increasing data, computation, communication, or governance requirements. These differences motivate the cross-layer organization used in this review [9–28].

To make this distinction explicit, Table 2 compares representative reviews that most closely overlap with the scope of the present work. The comparison considers not only the principal topic of each review but also its review method or evidence base, treatment of ML, coverage of blockchain and trust mechanisms, market/grid/implementation perspective, and the aspect that remains outside its principal organizing scope. The purpose of this comparison is not to portray previous reviews as incomplete, but to identify how their different analytical priorities position the present review within an established and multidisciplinary literature.

**Table 2.** Comparison of representative reviews most closely related to the scope and positioning of the present study.

| Study                     | Main Review Focus                                                                                                     | Method/Evidence/Dataset Basis                                                                                                                      | Treatment of ML                                                              | Blockchain, Market, Grid, and Implementation Coverage                                                                                        | Relative Positioning with Respect to the Present Review                                                                                                                         |
|---------------------------|-----------------------------------------------------------------------------------------------------------------------|----------------------------------------------------------------------------------------------------------------------------------------------------|------------------------------------------------------------------------------|----------------------------------------------------------------------------------------------------------------------------------------------|---------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| [10] Tanis et al. (2025)  | P2P market structure, operational layers, energy cooperatives, and multi-energy systems.                              | Literature review organized around five major P2P system components; no common empirical dataset used.                                             | Not a primary organizing axis.                                               | Broad treatment of market mechanisms, physical/virtual operational layers, cooperatives, and multi-energy integration.                       | Provides broad system-level coverage, but does not use a functional ML taxonomy or explicitly map ML roles to blockchain-supported transaction stages.                          |
| [11] Xia et al. (2023)    | Trading environment, optimization methodologies, network constraints, and extended resource-sharing markets.          | Review and classification of 180 papers, including market structures, optimization models, pilot practice, and policies.                           | DRL is considered within the wider optimization landscape.                   | Covers blockchain-based optimization, game theory, centralized/distributed optimization, physical constraints, policy, and resource sharing. | Detailed coverage of optimization and market design; ML remains one solution family rather than the functional organizing layer linked to blockchain trust and settlement.      |
| [13] Capper et al. (2022) | Local-energy-market design across P2P, community self-consumption, and transactive energy.                            | Systematic review of 139 peer-reviewed journal articles using a modified Business Ecosystem Architecture Modelling framework.                      | Not a primary focus.                                                         | Identifies market archetypes and evidence gaps related to physical constraints, scalability, information security, and privacy.              | Detailed market-design synthesis, but ML roles and blockchain transaction/trust mechanisms are not jointly organized within a common operational framework.                     |
| [15] Islam (2024)         | P2P market architectures, bidding strategies, auctions, and enabling solution methods.                                | Detailed critical review of market mechanisms and solution methods; no common empirical dataset is used.                                           | Explicitly discusses ML alongside game theory and mathematical optimization. | Covers real-life platforms, market mechanisms, optimization, and enabling technologies.                                                      | A closely related broad review; ML is treated as one solution family among several rather than categorized by functional role and linked to blockchain trust/settlement stages. |
| [16] Bukar et al. (2023)  | Six components of P2P electricity trading: platforms, market schemes, clearing, policy, networks, and ICT.            | Systematic literature review using Scopus and Web of Science with explicit keyword-based screening.                                                | Not a principal organizing axis.                                             | Covers physical and virtual layers, market clearing, policy, network representation, and ICT infrastructure.                                 | Provides a broad P2P component model, but does not center the synthesis on ML functions or ML-blockchain interaction across the transaction lifecycle.                          |
| [17] Mazrae et al. (2025) | Blockchain-based transactive and P2P energy trading; generalized cyber-physical framework.                            | Review of blockchain-enabled P2P/transactive energy; no empirical dataset used.                                                                    | Not a primary organizing axis.                                               | Covers smart contracts, consensus, privacy, interoperability, and blockchain platform design.                                                | Provides a broad blockchain-centric framework, but does not organize ML according to its functional roles across the P2P trading workflow.                                      |
| [19] Singh et al. (2025)  | Three foundational pillars: market economics, power-network capacity, and policy/regulation, supported by blockchain. | Structured synthesis of 168 documents plus a seven-stage conceptual blockchain trading model and game-theoretic numerical formulation.             | Not a primary organizing axis.                                               | Connects market economics, network considerations, policy/regulation, blockchain security, and transaction stages.                           | Integrates technical, economic, and regulatory pillars, but does not develop a cross-study functional taxonomy of ML or connect ML functions to trust/settlement stages.        |
| [20] Lin et al. (2025)    | Blockchain consensus mechanisms for P2P electricity trading.                                                          | WoS/Scopus-based review; 454 publications identified in the reported search, with representative consensus mechanisms and pilot projects analyzed. | Outside the principal scope.                                                 | Compares consensus categories, communication complexity, real-time suitability, security, and pilot applications.                            | Provides a consensus-specific treatment, but intentionally does not address the broader ML-market functional integration considered here.                                       |

Table 2. *Cont.*

| Study                         | Main Review Focus                                                                                                                                          | Method/Evidence/Dataset Basis                                                                                                                                       | Treatment of ML                                                                                                                                                       | Blockchain, Market, Grid, and Implementation Coverage                                                                                                             | Relative Positioning with Respect to the Present Review                                                                                                                             |
|-------------------------------|------------------------------------------------------------------------------------------------------------------------------------------------------------|---------------------------------------------------------------------------------------------------------------------------------------------------------------------|-----------------------------------------------------------------------------------------------------------------------------------------------------------------------|-------------------------------------------------------------------------------------------------------------------------------------------------------------------|-------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| [21] Tooki and Popoola (2025) | Blockchain-based energy trading in decentralized transactive energy systems.                                                                               | PRISMA-oriented systematic review of opportunities, complexities, strategic challenges, and research directions; no empirical dataset used.                         | Artificial intelligence or fast computing appears as an enabling or future direction rather than a functional classification.                                         | Covers blockchain, privacy, trust, traceability, dynamic pricing, and strategic challenges.                                                                       | Systematic and blockchain-centric, but does not establish a functional ML taxonomy or an integrated ML-to-blockchain operational workflow with illustrative computational examples. |
| [22] Tariq and Amin (2025)    | P2P multi-energy trading in decentralized electricity–hydrogen–heat networks.                                                                              | Review of network configurations, trading platforms, established and emerging methods, pilot projects, and simulation tools; no common dataset used.                | Discussed among enabling approaches rather than as a functional taxonomy.                                                                                             | Covers blockchain, game theory, multi-energy configurations, pilot projects, and implementation tools.                                                            | Extends P2P analysis to multiple energy carriers, whereas ML-blockchain functional coupling and trust-aware workflow integration are not the central organizing perspective.        |
| [25] Gorbacheva et al. (2024) | Definitions and distinguishing characteristics of P2P, transactive energy, and community self-consumption.                                                 | Expert-group interviews across 13 countries combined with systematic/targeted analysis of 133 academic and non-academic papers.                                     | Not a primary focus.                                                                                                                                                  | Covers market goals, governance, ICT/data requirements, participation, and contextual distinctions.                                                               | Clarifies terminology and system characteristics rather than integrating ML decision functions with blockchain-based trading operations.                                            |
| [28] Raza et al. (2024)       | Smart-home P2P energy networks with emphasis on forecasting, scheduling, pricing, and home energy management (HEM).                                        | Survey supplemented by a P2P home-energy-management simulation analysis.                                                                                            | Central focus on forecasting and scheduling methods.                                                                                                                  | Covers P2P structure, market design, platforms, pricing, and simulation; blockchain trust/settlement is not the principal focus.                                  | A closely related review-plus-simulation study, focused mainly on smart-home forecasting/scheduling rather than blockchain trust, consensus, and transaction workflow.              |
| Present review                | P2P energy-trading synthesis connecting ML functions, blockchain/trust mechanisms, market operation, physical/IoT layers, and implementation perspectives. | Structured qualitative synthesis of the selected evidence base, supplemented by explicitly illustrative computational examples rather than experimental validation. | ML is organized by functional role: forecasting; decision/optimization support; learning-driven market operation; behavioral/trust modeling; infrastructure/security. | Links ML functions with IoT/data acquisition, market decisions, blockchain validation/settlement, privacy/trust, physical-grid context, and real-world platforms. | Positions the contribution in the cross-layer organization of these dimensions; the numerical examples are explanatory and are not presented as evidence of practical deployment.   |

The comparison in Table 2 shows overlap among previous reviews in terms of the individual technologies and market concepts considered. The distinction of the present review therefore lies primarily in the cross-layer organization of these elements rather than in claiming first coverage of blockchain, ML, optimization, or market design. In particular, the subsequent analysis distinguishes the functional roles played by ML within P2P trading and relates these roles to the surrounding information, market, blockchain, trust, and physical-system layers. This functional perspective is then complemented by representative original studies to examine how the identified roles and architectural components are implemented in current research.

### 1.5. Research Gaps and Positioning of the Present Review

The comparison of previous reviews in Table 2 shows that the main components of P2P energy trading have already been examined from different perspectives. Existing reviews cover blockchain-based transactions and security, consensus mechanisms, market structures, optimization methods, multi-energy trading, business and regulatory aspects, physical-network considerations, and ML-based methods [9–17,19–28]. Therefore, the motivation for the present review is not based on claiming that these topics have been overlooked individually.

The reviewed literature instead shows differences in how these topics are organized and compared. Broad P2P energy-trading reviews generally structure the literature around market design, trading mechanisms, optimization methods, network operation, or implementation issues, whereas blockchain-oriented reviews place greater emphasis on smart contracts, consensus, privacy, security, and transaction management. ML methods are also considered in previous reviews, but often as one group of solution methods within broader discussions of forecasting, optimization, scheduling, or trading strategies. Consequently, a functional comparison of the different roles assigned to ML within P2P energy-trading studies, together with the associated market, blockchain, trust, and infrastructure characteristics, remains useful for interpreting a literature that has developed along several partly overlapping directions.

Against this background, the present review is organized around the following contributions:

- Previous review articles and representative original studies are compared using structured criteria to clarify their focus, methodological characteristics, implementation context, reported outcomes, and limitations. This comparison is used to establish the position of the present review without assuming that blockchain, ML, optimization, or market design are individually new topics.
- ML applications in P2P energy trading are organized according to their functional role in the studied system. The resulting categories distinguish forecasting-oriented applications, ML-assisted decision and optimization, learning-driven market operation, behavioral and trust-aware modeling, and infrastructure- and security-oriented applications. This classification focuses on what ML performs within the trading process rather than treating algorithm families as equivalent functional categories.
- The review brings together the main architectural and operational elements discussed across the literature, including DERs and storage, IoT-based information exchange, market and decision mechanisms, optimization approaches, blockchain-supported transaction management, consensus and trust mechanisms, and selected real-world P2P trading platforms. These elements are examined as related parts of P2P energy-trading systems while retaining their different technical functions.
- Two illustrative numerical examples are included to support the literature discussion. The first considers five prosumers over a 24-h period and compares a naïve forecast with a simple ML-based forecast to illustrate how forecasting differences affect planned P2P exchange and grid import. The second considers ten peers over twelve trading intervals and implements a simplified sequence involving surplus detection, bidding, reputation and credit assessment, matching, symbolic smart-contract formation, abstract transaction validation, settlement, illustrative ledger recording, and reputation updating. These examples are used for explanation and workflow demonstration and are not presented as validation of a new market mechanism, blockchain protocol, or large-scale P2P trading platform.

Accordingly, the contribution of this review lies in the structured synthesis and comparison of the above research directions and in clarifying the roles and relationships of ML,

market operation, blockchain-supported transaction management, and implementation-related considerations within the reviewed P2P energy-trading literature.

### 1.6. Paper Structure

The remainder of the paper is organized as follows. Section 2 reviews the architectural and operational organization of P2P energy trading, including physical and information layers, market and optimization mechanisms, representative platforms, the functional roles of ML, and the illustrative forecasting example. Section 3 examines blockchain-supported trust and consensus mechanisms, privacy-preserving approaches, and the illustrative transaction workflow. Section 4 separates the main challenges into scalability, physical-grid integration, and validation/evidence issues before outlining future research directions. Section 5 summarizes the main findings and the limits of the illustrative numerical results.

## 2. Architectural and Operational Structure of ML-Enabled P2P Energy Trading

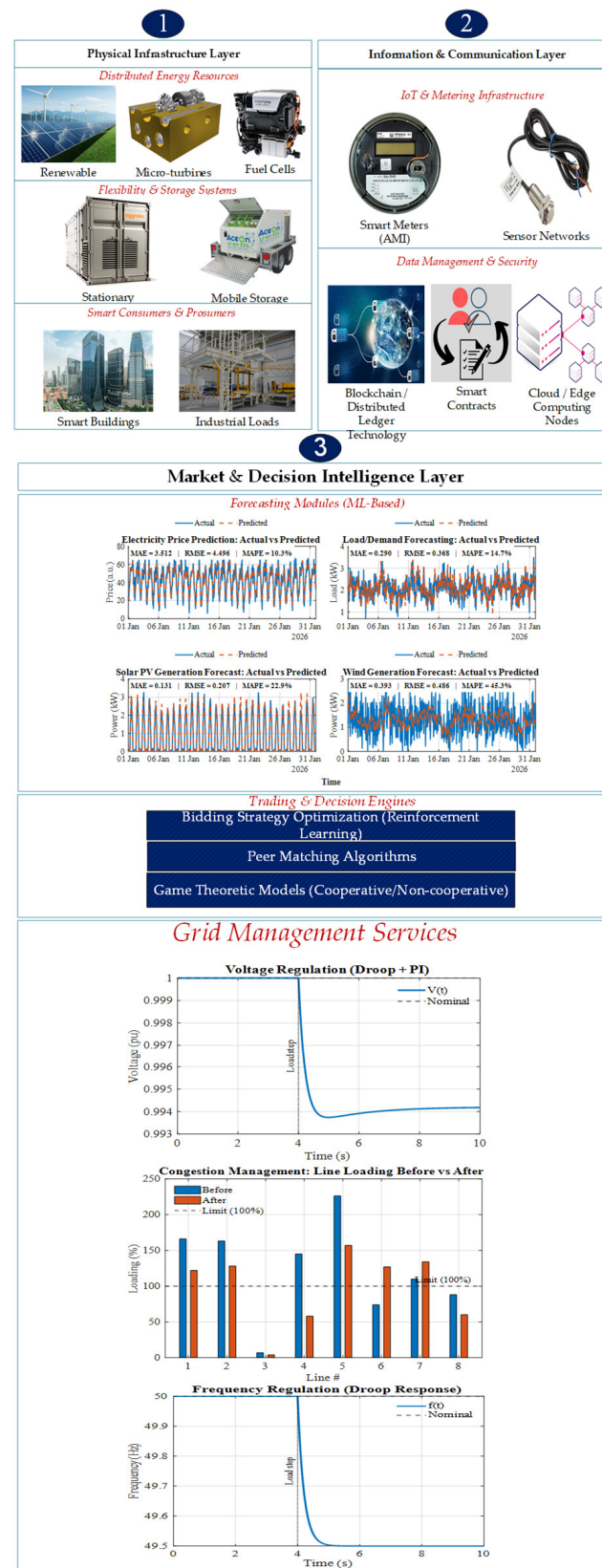
The studies reviewed in this section involve several interacting components, including DERs, prosumer loads and storage, sensing and communication infrastructure, market and decision mechanisms, and blockchain-supported transaction management. To organize these components consistently, Figure 2 presents a reference multilayer structure comprising a physical infrastructure layer, an information and communication layer, and a market and decision-intelligence layer. The purpose of this representation is to clarify the functional relationships among the components reported in the literature; it is not intended to define a universal physical-grid topology or a mandatory implementation architecture for all P2P energy markets. Figure 2 organizes the main components identified in the reviewed literature into three functional layers. The physical infrastructure layer contains the energy-producing, consuming, and storage assets associated with prosumers and their connection to the electricity network. The information and communication layer represents the acquisition and exchange of measurements and control-related information through smart meters, IoT devices, communication links, and digital platforms. The market and decision-intelligence layer represents forecasting, optimization, bidding, pricing, matching, and other decision functions used to support P2P transactions. Blockchain-related functions provide transaction validation, smart-contract execution, settlement recording, and trust-related services where these mechanisms are adopted.

### 2.1. Scope and Boundaries of the Reference Architecture

The physical boundary of the reference architecture includes prosumer-side generation, loads, stationary or mobile storage, and the electrical connection through which physical energy exchange takes place. The architecture does not prescribe a particular distribution-network topology and does not assume that blockchain or ML replaces conventional grid operation. Detailed network constraints such as voltage limits, line capacities, losses, protection requirements, and power-flow feasibility depend on the specific P2P market implementation and must be represented explicitly when network-constrained trading is considered. Thus, a market transaction and its digital validation should not by themselves be interpreted as evidence that the corresponding physical energy transfer is feasible.

The information and decision boundary separates physical energy exchange from digital information processing. Smart meters and IoT devices provide measurements such as consumption, generation, storage state, and other available operating information. These data may be used by ML models for forecasting, parameter estimation, decision support, pricing, bidding, matching, or learning-based market operation. The resulting information or decisions are then supplied to the relevant market participants or trading agents. The

market layer may employ auction-based, game-theoretic, optimization-based, learning-based, or hybrid mechanisms; therefore, Figure 2 does not impose a single market-clearing form.

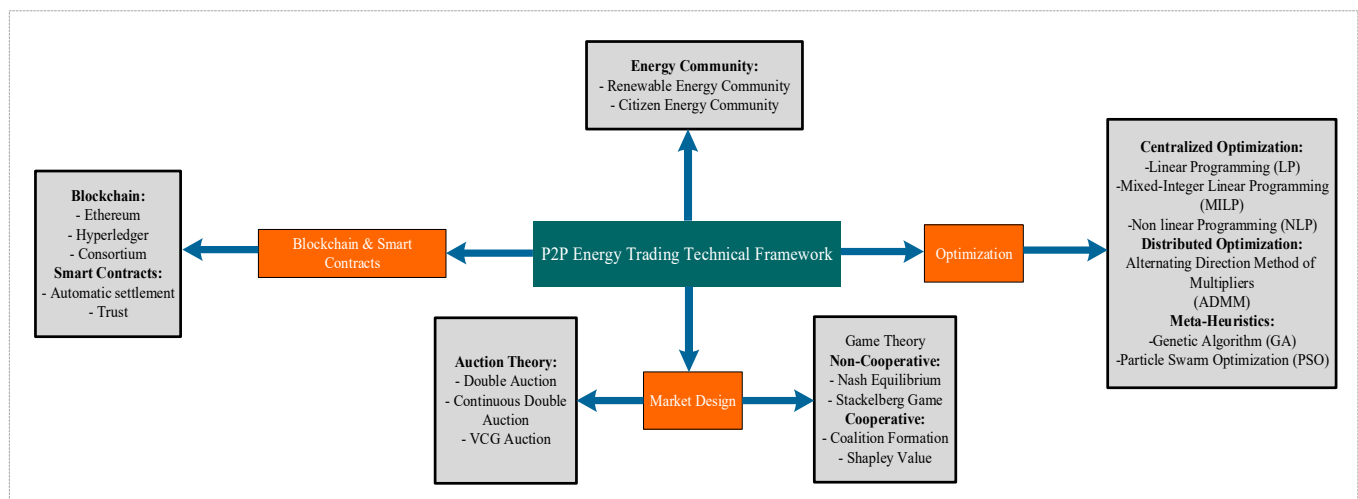


**Figure 2.** Reference multilayer structure used to organize the main components of ML- and blockchain-enabled P2P energy trading.

The blockchain and trust boundary concerns digital transaction management rather than physical power delivery. Depending on the implementation, blockchain may support participant authentication, smart-contract execution, transaction validation, consensus, settlement records, and immutable transaction storage. Trust-related information, such as reputation or account status, may additionally be considered before or after market matching. Blockchain therefore interacts with IoT and ML through exchanged data and transaction decisions, while the actual energy transfer remains subject to the physical network. This separation between physical operation, information processing, market decision-making, and blockchain-based trust control defines the scope used throughout the remainder of the review.

## 2.2. Market Design, Optimization, and Blockchain Implementation

Figure 3 complements the layer-based representation in Figure 2 by focusing on relationships among energy communities, market-design mechanisms, optimization approaches, and blockchain-supported implementation. The figure follows the structure reported in [9] and is used here to organize additional modeling and implementation aspects discussed in the reviewed P2P literature. At the community level, it distinguishes Renewable Energy Communities and Citizen Energy Communities without imposing a trading strategy. The market-design layer represents auction-based and game-theoretic approaches. The optimization layer includes centralized methods such as linear programming (LP), mixed-integer linear programming (MILP), and nonlinear programming (NLP), as well as the alternating direction method of multipliers (ADMM) for distributed optimization. Metaheuristic methods such as genetic algorithms (GA) and particle swarm optimization (PSO) are also represented. The final layer covers blockchain and smart-contract functions used for transaction execution, rule enforcement, and record keeping. Figure 3 is therefore used as an organizing view of market modeling, optimization, and blockchain implementation rather than as a universal P2P architecture.



**Figure 3.** P2P energy trading framework including energy communities, market design, optimization, and blockchain implementation.

## 2.3. Platforms and Market Context

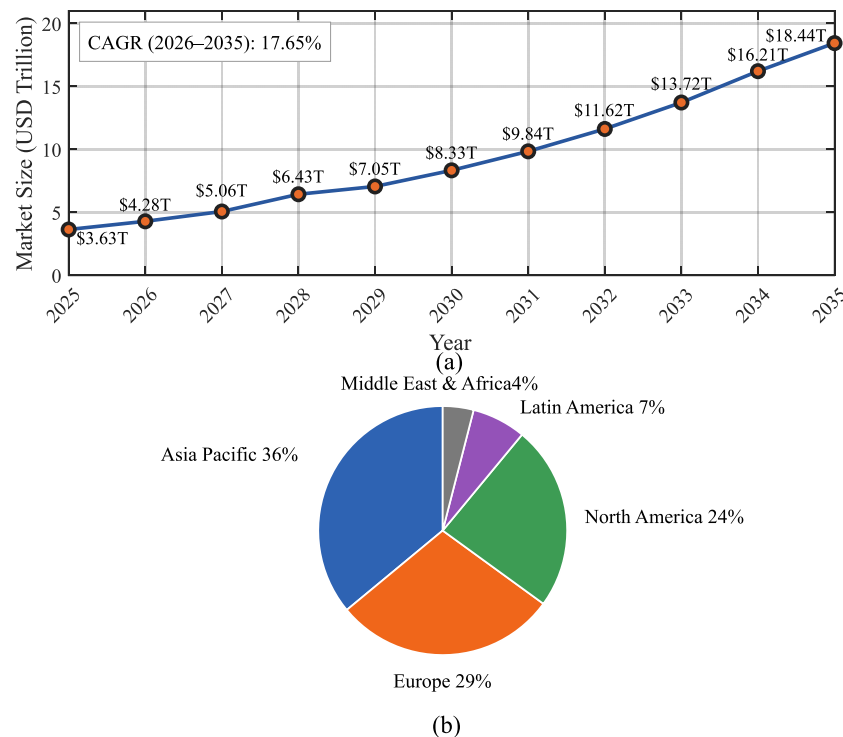
Several pilot and commercial platforms provide examples of how P2P energy trading has been implemented in different settings. Table 3 summarizes selected cases, their trading models, and the supporting technologies. The information is based mainly on the survey by the International Renewable Energy Agency (IRENA) [29]. These cases are included

as implementation context rather than as evidence that one market design or platform is generally preferable.

**Table 3.** Comparative overview of selected global P2P energy trading platforms, highlighting their trading models, technological infrastructures, and distinctive features [29].

| Platform Name                               | Country     | Primary Trading Mechanism/Model                                           | Key Technology & Infrastructure                                                                    | Distinctive Features & Focus                                                                                           |
|---------------------------------------------|-------------|---------------------------------------------------------------------------|----------------------------------------------------------------------------------------------------|------------------------------------------------------------------------------------------------------------------------|
| Brooklyn Microgrid                          | USA         | Community energy market within a microgrid.                               | Blockchain-based smart contracts.                                                                  | Enables direct member-to-member buying and selling of local energy.                                                    |
| Centrica plc (Cornwall Local Energy Market) | UK          | Virtual marketplace connecting flexible assets to grid/wholesale markets. | Flexible demand/generation/storage technologies; blockchain trial (using LO3).                     | Rewards consumers for flexibility; testing local market structures.                                                    |
| Lumenaza                                    | Germany     | “Utility-in-a-box” software platform serving communities.                 | Software for connecting producers/consumers and controlling demand/supply (e.g., battery loading). | Includes balance group management, aggregation, billing, and flow visualization.                                       |
| Piclo                                       | UK          | Preference-based matching engine (every 30 min).                          | Matching software with data visualization for consumption and generation control.                  | Matches consumers/prosumers based on locality and preference. Utility partner (Good Energy) handles balancing/billing. |
| SOLshare                                    | Bangladesh  | Localized P2P sharing within small-scale mini-grids.                      | Interconnected solar home systems forming a mini-grid.                                             | Focus on energy access; allows solar owners to supply surplus power to unconnected neighbors.                          |
| Sonnen Community                            | Germany     | Virtual energy pool sharing.                                              | Individual residential batteries (sonnen batteries).                                               | Surplus is shared within the virtual community pool rather than fed to the grid; fixed pricing model.                  |
| Transactive Energy Initiative               | Colombia    | Pilot project and policy roadmap development.                             | P2P trading application (pilot phase).                                                             | Focus on elaborating policy recommendations for national scale-up rather than immediate commercial operation.          |
| Vandebron                                   | Netherlands | Direct prosumer-to-consumer marketplace.                                  | Platform acts as energy supplier connecting participants.                                          | Consumers buy directly from prosumers at prices set by the prosumers. Platform manages balancing and forecasting.      |

Figure 4 provides contextual information on the broader P2P payment market rather than the P2P energy-trading market itself. As shown in Figure 4a, the global P2P payment market was estimated at USD 3.63 trillion in 2025 and is projected to increase to USD 4.28 trillion in 2026 and USD 18.44 trillion by 2035, corresponding to a reported compound annual growth rate (CAGR) of 17.65% over 2026–2035. Figure 4b complements this market outlook by presenting the regional distribution reported for 2025, with Asia Pacific accounting for the largest share at 36%. These third-party estimates are included only to provide background on the scale and projected development of digital P2P payment activity and should not be interpreted as estimates of the P2P energy-trading market or as evidence of the technical performance or deployment of blockchain-based energy-trading systems.



**Figure 4.** P2P payment market analysis: (a) market size forecast 2025–2035, (b) regional market share in 2025 [30].

#### 2.4. Functional Roles of ML in P2P Energy Trading

The transition toward decentralized energy systems has increased interest in P2P energy trading as a mechanism for enabling direct energy exchange among distributed participants. In such systems, prosumers independently decide when and how much energy to buy or sell based on local conditions. However, variability in renewable energy generation, uncertainty in user demand, and the dynamic nature of local electricity markets introduce challenges that limit the effectiveness of conventional rule-based or static optimization approaches. ML is used to support data-driven decision-making in P2P energy trading environments. A common application of ML in P2P energy trading is short-term forecasting. ML models are used to predict electricity consumption, renewable energy generation, and local market prices based on historical data and contextual information. These forecasts provide participants and market operators with estimates that can be used to plan trading actions and reduce supply–demand mismatches. Compared to traditional methods, ML-based models are also used to represent nonlinear patterns in energy-related time-series data. ML is also applied to pricing and market operation. In P2P markets, prices are often determined dynamically rather than being fixed in advance. ML-based approaches support adaptive pricing strategies by learning from previous transactions, observed demand–supply conditions, and participant behavior. This allows prices to reflect local market conditions while avoiding frequent manual parameter tuning. Another important use of ML is in participant matching and transaction selection. When multiple buyers and sellers are present, ML-based methods can assist in selecting trading pairs by considering factors such as bid prices, transaction history, proximity, and estimated network losses. Incorporating these factors helps improve transaction efficiency without relying solely on price-based matching. In addition, reinforcement learning techniques have been explored to enable participants or system agents to learn trading strategies through repeated interaction with the market. These approaches do not assume prior knowledge of optimal strategies and instead adapt decisions based on observed outcomes.

Such learning-based methods are particularly suitable for environments where market conditions change over time. ML techniques are further employed for monitoring and security purposes. By analyzing reported energy data and transaction patterns, ML-based anomaly detection methods can identify irregular behavior that may indicate faulty measurements or malicious actions. This supports more reliable market operation in decentralized settings.

Across the reviewed studies, ML is used mainly for forecasting, pricing, matching, decision support, and monitoring. Its role varies by application: in some studies, it supplies inputs to an optimization or market mechanism, while in others it directly supports sequential trading decisions.

Table 4 summarizes representative studies on ML applications in P2P energy trading. The comparison identifies each study's main objective, the function assigned to ML, the adopted method, the market or decision mechanism, data basis, validation approach, and stated limitation. This structure is used to separate functional roles from algorithm families.

**Table 4.** Summary of ML applications in P2P Energy trading.

| Ref. | Main Goal                                       | Role of ML                               | ML Technique                                                                             | Decision/Market Mechanism                 | Market Structure                   | Trading Scope         | Data Type                       | Validation                                                              | Key Limitations                |
|------|-------------------------------------------------|------------------------------------------|------------------------------------------------------------------------------------------|-------------------------------------------|------------------------------------|-----------------------|---------------------------------|-------------------------------------------------------------------------|--------------------------------|
| [31] | Flexibility-aware P2P trading under uncertainty | ML for point & quantile forecasting      | Clustering + tree-based ensembles                                                        | Optimization-driven (robust optimization) | Decentralized (ADMM)               | Prosumer community    | Historical net-load data        | Case study; autoregressive integrated moving average (ARIMA) comparison | ML limited to forecasting      |
| [32] | Autonomous P2P trading cost reduction           | ML as core decision engine               | Model-based asynchronous advantage actor centralized-critic with communication (MB-A3C3) | Learning-driven (double auction)          | Decentralized agents               | Large-scale community | Real-world household data       | Simulation vs. reinforcement-learning (RL) baselines                    | Simplified grid constraints    |
| [33] | Efficient nano/microgrid energy exchange        | ML for forecasting + decision-making     | Short-term forecasting + multi-agent reinforcement learning (MARL)                       | Hybrid learning-based                     | Decentralized multi-agent          | Nano/microgrid        | Real-world datasets             | Simulation vs. rule-based                                               | Limited scalability            |
| [34] | Price prediction for P2P platforms              | ML for price forecasting only            | Long short-term memory (LSTM) + decision tree                                            | Rule-based trading                        | Blockchain-supported decentralized | Community-level       | Historical market data          | Forecast accuracy metrics                                               | No ML-based decision-making    |
| [35] | Energy-saving P2P trading                       | ML for trading decisions                 | Multi-agent reinforcement learning                                                       | Learning-driven                           | Community-based decentralized      | Community-level       | Simulated data                  | Simulation analysis                                                     | No physical grid constraints   |
| [36] | P2P market operation under uncertainty          | ML for learning optimal control policies | Learning-based policy approximation                                                      | Hybrid optimization + learning            | Distributed (ADMM)                 | Local P2P markets     | Simulated uncertainty scenarios | Benchmark comparison                                                    | No behavioral modeling         |
| [37] | Behavior-aware P2P trading                      | ML for risk-sensitive pricing            | Q-learning + deep Q-network (DQN) + prospect theory                                      | Hybrid (RL + evolutionary)                | Fully decentralized                | Community-level       | Real consumption traces         | Performance evaluation                                                  | Computational cost can be high |
| [38] | Agent-based P2P trading review                  | Conceptual ML discussion                 | Conceptual taxonomy                                                                      | Agent-based models                        | Community-based                    | Building/community    | Literature-based                | Conceptual review                                                       | No executable framework        |
| [39] | Joint pricing and scheduling                    | ML fully controls pricing & scheduling   | Hierarchical DRL + multi-agent deep reinforcement learning (MADRL)                       | Learning-driven hierarchical              | Community-based with manager       | Neighborhood-level    | Realistic household data        | Simulation benchmarks                                                   | Requires community manager     |

Note: Functional categories refer to the primary role performed by ML in the P2P trading system; individual algorithmic techniques may support more than one functional category.

ML applications in P2P energy trading are classified here according to the primary function performed by ML within the trading system rather than according to the algorithm family employed. This distinction is important because algorithmic categories are not mutually exclusive; for example, deep neural networks may be used for supervised forecasting or reinforcement learning, while graph-based models may support forecasting, decision-making, or network-related tasks. Accordingly, each study is interpreted primarily according to the role that ML performs in the trading framework. Five functional categories are considered: forecasting-oriented applications, ML-assisted decision and optimization, learning-driven market operation, behavioral and trust-aware modeling, and infrastructure- and security-oriented applications.

#### 2.4.1. Forecasting-Oriented Applications

In the first category, ML is employed primarily as a forecasting tool to support P2P trading decisions [40]. In these studies, ML models are used to predict quantities such as electricity demand, renewable generation, net load, market prices, or flexibility margins. The forecasting outputs are then fed into optimization-based or rule-based trading mechanisms. In this category, ML does not directly determine trading decisions, prices, or market clearing outcomes. Instead, it improves the quality of input information used by downstream decision-making processes. Typical approaches include regression models, tree-based ensemble methods, and neural networks for point or probabilistic forecasting. This category represents a common use of ML in P2P energy trading, particularly when forecasting is used as an input to a separate market or optimization step.

#### 2.4.2. ML-Assisted Decision and Optimization

The second category includes studies where ML plays a decision-support role by assisting optimization, control, or game-theoretic models [41]. In these approaches, ML is used to learn system parameters, approximate complex mappings, or reduce computational complexity, while the final trading decisions are still governed by analytical or optimization-based formulations. Typical applications include learning price adjustment rules, approximating optimal policies, estimating user behavior parameters, or supporting distributed optimization methods such as ADMM. ML and optimization are therefore tightly coupled, with learning providing data-driven support rather than replacing the model-based decision layer. This category represents a transitional approach between purely optimization-driven systems and fully learning-driven markets.

#### 2.4.3. Learning-Driven Market Operation

In the third category, ML is directly responsible for market operation and decision-making. Here, trading quantities, internal prices, matching strategies, or consumption schedules are learned through interaction with the environment, often without explicit optimization models. Most studies in this category rely on reinforcement learning, including multi-agent and hierarchical variants, to capture the sequential and decentralized nature of P2P trading. These approaches can adapt to changing system conditions but typically introduce increased computational complexity and training requirements. In practice, some learning-driven frameworks also rely on semi-centralized coordination structures, such as community managers or aggregators, to support coordination or training stability; convergence properties remain method-specific.

#### 2.4.4. Behavioral and Trust-Aware Modeling

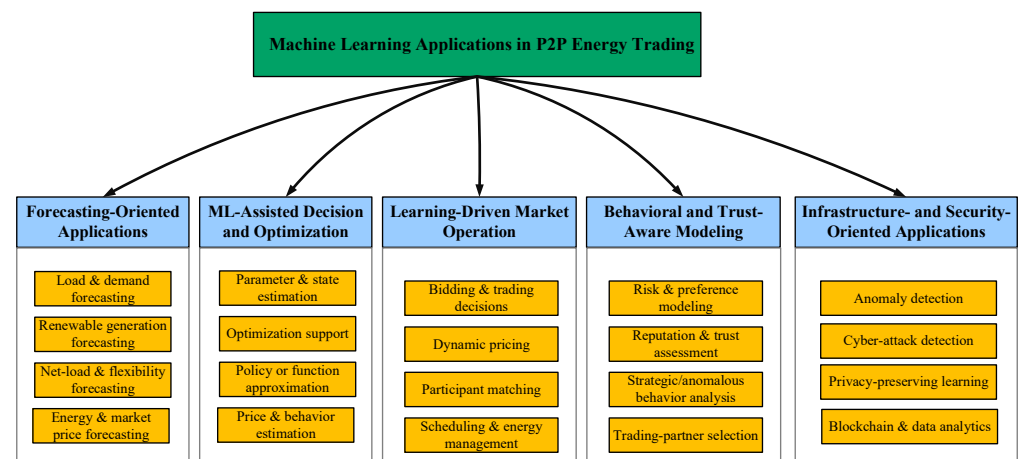
The fourth category focuses on the use of ML to capture participant behavior and trust-related aspects in P2P energy trading [42]. Rather than modeling energy flows alone, these studies incorporate behavioral uncertainty, risk preferences, or reputation dynamics into the

trading framework. Applications include modeling prosumer risk attitudes, learning trust or reputation scores, detecting strategic or anomalous behavior, and supporting partner selection in decentralized markets. ML is often combined with behavioral economics concepts or heuristic decision models. Although this category is less represented than forecasting or decision-driven applications, it addresses behavioral and trust-related aspects that are not represented by energy-balance models alone.

#### 2.4.5. Infrastructure- and Security-Oriented Applications

The final category includes ML applications that target infrastructure-level and security-related challenges associated with P2P energy trading platforms. In these studies, ML is not directly involved in trading decisions but supports the reliable and secure operation of the underlying system. Typical applications include anomaly detection, cyber-attack detection, privacy preservation, and blockchain analytics. These methods are often adapted from broader smart grid or cybersecurity literature and applied to P2P trading environments. Although these functions are indirect, they can support monitoring, security analysis, and user trust.

Figure 5 summarizes the same functional classification used in the preceding discussion. The taxonomy is therefore organized by the primary role of ML in P2P energy trading rather than by learning paradigm or model architecture. Algorithmic approaches such as supervised learning, reinforcement learning, deep neural networks, and graph-based models are treated as methods that may support one or more functional roles and are not used as mutually exclusive top-level categories.



**Figure 5.** Functional taxonomy of ML applications in P2P energy trading based on their primary role in the trading system.

#### 2.5. Illustrative Forecasting and P2P Planning Example

To complement the review discussion with a transparent numerical example, a small forecasting-based P2P trading case is considered. Its purpose is limited to illustrating how forecast errors propagate into planned community energy exchanges. The example does not introduce a new forecasting method, market-clearing mechanism, or network model, and the results are not used as evidence of physical-grid feasibility or practical deployment.

To provide a transparent numerical illustration of the forecasting role discussed above, a five-prosumer synthetic community was evaluated over eight consecutive days at hourly resolution. The first seven days (168 h) were used for model fitting, while the final 24 h were retained as an unseen test period. Synthetic load profiles include time-varying daily demand patterns, whereas photovoltaic (PV) generation follows daylight-dependent profiles; peer-specific scaling factors and bounded deterministic perturbations introduce

heterogeneity while keeping the example deterministic. No external or field dataset is used in this example.

The naive benchmark uses one-hour persistence. The ML-based case uses an ordinary least-squares (OLS) regression model fitted separately for each prosumer using 1-h, 2-h, and 24-h net-energy lags together with sine and cosine time-of-day terms. At each test hour, forecast net-energy values are converted into community-level planned P2P exchange and grid import using the same aggregate energy-balance rule applied to the realized values. The configuration and resulting quantitative indicators are summarized in Table 5.

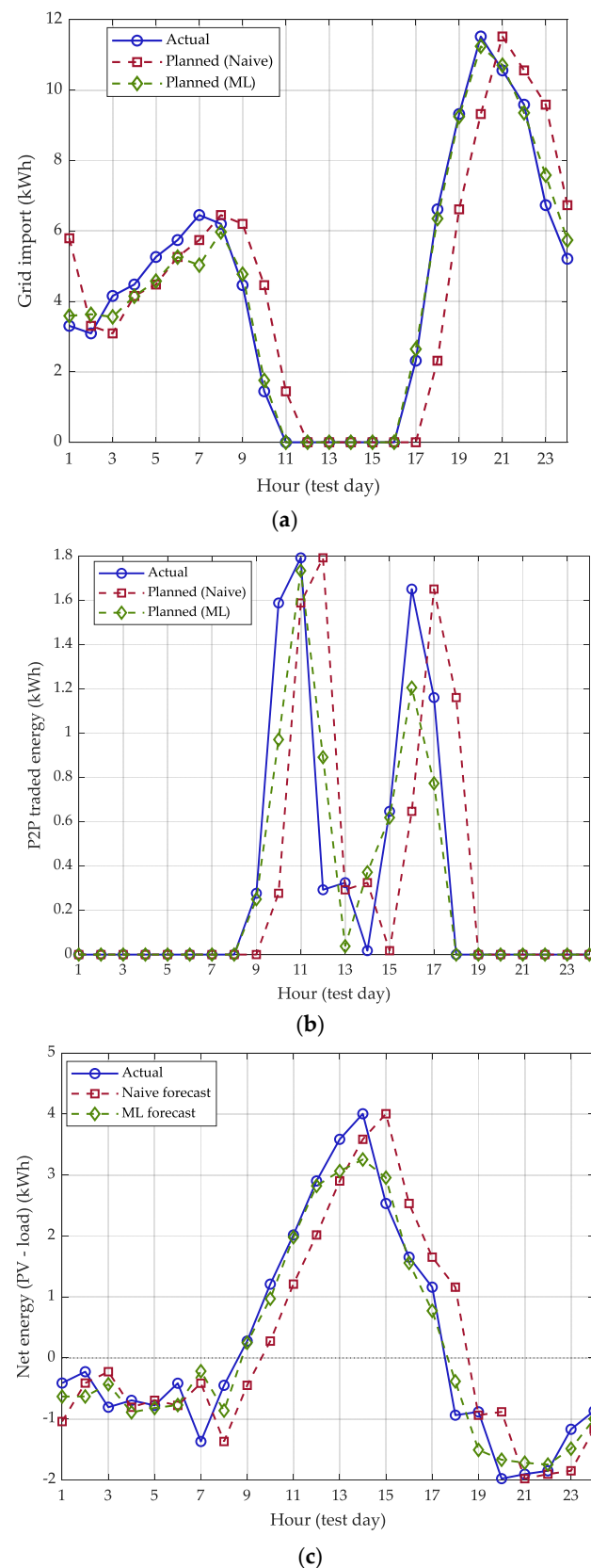
**Table 5.** Configuration and quantitative outcomes of the illustrative forecasting example.

| Item                                                      | Actual/Setup                                                                      | Naive Benchmark      | ML-Based Forecast                                             | Reduction vs. Naive |
|-----------------------------------------------------------|-----------------------------------------------------------------------------------|----------------------|---------------------------------------------------------------|---------------------|
| Community and horizon                                     | 5 prosumers; 8 synthetic days; hourly resolution                                  | -                    | -                                                             | -                   |
| Train/test split                                          | First 7 days (168 h) for fitting; final 24 h for testing                          | -                    | -                                                             | -                   |
| Data generation                                           | Synthetic heterogeneous load/PV profiles with bounded deterministic perturbations | -                    | -                                                             | -                   |
| Forecast formulation                                      | One-step-ahead net energy                                                         | One-hour persistence | OLS regression: lags 1, 2, 24 + time-of-day sine/cosine terms | -                   |
| P2P/grid calculation                                      | Aggregate energy balance; no network power-flow model                             | Same rule            | Same rule                                                     | -                   |
| MAE (kWh)                                                 | -                                                                                 | 0.4240               | 0.2219                                                        | 47.67%              |
| RMSE (kWh)                                                | -                                                                                 | 0.5660               | 0.2885                                                        | 49.03%              |
| MAPE (%) †                                                | -                                                                                 | 48.51                | 22.94                                                         | 52.70%              |
| Total grid import (kWh)                                   | 106.4709                                                                          | 107.0539             | 105.1870                                                      | -                   |
| Total P2P traded energy (kWh)                             | 7.7494                                                                            | 7.7494               | 6.8521                                                        | -                   |
| Total absolute hourly grid-import planning mismatch (kWh) | -                                                                                 | 30.3529              | 7.9029                                                        | 73.96%              |
| Total absolute hourly P2P planning mismatch (kWh)         | -                                                                                 | 6.9140               | 2.8024                                                        | 59.47%              |
| Absolute difference in daily total grid import (kWh)      | 0                                                                                 | 0.5830               | 1.2839                                                        | -                   |
| Absolute difference in daily total P2P energy (kWh)       | 0                                                                                 | 0.0000               | 0.8973                                                        | -                   |

† MAPE is evaluated only for samples with  $|\text{actual net energy}| \geq 0.25$  kWh; 111 of the 120 prosumer-hour observations satisfy this condition.

Forecast error is reported using MAE, root mean square error (RMSE), and mean absolute percentage error (MAPE). The planning analysis also reports total grid import, total P2P traded energy, and absolute hourly mismatches between planned and realized profiles.

Table 5 shows that the regression-based forecast produces lower point-wise forecasting errors and smaller hour-by-hour planning mismatches than the persistence benchmark. However, the aggregate daily totals should be interpreted separately from temporal tracking accuracy. In particular, the naive case happens to reproduce the realized total P2P energy exactly and gives a smaller absolute error in total daily grid import, whereas the ML-based case provides lower cumulative hourly deviations. Figure 6 therefore complements Table 5 by showing where these differences occur over the 24-h test period.



**Figure 6.** Hourly behavior of the illustrative forecasting example over the 24-h test period: (a) realized and forecast-based planned community grid import; (b) realized and forecast-based planned P2P traded energy; and (c) realized net energy of Prosumer 1 compared with the naive persistence and regression-based forecasts.

Figure 6a shows the hourly grid-import profiles obtained from the realized and forecast net-energy values. The realized community grid import remains positive during hours 1–10, falls to zero during hours 11–16, and becomes positive again from hour 17 onward. The persistence-based plan exhibits pronounced temporal deviations around several rapid transitions. For example, it retains a positive grid-import requirement at hour 11 after the realized requirement has already fallen to zero, and it continues to predict zero grid import at hour 17 when the realized value has returned to 2.3165 kWh. Overall, the regression-based profile follows these transition periods more closely in the audited run. Consequently, the total absolute hourly grid-import planning mismatch decreases from 30.3529 kWh for the naive forecast to 7.9029 kWh for the ML-based forecast, corresponding to a 73.96% reduction. This reduction refers to hour-by-hour profile consistency rather than the daily energy total: the absolute error in total grid import is 0.5830 kWh for the naive case and 1.2839 kWh for the ML-based case.

Figure 6b focuses on local P2P exchange. In the realized profile, P2P trading occurs only between hours 9 and 17, when local surplus and deficit coexist within the synthetic community. The persistence benchmark shifts several of these trading quantities in time, particularly around hours 10–12 and 15–18. The regression-based plan reduces the cumulative temporal deviation, with the total absolute hourly P2P planning mismatch decreasing from 6.9140 to 2.8024 kWh, equivalent to a 59.47% reduction. This result should not be interpreted as an improvement in the daily aggregate P2P volume. The naive planned total equals the realized total of 7.7494 kWh in this test day, whereas the ML-based planned total is 6.8521 kWh. The improvement observed here therefore concerns the temporal distribution of planned exchanges rather than their 24-h aggregate.

Figure 6c provides a peer-level view using Prosumer 1 as a representative example. The realized net-energy profile changes from net deficit during the early hours to positive PV-driven surplus around the middle of the day and returns to deficit later in the horizon. Because the persistence forecast uses the immediately preceding observation, visible lag appears around several of these changes. The regression-based forecast reduces the overall discrepancy for this prosumer, although it does not reproduce every hourly value exactly. For Prosumer 1, MAE decreases from 0.6454 to 0.3315 kWh, RMSE from 0.8038 to 0.4193 kWh, and MAPE from 69.25% to 31.45%. At the individual-peer level, all five prosumers show lower MAE, RMSE, and MAPE under the regression-based forecast in this synthetic run. Across the full five-prosumer test set, MAE decreases from 0.4240 to 0.2219 kWh, RMSE from 0.5660 to 0.2885 kWh, and MAPE from 48.51% to 22.94%, corresponding to reductions of 47.67%, 49.03%, and 52.70%, respectively.

Taken together, Table 5 and Figure 6 show that the regression-based forecast improves point-wise net-energy prediction and reduces the temporal mismatch between planned and realized grid/P2P exchanges in this synthetic test case. At the same time, the results also show why hourly mismatch and aggregate daily totals should not be treated as equivalent indicators: the persistence benchmark happens to reproduce some daily totals more closely despite its larger temporal deviations. The numerical example is therefore used only to illustrate the operational consequence of forecasting error on short-term P2P planning. It does not constitute a benchmark of forecasting algorithms, a physical power-flow validation, or evidence of practical market performance.

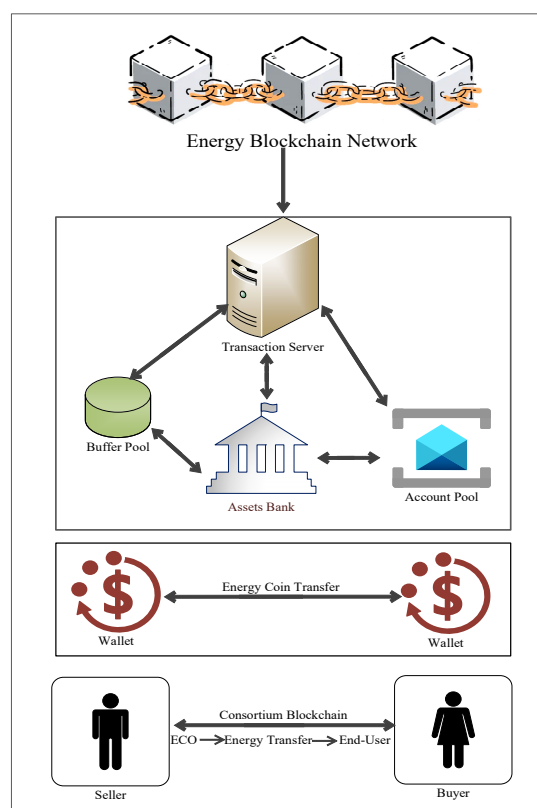
### 3. Blockchain-Supported Trust, Privacy, and Illustrative Transaction Workflow

#### 3.1. Trust Architecture and Consensus Considerations

Building on the architectural discussion in Section 2, this section focuses on the transaction and trust-related operation of blockchain-supported P2P energy trading. The

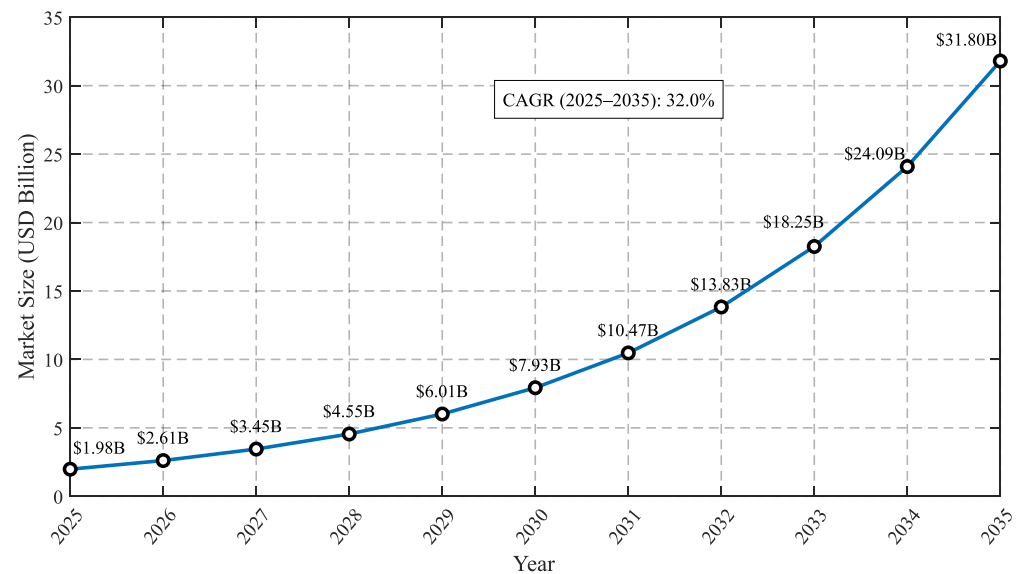
purpose is not to introduce a second system architecture, but to examine how transaction management, trust assessment, blockchain validation, settlement, and ledger recording are represented in the reviewed literature and in the subsequent illustrative workflow. The discussion therefore proceeds from a literature-based trust and payment architecture to a comparison of trustworthy trading mechanisms and, finally, to a simplified executable workflow used for illustration.

Figure 7 illustrates a trust-based payment and energy trading architecture for P2P energy markets implemented on a consortium blockchain [43]. The framework separates transaction management, financial settlement, and physical energy transfer while maintaining coordination among these components. At the top level, the Energy Blockchain Network is responsible for validating transactions and recording confirmed events through a consensus process. The Transaction Server interfaces with the blockchain and manages transaction submission, verification, and confirmation handling. The intermediate layer supports payment and trust management. The Buffer Pool temporarily stores pending transactions, while the Account Pool maintains participant account information and trust-related data. The Assets Bank provides energy coin loans to buyers based on their trust values when their wallet balance is insufficient, which helps reduce transaction confirmation delays. At the lower level, financial settlement and energy delivery are executed. Energy coin transfers occur from the buyer's wallet to the seller's wallet after transaction confirmation. In parallel, energy is delivered from the Energy Collector (ECO) to the End-User through the physical energy network. All payment and transfer records are stored on the consortium blockchain. Overall, Figure 7 presents the interaction between blockchain validation, trust-based payment support, and physical energy exchange within a P2P energy trading system.



**Figure 7.** Trust-based payment and energy trading architecture for P2P energy markets using a consortium blockchain.

Figure 8 reports a third-party market forecast for blockchain in energy trading [44]. The source estimates a market size of USD 1.98 billion in 2025 and USD 2.61 billion in 2026, with a projection of USD 31.80 billion by 2035 and a reported CAGR of 32.00% for 2026–2035. The figure is included as market context; these projections are not used as evidence of technical performance or deployment readiness in the review.



**Figure 8.** Blockchain in Energy Trading Market forecast (2025–2035) [44].

Table 6 compares recent P2P energy-trading studies according to three forms of trust considered in their formulations:

- Computational and transaction trust: consensus, verification, or coordination mechanisms determine how transaction states, market outcomes, or submitted solutions are accepted and recorded. The guarantee depends on the adopted protocol and should not be interpreted as verification of physical-grid feasibility.
- Operational trust: physical-grid constraints, where modeled, are used to test whether market activity remains within stated network limits.
- Data trust: privacy-preserving methods and data-handling rules are used to limit information exposure or manipulation within the trading process.

**Table 6.** Comparative analysis of trustworthy operations in blockchain-based P2P energy trading mechanisms.

| References | Focus                                        | Primary Problem                                                       | Core Methodology                                                      | Consensus/Algorithm                                   |
|------------|----------------------------------------------|-----------------------------------------------------------------------|-----------------------------------------------------------------------|-------------------------------------------------------|
| [45]       | Blockchain Network-Constrained               | Complexity of on-chain optimization & reliance on untrusted entities. | On-chain/off-chain collaborative architecture to offload computation. | Proof-of-Mixed-Integer-Programming (PoMIP)            |
| [46]       | P2P Trading Trilemma                         | The “P2P energy trading trilemma” & lack of incentive compatibility.  | Decentralized negotiation with alternating update algorithm (AUA).    | Consensus inspired by Proof of Solution               |
| [47]       | On-chain linear power flow & Loss Allocation | Limited blockchain capacity for on-chain flow/loss analysis.          | On-chain linear power flow for simplified calculation.                | Distributed market clearing algorithm                 |
| [48]       | Privacy-Preserving Optimization              | Vulnerability to manipulation & privacy leakage in standard schemes.  | Encrypted Bids/Offers submission protocol.                            | Privacy-preserving Byzantine fault tolerance (PP-BFT) |

Table 6. *Cont.*

| References | Focus                                                                                       | Primary Problem                                                                          | Core Methodology                                                                                                                  | Consensus/Algorithm                              |
|------------|---------------------------------------------------------------------------------------------|------------------------------------------------------------------------------------------|-----------------------------------------------------------------------------------------------------------------------------------|--------------------------------------------------|
| [49]       | Large-Scale Reconfiguration                                                                 | Computational burden in large-scale active distribution networks.                        | Distributed optimization integrated with dynamic network reconfiguration.                                                         | PoA                                              |
| [50]       | Stackelberg Game & Comm. Loss                                                               | Low trading efficiency and communication losses.                                         | Stackelberg Game (Leader–Follower) & market type determination.                                                                   | Feasible region-based trading strategy           |
| [51]       | Unified permissioned blockchain-based P2P energy-trading architecture and IBFT              | Public blockchains are slow; permissioned ones lack BFT; fragmented markets.             | Unified permissioned blockchain-based P2P energy-trading architecture (UBETA) on Hyperledger Besu integrating three market types. | IBFT                                             |
| [52]       | Polkadot & Multi-Period Market                                                              | Simplistic markets ignore inter-temporal constraints (devices running multiple periods). | Polkadot Sidechain implementation with MILP optimization model.                                                                   | Polkadot Network Architecture (Secure Sidechain) |
| [53]       | Joint Energy-Reserve and pipelined delegated Byzantine fault tolerance (PDBFT)              | Lack of pricing for Joint Energy & Reserves; Inefficiency of standard PBFT.              | Joint Energy-Reserve Mechanism quantifying flexibility value.                                                                     | PDBFT                                            |
| [54]       | Multi-round double auction (MRDA) with average pricing mechanism (APM) and zonal clustering | Integrating technical costs (congestion/voltage) without high complexity.                | MRDA with APM.                                                                                                                    | Zonal Matching Algorithm (Market Clearing)       |

Table 6 therefore provides a study-level view of how different trust, validation, and market-coordination mechanisms have been incorporated into blockchain-supported P2P energy trading. Because the listed consensus approaches rely on different validator structures, fault assumptions, and agreement procedures, their implications for scalability, latency, fault tolerance, and market suitability require a separate protocol-level comparison.

For clarity, the protocol abbreviations used below are Byzantine fault tolerance (BFT), practical Byzantine fault tolerance (PBFT), Istanbul Byzantine fault tolerance (IBFT), and proof-of-authority (PoA).

The mechanisms reported in Table 6 should not be interpreted as interchangeable consensus solutions. Their operational characteristics depend on the validator model, fault assumptions, communication pattern, and finality mechanism adopted by the underlying protocol. These differences are particularly relevant to P2P energy markets, where the validator population may range from a small set of authorized market entities to a larger consortium of distributed participants. Accordingly, the main trade-offs of PBFT, IBFT, PoA, and application-oriented BFT variants are considered below.

PBFT provides Byzantine-fault-tolerant agreement among a known set of replicas and conventionally requires  $n \geq 3f + 1$  replicas to tolerate up to  $f$  Byzantine faults [55]. Its multi-phase message exchange provides deterministic agreement without mining-based competition, but the communication burden increases with the validator population. PBFT is therefore more naturally suited to permissioned P2P-market settings with a bounded number of validators and an explicit requirement for Byzantine fault tolerance than to networks in which validator participation is expected to grow without tight control.

IBFT follows a related BFT-oriented design for permissioned blockchain environments with identified validators. Formal analyses of IBFT report the same  $n \geq 3f + 1$  resilience condition and quadratic communication complexity, while termination under favorable communication conditions can be achieved within a small number of message delays [56]. IBFT 2.0 further addresses safety and liveness limitations identified in the earlier protocol and provides immediate finality under its stated eventually synchronous network assumptions, together with support for a dynamic validator set [57]. These characteristics make IBFT relevant to consortium-based P2P energy markets in which participating validators are known, although communication and round-change overhead remain important as the validator set expands.

PoA requires a more careful interpretation because it describes an authority-based validator model rather than one uniform fault-tolerance guarantee. In Clique, for example, block creation is restricted to authorized signers and signer authorization is itself governed through protocol-defined voting rules [58]. This avoids mining-based competition and can simplify operation in permissioned environments, but its resistance to malicious or unavailable authorities and its finality behavior are protocol-specific and should not be assumed to be equivalent to PBFT or IBFT. For P2P energy trading, PoA is therefore most relevant where validator identities and governance responsibilities can be established institutionally and where the resulting trust assumptions are acceptable to the participating market actors.

The application-oriented variants listed in Table 6 should be interpreted in the same context. PP-BFT and PDBFT adapt BFT-related mechanisms to particular privacy, trading, or coordination requirements, whereas other entries in the table employ market-clearing or sidechain mechanisms rather than a directly comparable BFT protocol. Their reported benefits therefore cannot be attributed to the consensus layer alone. For P2P energy markets, protocol selection should instead be based on the expected validator population, tolerated fault model, required transaction finality, communication conditions, governance structure, and permissible settlement delay. In this respect, PBFT emphasizes explicit Byzantine tolerance for bounded permissioned validator sets; IBFT combines BFT-style agreement with blockchain-oriented validator management and immediate finality under its stated assumptions; and PoA can reduce operational complexity through identified authorities but places greater importance on the associated governance and signer-trust model.

### 3.2. Privacy-Preserving Mechanisms for P2P Energy Trading and Data Sharing

Beyond consensus-related trust, Table 6 also identifies the protection of participant data as an important requirement in blockchain-supported P2P energy trading. This issue is particularly relevant because fine-grained consumption and generation profiles, bids and offers, model parameters, and transaction records may reveal information about individual prosumers. Privacy-preserving mechanisms address different stages of this information flow and should therefore be distinguished according to what information they protect and how that protection is achieved. Four representative approaches are federated learning (FL), differential privacy (DP), zero-knowledge proof (ZKP) methods, and secure multiparty computation (SMPC).

FL supports collaborative learning without requiring participants to transfer their raw local datasets to a central training repository. In P2P energy trading, prosumers can train local forecasting or decision models and share model parameters or updates for aggregation while retaining their underlying consumption, generation, or operational data locally [59]. This reduces direct exposure of raw participant data, although FL alone should not be interpreted as a complete privacy guarantee because information may still be inferred from exchanged model updates. DP addresses a different form of information

exposure by introducing controlled randomization into released data, statistics, or model outputs. In P2P energy markets, DP can be used when consumption, generation, or trading-related information must be reported or shared while limiting the extent to which an individual participant can be inferred from the released information [60]. Its use consequently introduces a privacy–utility trade-off, since stronger perturbation may reduce the accuracy of the information available for market or operational decisions.

ZKP methods provide a different capability: they allow one party to demonstrate that a specified statement or computation is valid without disclosing the private information used to establish that result. In blockchain-supported P2P energy trading, this can allow transaction conditions or off-chain computations to be verified while limiting the amount of sensitive participant information exposed on the ledger [61]. SMPC, in contrast, enables several parties to jointly evaluate a function over their private inputs without directly revealing those inputs to one another. For P2P energy markets, SMPC can therefore support privacy-preserving processing of bids, offers, flexibility quantities, or other inputs required for joint trading and market operations [62].

These mechanisms are complementary rather than interchangeable. FL primarily limits the centralized collection of raw training data; DP limits information leakage from data or outputs that must be released; ZKP methods provide verification without disclosure of the underlying private information; and SMPC enables joint computation over private inputs. Their suitability for P2P energy trading therefore depends on the information to be protected, the required market function, and the associated computational, communication, and information-utility trade-offs.

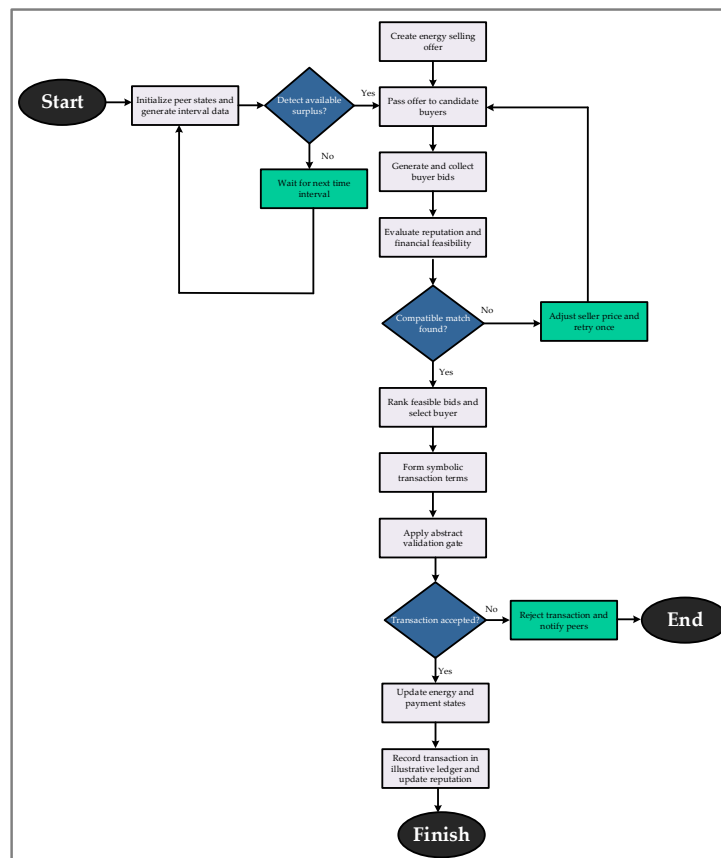
### 3.3. Illustrative Transaction Workflow and Simulation

Figure 9 presents the transaction workflow at two levels. Figure 9a provides a conceptual view of the sequence used in the illustrative P2P trading example. At each trading interval, synthetic generation and consumption values are used to determine the net energy position of each peer. A peer with an eligible surplus can create a sell offer, while peers with sufficient deficits are considered as potential buyers. Buyer responses are then screened according to price compatibility, reputation, and available cash plus credit. If no compatible buyer is found, the seller price is reduced by 2% and the matching process is repeated once. Otherwise, the feasible bids are ranked using the price- and reputation-based score defined in the simulation, and the highest-ranked buyer is selected.

Following buyer selection, the seller, buyer, traded energy, and transaction price define the symbolic transaction terms. As shown in Figure 9a, these terms then pass through an abstract validation stage. This stage represents only a deterministic accept/reject condition used to exercise the corresponding branch of the workflow; it does not implement a specific blockchain consensus protocol. If validation is unsuccessful, the transaction is rejected. If it is accepted and the financial condition remains satisfied, the residual energy positions and payment balances are updated. The transaction record is then added to the illustrative ledger, and the reputation scores of the participating peers are updated.

Figure 9b maps this logic to the main steps traced in the MATLAB implementation. The first five steps cover peer-state initialization, synthetic interval-data generation, surplus detection, offer formation, bid collection, and feasibility screening. Step 6 represents the conditional retry used only when an acceptable match is not obtained on the first evaluation. Step 7 selects the buyer from the feasible candidates, while Steps 8 and 9 define the symbolic transaction terms and apply the abstract validation gate. The final two steps update the energy and financial states and record the accepted transaction together with the corresponding reputation changes. This representation links the conceptual sequence in Figure 9a to the operations implemented in the simulation without implying physical

power-flow validation, cryptographic execution, or the implementation of PBFT, IBFT, PoA, or another consensus protocol.



(a)



(b)

**Figure 9.** Conceptual and executable views of the illustrative P2P energy-trading workflow: (a) general transaction sequence covering synthetic interval-data generation, surplus detection, offer and bid processing, feasibility screening, conditional price adjustment, buyer selection, abstract validation, state updating, and transaction recording; (b) corresponding 11-step representation used to trace the MATLAB R 2023b implementation.

To examine the internal operation of the workflow, a deterministic illustrative MATLAB simulation was implemented for 10 peers over 12 trading intervals. Synthetic PV-generation and consumption profiles are generated from common time-varying shapes, peer-specific scaling factors, and bounded deterministic perturbations. Each peer is initialized with a reputation score, cash balance, and credit allowance. The model does not include power-flow equations, bus voltages, line limits, network losses, communication delay, cryptographic execution, or an implementation of a particular PBFT-, IBFT-, PoA-, or other consensus protocol. Accordingly, its outputs are interpreted only at the transaction-workflow level.

At each interval, peers with a net surplus greater than 0.8 kWh may submit sell offers, whereas peers with deficits larger than 0.8 kWh in magnitude may submit bids. Individual transactions are limited to 5 kWh. Seller minimum prices and buyer maximum prices are generated within 0.95–1.30 times the reference price. Candidate transactions must satisfy the price condition, minimum-reputation threshold, and available cash-plus-credit condition. Feasible buyers are ranked using an illustrative score consisting of 60% normalized transaction price and 40% average buyer-seller reputation. If no compatible match is obtained, the seller minimum price is reduced by 2% and the offer is evaluated once more.

After matching, a symbolic smart-contract stage is followed by an abstract validation gate. The validation threshold is set to 0.90 only to create a reproducible accept/reject event in the workflow; the resulting acceptance frequency is not a performance measure of any blockchain consensus protocol. Confirmed transactions update the residual energy positions of both peers before subsequent matching, transfer payment using available cash and credit, assign a deterministic symbolic transaction identifier for ledger traceability, and increment the reputation of the buyer and seller. The identifier is not presented as a cryptographic hash.

The principal simulation settings and workflow-level indicators are summarized in Table 7. The table reports both the configuration assumptions and the quantitative outcomes obtained from the same deterministic run visualized in Figure 10.

**Table 7.** Configuration and workflow-level outcomes of the illustrative P2P transaction-workflow simulation with symbolic blockchain-related stages.

| Item                                | Specification/Result                                                                                                 | Interpretation                                                     |
|-------------------------------------|----------------------------------------------------------------------------------------------------------------------|--------------------------------------------------------------------|
| Peers/intervals                     | 10 peers/12 trading intervals                                                                                        | Small illustrative workflow case                                   |
| Synthetic energy data               | Time-varying synthetic PV-generation and load profiles + peer-specific scaling + bounded deterministic perturbations | No external feeder or field dataset                                |
| Seller/buyer eligibility            | Surplus > 0.8 kWh/deficit < −0.8 kWh                                                                                 | Avoids very small offers and bids                                  |
| Maximum trade                       | 5 kWh per transaction                                                                                                | Illustrative transaction cap                                       |
| Price range                         | Seller minimum and buyer maximum: $0.95\text{--}1.30 \times \text{reference price}$                                  | Used only for bid compatibility and ranking                        |
| Matching score                      | 60% normalized price + 40% mean buyer-seller reputation                                                              | Illustrative heuristic; not an optimal market-clearing claim       |
| Retry rule                          | 2% seller-price reduction; one retry                                                                                 | Makes the no-match branch executable                               |
| Validation gate                     | Threshold = 0.90                                                                                                     | Abstract accept/reject event; not a consensus-protocol benchmark   |
| Sell offers/bid responses evaluated | 7/21                                                                                                                 | Observed across initial and retry evaluations                      |
| Offer adjustments/unmatched offers  | 2/1                                                                                                                  | The retry branch was exercised twice; one offer remained unmatched |

Table 7. *Cont.*

| Item                                | Specification/Result                                            | Interpretation                                                                      |
|-------------------------------------|-----------------------------------------------------------------|-------------------------------------------------------------------------------------|
| Abstract-gate attempts/rejections   | 6/1                                                             | One matched transaction was rejected by the abstract validation gate                |
| Abstract-gate acceptance rate       | 83.33%                                                          | Run-specific workflow outcome; not PBFT/IBFT/PoA performance                        |
| Settlement-stage rejections         | 0                                                               | All validation-approved transactions satisfied the final cash-plus-credit condition |
| Confirmed trades/confirmation rate  | 5/71.43%                                                        | Five settlements from seven submitted sell offers                                   |
| Confirmed energy                    | 7.7587 kWh                                                      | Total energy transferred by confirmed P2P transactions                              |
| Horizon-level surplus–deficit ratio | 59.35%                                                          | Confirmed energy/min (accumulated potential surplus, accumulated potential deficit) |
| Settled value                       | 1.8117 currency units                                           | Illustrative internal monetary transfer only                                        |
| Mean reputation, initial/final      | 0.7030/0.7208                                                   | Increase reflects reputation updates after confirmed transactions; see Figure 10c   |
| Aggregate cash, initial/final       | 151.0/151.0 currency units                                      | Internal payments conserve aggregate cash in this run; see Figure 10d               |
| Total credit used                   | 0 currency units                                                | All confirmed purchases were covered by available cash                              |
| Physical-grid scope                 | No power flow, voltage, congestion, losses, or protection model | No claim of grid feasibility or deployment readiness                                |

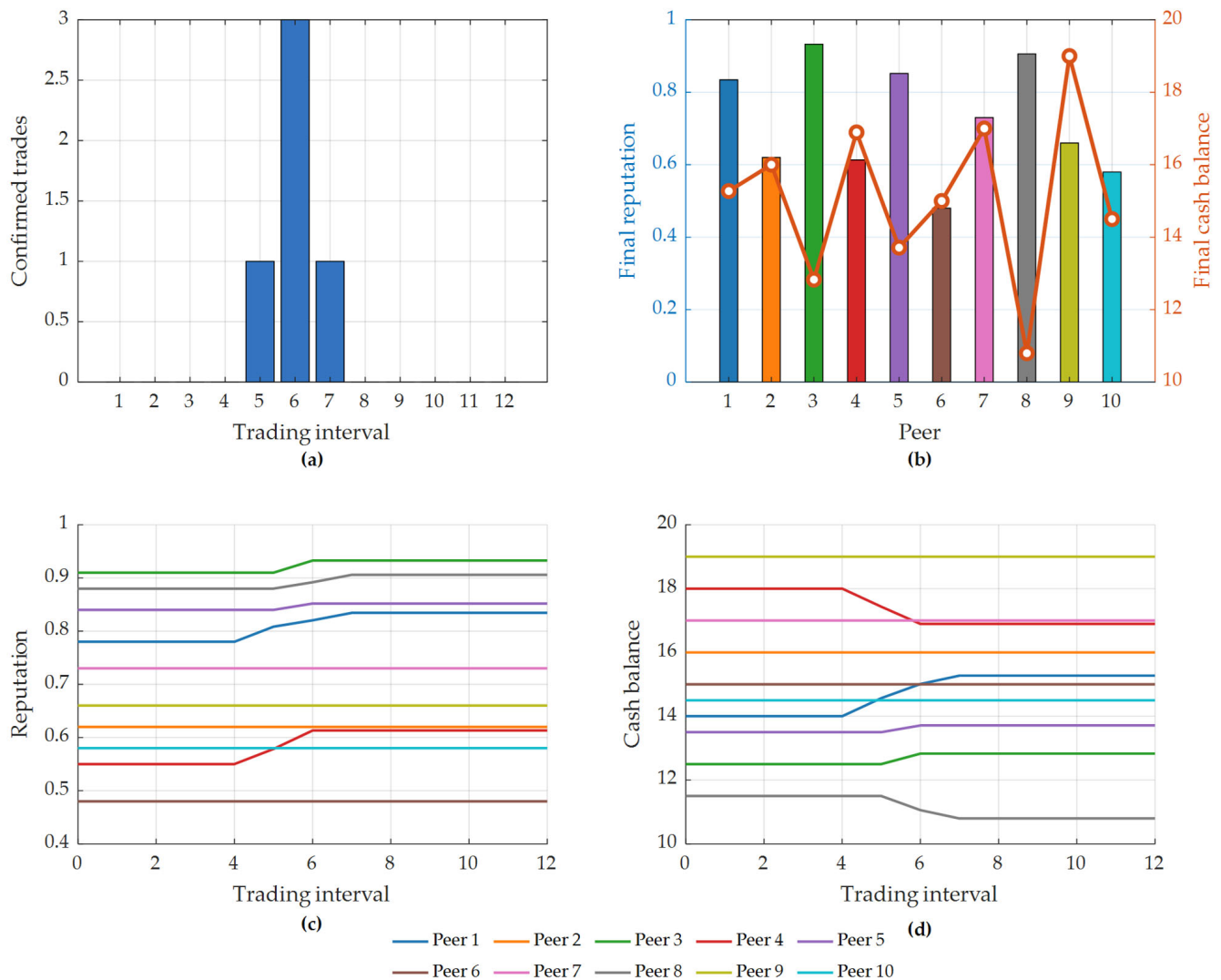
Figure 10 presents the graphical outputs of the same deterministic run summarized in Table 7. Figure 10a reports the number of confirmed transactions in each trading interval, Figure 10b compares the final reputation score and cash balance of each peer, and Figure 10c,d trace the interval-by-interval evolution of reputation and cash, respectively. The common legend identifies Peer 1 through Peer 10 consistently in both trajectory panels.

The transaction timing in Figure 10a shows that all five confirmed trades occur within intervals 5–7: one transaction is settled in interval 5, three in interval 6, and one in interval 7, while no confirmed trade occurs in the remaining intervals. This concentration is consistent with the synthetic profiles because eligible local surplus and deficit must coexist before a transaction can proceed. Across the complete run, seven sell offers are generated and 21 bid responses are evaluated across the initial and retry attempts. Two offers require the single permitted 2% price adjustment, one offer remains unmatched, and six matched transactions reach the abstract validation stage. One of these six transactions is rejected, leaving five confirmed settlements and a 71.43% confirmation rate relative to the seven submitted sell offers.

Figure 10b provides the final peer-level state after settlement. The five confirmed transactions transfer 7.7587 kWh in total, corresponding to 59.35% of the horizon-level surplus–deficit denominator, defined as the minimum of the accumulated potential surplus and accumulated potential deficit over the 12-interval horizon. The associated settled value is 1.8117 currency units. Reputation and cash changes are limited to Peers 1, 3, 4, 5, and 8 because these are the peers participating in the confirmed transactions; the remaining peers retain their initial states. The final mean reputation therefore increases from 0.7030 to 0.7208.

The dynamic trajectories in Figure 10c confirm that reputation changes occur only after confirmed participation, while Figure 10d shows the corresponding internal payment

transfers between buyers and sellers. Aggregate peer cash remains 151.0 currency units from initialization to the end of the run, and no credit is used, which provides an internal accounting-consistency check for the settlement logic. The flat trajectories of nonparticipating peers further confirm that their states are not modified when no confirmed transaction involves them.



**Figure 10.** Workflow-level outputs of the illustrative blockchain-supported P2P trading simulation: (a) confirmed transactions per trading interval; (b) final reputation scores and cash balances of the ten peers; (c) evolution of peer-level reputation scores; and (d) evolution of peer-level cash balances. Each curve in panels (c,d) corresponds to one peer, using the same peer identification in both panels.

#### 4. Challenges and Future Research Directions

The reviewed literature indicates that the remaining limitations of P2P energy trading arise at different technical layers and should be considered separately. Scalability, physical-grid integration, model reliability, and deployment readiness involve different assumptions and evaluation requirements. Distinguishing these issues is important because acceptable performance at the forecasting or market layer does not necessarily demonstrate satisfactory performance at the blockchain or physical-network layer.

##### 4.1. Scalability and Computational/Communication Requirements

Scalability remains a practical concern as the number of participants, bids, transactions, and decision variables increases. At the market layer, larger communities increase the compu-

tational burden of optimization, matching, and learning-based decision methods. Distributed and multi-agent approaches may also require more frequent information exchange among participants. At the blockchain layer, validator communication and transaction-processing requirements depend on the adopted consensus protocol, validator population, and network conditions. As discussed in the preceding consensus comparison, these factors should be reported separately rather than represented by a single scalability indicator.

#### *4.2. Physical-Grid Integration*

Physical-grid integration is another distinct issue. A transaction that is accepted by a market mechanism or recorded on a blockchain does not by itself demonstrate that the associated energy exchange can be accommodated by the distribution network. Voltage limits, line capacities, losses, congestion, protection requirements, and power balance remain dependent on the physical network and operating conditions. Network-constrained P2P trading models account for some of these requirements, but the reviewed studies do not use a common network representation. Claims related to physical feasibility should therefore be supported by explicit network constraints and corresponding technical indicators.

#### *4.3. Model Validation and Evidence Boundaries*

Model reliability and validation evidence also require closer attention. Forecasting, optimization, and learning-based studies are evaluated using different datasets, time horizons, participant populations, and baseline methods, which limits direct comparison across studies. Performance may also change when participant behavior, renewable generation, prices, or communication conditions differ from those represented during model development. Similarly, blockchain-oriented studies may evaluate transaction logic without implementing a complete consensus network, communication layer, or cryptographic execution environment. These different levels of validation should be reported separately so that predictive accuracy, market performance, blockchain execution, physical-grid feasibility, and practical deployment are not interpreted as equivalent forms of evidence.

#### *4.4. Future Research Directions*

Future research should therefore place greater emphasis on controlled and reproducible cross-layer evaluation. Studies using forecasting or learning methods should report data origin, training and testing procedures, prediction errors, computational time, and sensitivity to changing operating conditions.

Future work should also validate the illustrative forecasting and P2P transaction-workflow examples using publicly available real-world energy datasets, such as Pecan Street or UK-DALE, to examine whether the observed planning and trading behaviors remain consistent under measured household demand and generation variability. Such validation would provide a reproducible benchmark for assessing the transferability of the illustrative results beyond the deterministic synthetic profiles considered in this review.

Market and blockchain studies should state the participant and validator populations, transaction workload, consensus assumptions, communication conditions, and settlement or finality criteria. When physical-network benefits are claimed, market outcomes should be evaluated together with voltage, thermal, congestion, loss, and power-balance constraints. Larger pilot studies and communication-aware or hardware-supported experiments would also help determine whether conclusions obtained from simulation remain valid under measurement errors, changing participant behavior, communication failures, and operational constraints.

## **5. Conclusions**

This review examined blockchain- and ML-enabled P2P energy trading by separating the functions performed at the forecasting and decision, market, physical-network, and

transaction/trust layers. The literature already contains prior work on blockchain, optimization, market design, network constraints, and ML. The contribution here is therefore organizational: the review compares these strands within one cross-layer structure, classifies ML by function, and distinguishes physical energy delivery from blockchain-supported transaction management.

The forecasting example shows how prediction error can affect short-term P2P planning in the synthetic five-prosumer case. Across the test set, regression reduced MAE from 0.4240 to 0.2219 kWh, RMSE from 0.5660 to 0.2885 kWh, and MAPE from 48.51% to 22.94%. The cumulative hourly grid-import mismatch decreased from 30.3529 to 7.9029 kWh, and the hourly P2P-planning mismatch from 6.9140 to 2.8024 kWh. These results concern point-wise forecasts and hourly planning. They do not show improvement in every daily total: the persistence benchmark reproduces the realized daily P2P total exactly and has the smaller daily grid-import error in this case.

The blockchain-supported example addresses a different question. For 10 peers over 12 intervals, seven sell offers generated 21 evaluated bid responses; five transactions were confirmed and 7.7587 kWh was settled, corresponding to 59.35% of the defined horizon-level surplus–deficit denominator. Mean reputation changed from 0.7030 to 0.7208, aggregate peer cash remained 151.0 currency units, and no credit was used. These checks support the internal consistency of the workflow. They are not measurements of PBFT, IBFT, or PoA performance, cryptographic security, communication latency, or distribution-network feasibility.

Across the reviewed studies, protocol and model choices depend on the layer being evaluated. Consensus mechanisms differ in validator assumptions, communication burden, and finality; privacy methods protect different information flows; and market or forecasting results do not establish physical-grid feasibility unless network constraints are modeled explicitly. Future studies should therefore report evidence at these layers separately and document the data, validator, communication, network, and implementation assumptions needed to interpret each result.

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## Abbreviations

The following abbreviations are used in this manuscript:

|         |                                                                                |
|---------|--------------------------------------------------------------------------------|
| ACM     | Association for Computing Machinery                                            |
| ADMM    | Alternating Direction Method of Multipliers                                    |
| AI      | Artificial Intelligence                                                        |
| APM     | Average Pricing Mechanism                                                      |
| ARIMA   | Autoregressive Integrated Moving Average                                       |
| AUA     | Alternating Update Algorithm                                                   |
| BFT     | Byzantine Fault Tolerance                                                      |
| CAGR    | Compound Annual Growth Rate                                                    |
| DERs    | Distributed Energy Resources                                                   |
| DP      | Differential Privacy                                                           |
| DQN     | Deep Q-Network                                                                 |
| DRL     | Deep Reinforcement Learning                                                    |
| ECO     | Energy Collector                                                               |
| FL      | Federated Learning                                                             |
| GA      | Genetic Algorithm                                                              |
| HEM     | Home Energy Management                                                         |
| IBFT    | Istanbul Byzantine Fault Tolerance                                             |
| ICT     | Information and Communication Technology                                       |
| IEEE    | Institute of Electrical and Electronics Engineers                              |
| IET     | Institution of Engineering and Technology                                      |
| IoT     | Internet of Things                                                             |
| IRENA   | International Renewable Energy Agency                                          |
| kWh     | kilowatt-hour                                                                  |
| LP      | Linear Programming                                                             |
| LSTM    | Long Short-Term Memory                                                         |
| MADRL   | Multi-Agent Deep Reinforcement Learning                                        |
| MAE     | Mean Absolute Error                                                            |
| MAPE    | Mean Absolute Percentage Error                                                 |
| MARL    | Multi-Agent Reinforcement Learning                                             |
| MB-A3C3 | Model-Based Asynchronous Advantage Actor-Centralized-Critic with Communication |
| MILP    | Mixed-Integer Linear Programming                                               |
| ML      | Machine Learning                                                               |
| MRDA    | Multi-Round Double Auction                                                     |
| NLP     | Nonlinear Programming                                                          |
| OLS     | Ordinary Least Squares                                                         |
| P2P     | Peer-to-Peer                                                                   |
| PBFT    | Practical Byzantine Fault Tolerance                                            |
| PDBFT   | Pipelined Delegated Byzantine Fault Tolerance                                  |
| PoA     | Proof-of-Authority                                                             |
| PoMIP   | Proof-of-Mixed-Integer-Programming                                             |
| PP-BFT  | Privacy-Preserving Byzantine Fault Tolerance                                   |
| PRISMA  | Preferred Reporting Items for Systematic Reviews and Meta-Analyses             |
| PSO     | Particle Swarm Optimization                                                    |
| PV      | Photovoltaic                                                                   |
| RL      | Reinforcement Learning                                                         |
| RMSE    | Root Mean Square Error                                                         |
| SMPC    | Secure Multiparty Computation                                                  |
| UBETA   | Unified Permissioned Blockchain-Based P2P Energy-Trading Architecture          |
| USD     | United States dollar                                                           |
| ZKP     | Zero-Knowledge Proof                                                           |

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