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Review

Energy Trading in Local Energy Markets: A Comprehensive Review of Models, Solution Strategies, and Machine Learning Approaches

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Abstract: The increasing adoption of renewable energy sources and the emergence of distributed generation have significantly transformed the traditional energy landscape, leading to the rise of local energy markets. These markets facilitate decentralized energy trading among different market participants at the community level, fostering greater energy autonomy and sustainability. As local energy markets gain momentum, the application of artificial intelligence techniques, particularly reinforcement learning, has gained substantial interest in optimizing energy trading strategies by interacting with the environment and maximizing the rewards by addressing the decision complexities by learning. This paper comprehensively reviews the different energy trading projects initiated at the global level and machine learning approaches and solution strategies for local energy markets. State-of-the-art reinforcement learning algorithms are classified into model-free and model-based methods. This classification examines various algorithms for energy transactions considering the agent type, learning methods, policy, state space, action space, and action selection for state, action, and reward function outputs. The findings of this work will serve as a valuable resource for researchers, stakeholders, and policymakers to accelerate the adoption of the local energy market for a more efficient, sustainable, and resilient energy future.

Keywords: energy trading; local energy markets; bidding and auction; artificial intelligence; machine learning; reinforcement learning

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1. Introduction

1.1. Background

The global world is continuously witnessing ever-increasing energy demand due to commercialization, industrialization, and, more importantly, urbanization. On the other hand, there has unfortunately been no significant discovery of large-scale energy reserves in the past two to three decades [1]. It is anticipated that post-pandemic recovery and increasing global warming will drive global energy consumption up to 1.8% in 2024, compared to just 1.2% in 2023 [2]. In addition, there is increasing demand in Asia, despite high energy prices in the region, and globally due to ongoing geopolitical tensions [3]. As a result, threats of upcoming energy crises are becoming more prominent since the relationship between energy reserves and energy consumption is becoming non-linear [4]. According to [5], it is estimated that by 2030, renewable power consumption accounts for 36% of the total global RE use, whereas end-use sectors account for 64% (including the traditional use of biomass), as shown in Figure 1. When only modern renewables are considered, the share of power and the end-use sectors in the total global RE are 40% and 60%, respectively.

The traditional electricity network is characterized by a centralized structure where energy is generated from large power plants and then distributed to consumers after traveling a long distance through complex energy transportation meshes. This complex structure is vulnerable to single points of failure, often failing to provide universal energy access, especially in remote or underserved areas. Additionally, it does not empower consumers to actively participate in energy markets or provide pricing opacity for consumers in the sale or purchase of energy. It is also subject to polluted environmental impacts [6], and consequently, it faces increased risks of supply disruptions and unexpected outages due to climate change vulnerabilities. In recent years, the global energy system has undergone a significant transformation driven by the rising demand for distributed energy resources (DERs), advancements in energy technology, and reduction in greenhouse gas emissions [7]. The risks associated with DERs have led to a shift from only a consumer-driven market to all electricity market players [8] through a competitive energy market (CEM). Traditionally, the electricity market comprises the wholesale electricity market (WEM) and the retail electricity market (REM) [9], as shown in Figure 2.

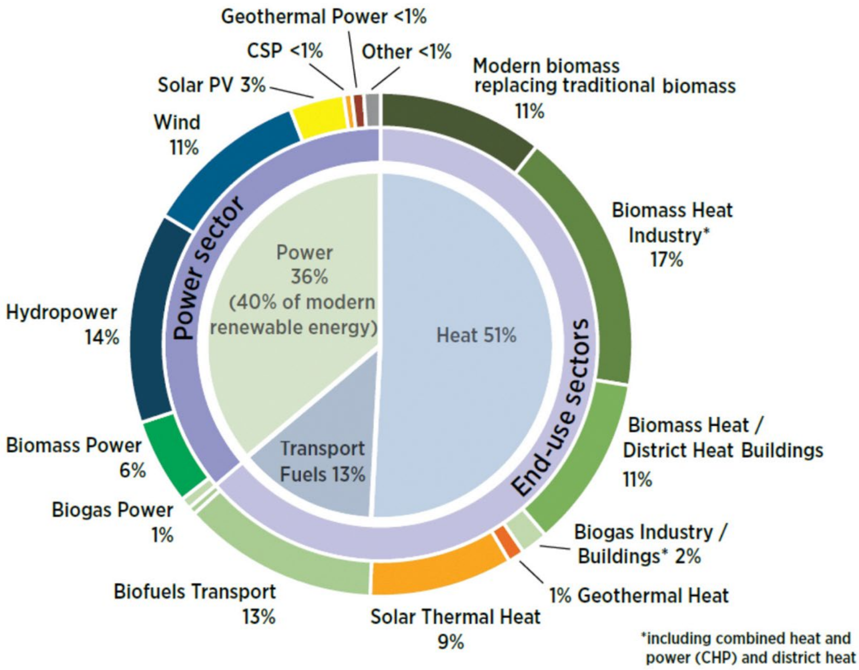

Figure 1. Breakdown of global renewable energy use for 2030 roadmap [5].

In a typical power system structure, the large power generators and consumers participate in the WEM to sell and buy energy, facilitating the efficient exchange of electricity on a broader scale, particularly to a specific geographic area or region to meet the energy demand [10]. While supply and demand management in the WEM is generally effective, there are certain limitations, particularly for small consumers, who have limited options to choose their power supplier and can only receive power from affiliated distribution companies, which are authorized to set electricity prices. This lack of competition in the CEM restricts consumer preference and choices. This makes the WEM ineffective for renewable energy sources (RES), which have negligible or zero marginal cost, whereas in the WEM, the electricity price is set by system marginal cost. On the other hand, in the REM, distribution and supply systems are unbundled. With the introduction of the distribution system operator (DSO), the retail electricity market was introduced, whose primary task is to purchase energy from the WEM and transfer it to customers [11]. The DSO acts as a market service gateway that regulates and provides access to the distribution network to the retail supplier, who delivers electricity to the end-users [12].

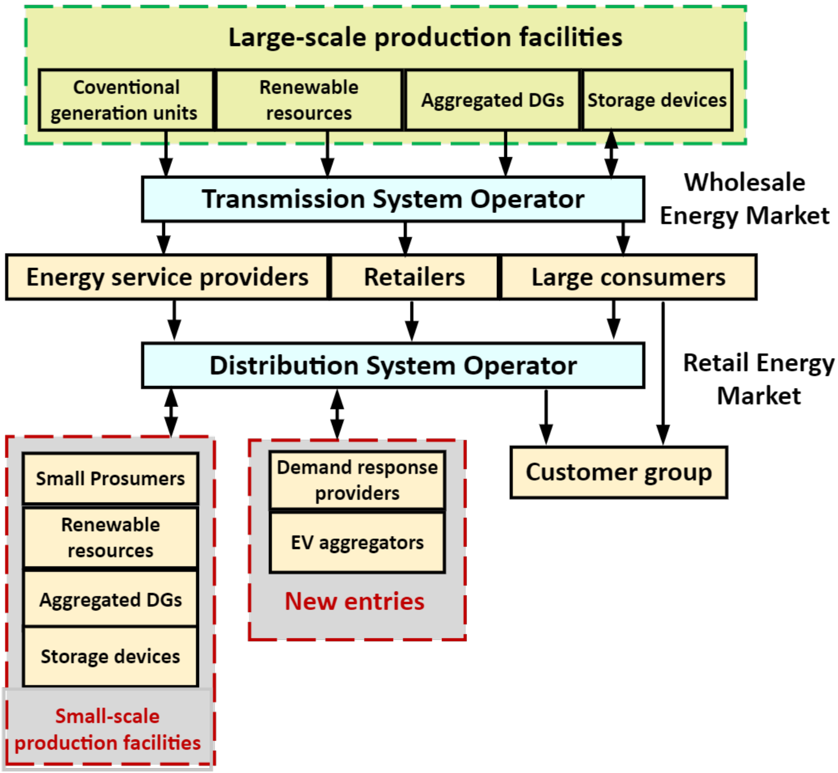

Figure 2. Representation of wholesale and retail electricity markets.

1.2. Scope and Contributions

Over the years, there has been an ample amount of work carried out in energy markets. Nevertheless, the REM still has some challenges to overcome. The utmost challenge is that retailer charges are fixed averaged prices for the consumers, thus benefits of low-cost power during off-peak load are not truly translated to the consumers [13]. Thus, system operators fail to curtail the peak demands and alter the energy usage pattern of consumers, although consumers are offered different price slabs, like real-time, flat rate, and time-of-use [14]. In the REM, although consumers can change suppliers, the execution and cancellation of the supplier are not free of cost; as a result, this additional cost restricts the number of consumers who avail themselves of such a facility [15]. The problems being faced by consumers in the WEM and REMs can be solved by combined operation of generation, storage, and demand response through introducing local energy markets (LEMs).

LEMs are decentralized systems operating at the microgrid or community level, focusing on peer-to-peer (P2P) energy trading, local optimization, and demand–response using distributed energy resources (DERs), like solar panels and batteries. They rely on smart grid technologies, IoT, and blockchain for real-time monitoring and transactions, with shorter settlement periods and emerging regulatory frameworks. In contrast, large-scale energy markets (LSEMs) operate at regional or national levels, managing bulk energy generation and transmission using centralized power plants and established market structures (e.g., day-ahead and ancillary services). LSEMs prioritize grid stability, large-scale optimization, and compliance with stringent regulations. The key technical difference lies in their infrastructure, scale, participants, and goals—LEMs emphasize local resilience and sustainability, while LSEMs focus on reliability, efficiency, and macro-level energy policy alignment.

1.3. Significance of Work

During this research, an exhaustive literature review was undertaken to assess the state of LEMs within the CEM. Figure 3 shows the network visualization mapping generated in VOS Viewer to represent the relationships between different concepts or terms based on their co-occurrence in the data or in the literature review that was carried out. In this network visualization map, each node is denoted by a colored node and represents a specific term or concept related to energy markets and technologies such as "demand response", "P2P trading", and "reinforcement learning", while the frequency of the research item's usage determines the node size. The higher the frequency of item usage, the larger the item's label. The lines (edges) connecting the nodes indicate the relationships between terms. Thicker lines or closer proximity generally signify stronger relationships or higher co-occurrence. The keyword co-occurrence network analysis signifies the scientific footsteps and trends that have progressed over time, sketches the conceptual structure, and summarizes it in a bibliographic collection to map and cluster the terms extracted from the keywords [16]. As can also be observed, nodes like "demand response" and "transactive energy" are centrally located, suggesting they are key terms with many connections to other terms, indicating their importance in the network. The "Demand Response" node is central, connecting to various other concepts, showing its pivotal role in energy management and smart grid systems, where the "Transactive Energy" node links heavily to concepts in the red cluster, emphasizing its relevance in modern energy trading systems involving blockchain and prosumers. The "Reinforcement Learning" node located in the blue cluster is associated with LEM and P2P trading, highlighting its emerging role in adaptive and intelligent energy management systems. The "Energy Market Design" node represents the market design, distributed energy resources, and storage, indicating ongoing research and development in optimizing energy systems for efficiency and resilience, whereas "Smart Grids and Microgrids" defines the connections between "smart grid", "microgrid", and "distributed energy resources", highlighting the integration of localized and distributed systems in modern electricity grids. In addition, "Blockchain and Energy Trading" characterize the relationship between "blockchain" and "energy trading", and "P2P" indicates the innovative approaches being explored for decentralized and secure energy transactions.

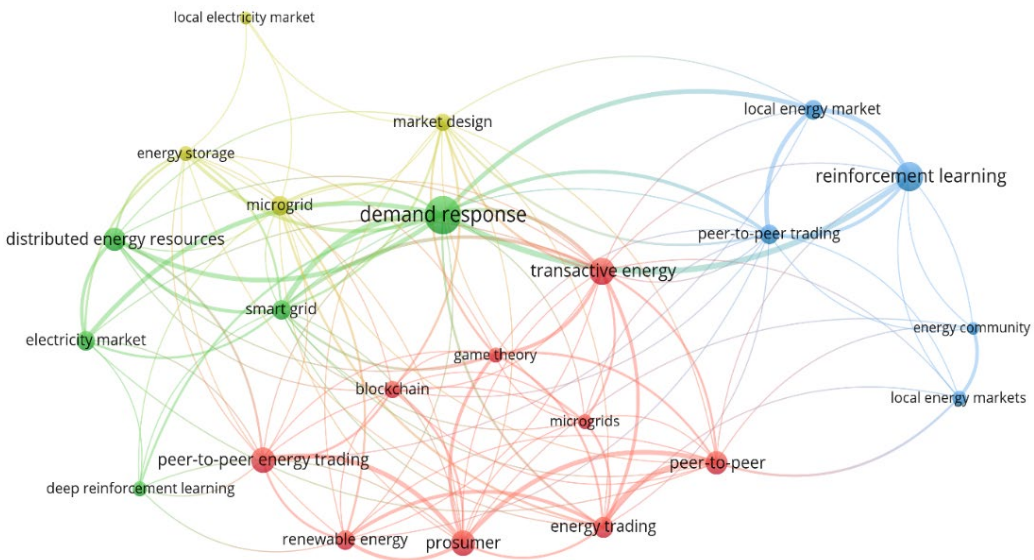

Figure 3. Network visualization mapping of research trends in energy market.

From the reviewed literature and network visualization mapping, two distinct market types can be identified: large-scale energy markets and local energy markets. The large-scale energy markets encompass geographic considerations at the scale of countries, multiple countries, or even the global stage. In contrast, the LEM focuses on smaller geo-graphic regions, including cities, specific regions, or residential communities.

In this work, both large-scale and local energy markets are studied. Large-scale energy markets are essential when studying local markets because the two are deeply interconnected but still address different aspects of energy systems. Local markets operate within broader systems where energy flows, pricing, and policies are influenced by national or regional dynamics. Large-scale markets impact local pricing, renewable energy integration, and grid stability while providing critical context for regulatory compliance and investment planning. Understanding these larger systems helps ensure that local market strategies are resilient, aligned with broader trends, and capable of adapting to external influences, such as shifts in supply–demand balance or policy changes. Figure 4 summarizes the number of papers reviewed in terms of the type of market. It is evident from the network visualization mapping that in recent years, a lot of research has been carried out in the domain of the LEM. Before 2016, researchers identified the potential benefits of LEMs in addressing the shortcomings of the existing centralized electricity system, including grid inflexibility, unreliability, load curtailment, high costs, environmental impact, and security vulnerabilities. Subsequently, a surge in project initiatives led to a significant increase in the number of publications in the field.

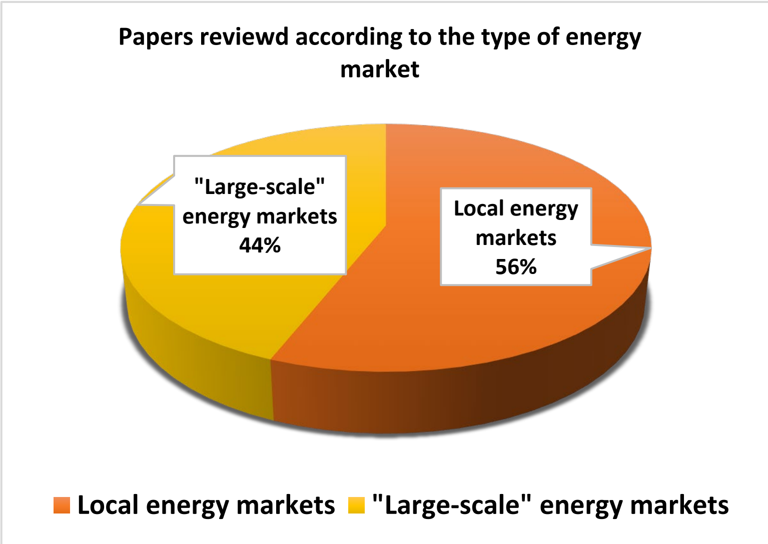

Figure 4. Papers reviewed in terms of the type of energy market.

2. Local Energy Markets

The current understanding of the LEM diverges somewhat from the expectations held by researchers in the early 2000s. At that time, LEMs were envisioned to encompass large regions or even entire countries, such as California [17], Poland [18], Slovenia [19], and Denmark [20]. The differentiation between local and national energy markets was primarily based on technical factors like power grid capacity and voltage levels, rather than on market participants' benefits, stakeholder involvement, or market designs. Recently, LEMs have been characterized as decentralized, contrasting with traditional top-down and centralized markets [21]. Today, LEMs are viewed as decentralized, horizontally scaled markets confined to smaller communities. In these markets, energy trading is dynamic due to the variability of local renewable energy sources (RES), with small energy prosumers selling surplus energy as available, which renders long-term energy trading contracts less practical.

In any market design, each participant has specific roles and objectives, which may differ from those of other players. In an LEM, the key players include (i) local energy suppliers or sellers, (ii) local energy consumers or buyers, and (iii) local energy intermediaries. A critical aspect of market operations is how these players interact with one another to buy and sell energy and services, not only for their own benefit but also to contribute to market stability. Figure 5 illustrates the interactions among these participants in the LEM.

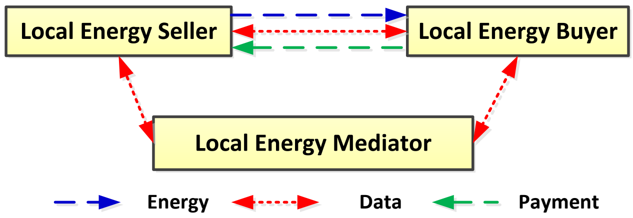

Figure 5. Interactions among the LEM entities.

(i) Local Sellers: In LEMs, local sellers are players who provide the energy by dispatching their distributed generator units (DGs) and/or energy storage systems (EESs). Local sellers within the market can include individuals, households, businesses, co-generation units, or community-based organizations that have integrated energy sources (renewables and/or conventional). They actively sell their surplus energy to local buyers or electricity retailers with the aim of reducing overall energy costs and maximizing their profits through optimal dispatch of energy sources.

(ii) Local Buyers: In LEMs, local buyers represent consumers seeking energy from local generation resources. These consumers encompass households, businesses, and institutions, serving as the ultimate end-users of energy. They procure energy either directly from local producers or through electricity retailers. It is worth mentioning that LEMs offer consumers the opportunity to directly source energy from prosumers, thereby eliminating intermediaries within the energy supply chain. This direct interaction empowers consumers to access energy at a potentially lower cost, while prosumers can generate additional revenue by selling their surplus energy.

(iii) Local Energy Mediators: All the other players except local sellers and buyers in the LEMs are the local energy mediators, i.e., operators, auctioneers, aggregators, and regulators. The LEM's operator can be a local energy system (LES), which will be responsible for collecting and matching the energy trading requests/demands from buyers and sellers within the local premises and broadcasting and publishing the trading prices in a defined time window, as shown in Figure 6. Every LES must have an advanced metering unit as an energy consumption data-reading server, energy transaction server, account database, and energy transaction database. The meter-reading server collects power generation or consumption data from smart meters (SMs). The transaction server is responsible for collecting trading requests from buyers and sellers, matching the trading requests, and publishing the price in defined time windows. An energy transaction meter is responsible for recording and measuring information on energy transactions between energy sellers and buyers. Modern energy transaction meters are equipped with data logging capabilities. They record data over time, allowing for historical analysis of energy consumption or production patterns. These data can be used for billing, monitoring energy usage trends, and optimizing energy systems. The account database records the information of accounts. An account database is a structured collection of data that stores information related to user accounts. Auctioneers are the team players in the LEM who enter competitive bids simultaneously for selling and buying the energy. Aggregators are intermediary entities that provide an opportunity for prosumers to access the market and facilities of the intermediary's entities. The intermediary's entities collect the energy from multiple producers to facilitate energy transactions within the LEC, which provide services such as metering, billing, and settlement. In the LEM, energy market regulators ensure the integrity and stability of the energy market. They may include government agencies, utilities, or independent regulatory bodies, and develop policies and regulations that promote fair competition, protect consumer rights, and encourage the adoption of DERs. Table 1 summarizes the market players' classifications and relevant references in LEM.

Table 1. Summary of market players' classifications in LEM.

Entity	Market Players
Local Sellers	Local Electricity Sources—DGs [22–24] Local Grid—ESS [25–27] Electric Vehicles [28–30] Utility Companies and Generators [31,32] Prosumers [33]
Local Buyer	Consumers and Prosumers [34–36]
Local Energy Mediator	Market Operators [37,38] Market Auctioneers [39,40] Market Aggregators [41,42] Market Regulators [43,44]

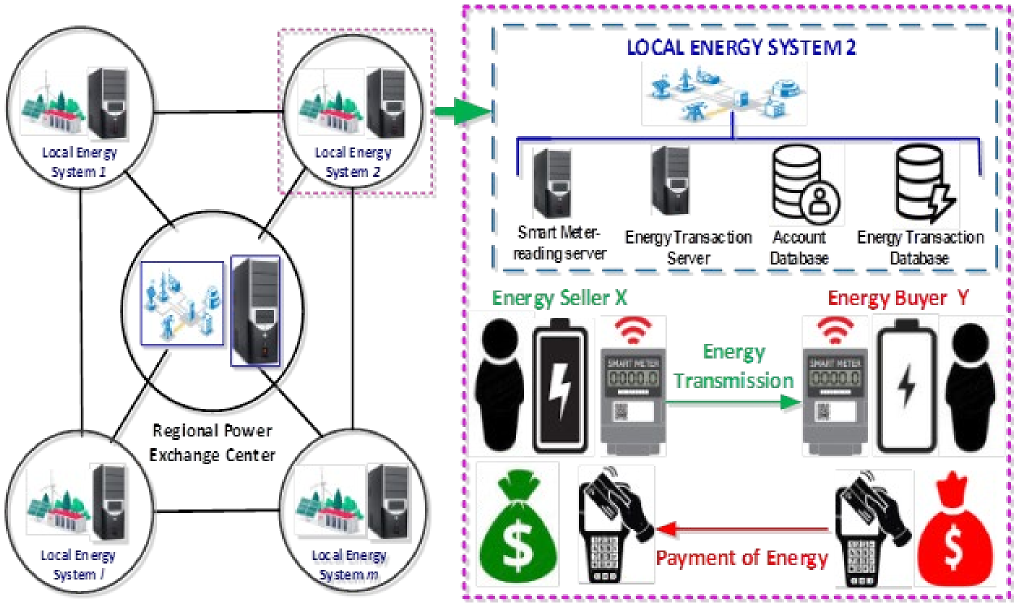

Figure 6. Framework of local energy market.

Although LEMs are emerging as a promising solution for managing decentralized energy resources and promoting renewable energy adoption, they face several challenges. These include planning and regulatory barriers, technical complexities, scalability issues, market fragmentation, and economic constraints. Planning for an LEM involves addressing participant preferences, goals, procedures, policies, and implementation strategies. Regulatory challenges may include complex licensing and permitting requirements, which can hinder small-scale producers from participating. Technical barriers cover aspects such as design, installation, local resource availability, infrastructure, interoperability, cybersecurity, data privacy, and the skills needed for operation and maintenance. Additionally, the small-scale nature of LEMs can lead to market fragmentation, making it difficult to achieve economies of scale and liquidity.

2.1. Design of LEM

To enable local energy trading, an LEM is operated at the distribution level to actively involve local end-users in the CEM, offering a decentralized platform for the energy trading between sellers and buyers within a specific geographic area, such as a neighborhood, community, town, or city. LEMs have gained significant attention in recent years to increase the integration of DERs and promote local energy generation and consumption [45]. LEMs offer a decentralized structure enabled by local generation and distribution of energy and different technology domains, like smart contracts, ML, blockchain technology (BCT), and the Internet of Things, to facilitate energy exchange, thus creating a sustainable and efficient energy system. The design of an LEM depends on the characteristics, active involvement, interaction, and objectives of the market's participating players and stakeholders, like prosumers, consumers, suppliers, network operators, aggregators, etc., at the distribution network level [46]. The design of LEMs can be based on a systematic structure that encompasses local energy dynamics, driving mechanisms, and market platforms. This structure can be analyzed from both technical and economic perspectives [47]. Technical considerations include voltage, power, frequency and transient stability, and active and reactive power control, while economic perspectives are centered around energy trading price structures and business models. The pricing model in LEMs is dynamic, constantly adjusting based on factors such as the time of day, supply availability, and demand fluctuations. Consequently, short-term or real-time energy contracts are typically favored, which differs from earlier theories that compared LEM trading to traditional markets with medium- and long-term energy contracts. In LEM design, two pivotal entities emerge: prosumers, who engage in energy trading, and LEM coordinators, who facilitate these transactions. The roles of energy trading participation and facilitation can be further categorized into two trading models: auction-based and non-auction-based designs. Figure 7 illustrates the available LEM design options.

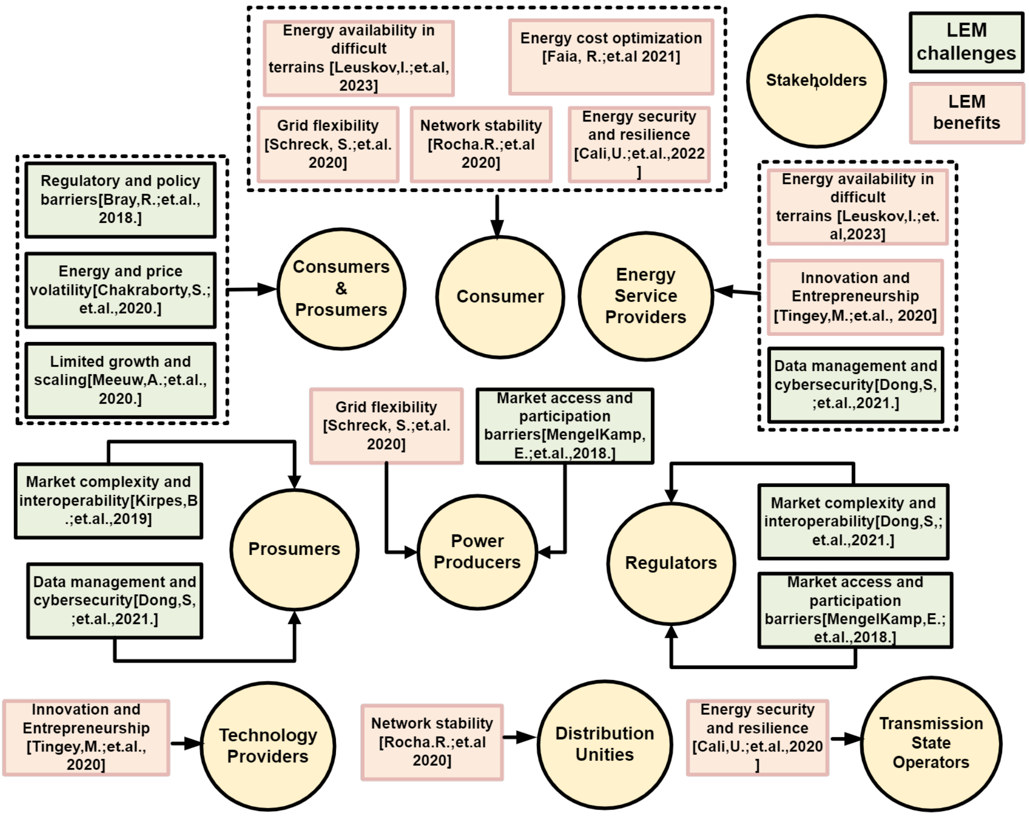

Figure 7. LEM benefits and challenges and corresponding beneficial and affected stakeholders [48–59].

2.1.1. Auction-Based Designs

Auction-based designs are concerned with individual participants' bids and offer details and the subsequent matching by an LEM coordinator. The bidding process enables all the prosumers to directly access the LEM. Bidding quantity, bidding price, and bidding price–quantity are the three variants of auction-based LEM designs.

Bidding quantity: LEM auctions based on bidding quantity allow prosumer participation through the bid and offer process, which only includes information on the amount of energy being demanded or offered. For participants, individual profit maximization through iterative quantity can be targeted, whereas an LEM coordinator will be responsible for residual load minimization by matching the quantity bids.

Bidding price: In this case, the LEM coordinator determines the bidding prices and adjusts the prices in an iterative process until price equilibrium is achieved. The participating prosumer targets profit optimization through iterative prices, while the LEM coordinator determines and matches the pricing.

Bidding price–quantity: Bidding based on simultaneous price and quantity matching does not necessitate any iterative approach, as other related valuable information is also available in the prosumers' bidding details. The participants are responsible for individually determining the constraints' price-quantity function, where the LEM coordinator must communicate the prosumers' price valuation, time-coupling constraints, and flexibility potential, along with the amount of energy being offered or demanded.

2.1.2. Non-Auction-Based Design

For non-auction-based designs, direct (i.e., P2P) and indirect (central coordinator) market access methods are possible.

Direct market access: In direct market access designs, the buyers and sellers directly negotiate and finalize the quantity and price. The bilateral negotiation and contract approach offers extended degrees of freedom, as market participants can set their price range, which can significantly differ from market-based equilibrium prices. In this case, the LEM coordinator only provides the necessary digital infrastructure to carry out the negotiation process and acts as a regulating institution.

Indirect market access: In this case, the central coordinator takes over all tasks, i.e., optimal resource allocation, determines the participant's schedule within the LEM to maximize social welfare, and finds the equilibrium prices. Market participants are required to provide all the necessary information regarding their assets, quantity and price valuation, and behavioral flexibility to the coordinator. Although social welfare maximization is possible, in this case, a player's active engagement in energy trading activities cannot be guaranteed.

2.2. LEM Benefits and Challenges

While a substantial number of articles have made valuable contributions to understanding the current state of the art of LEMs, there is still a need for further evaluation of the adoption of the LEM concept at the consumer level. This assessment is crucial to delineate the benefits and challenges it presents to all stakeholders and actors involved. LEMs introduce competition and price transparency, allowing consumers to choose from a variety of energy providers and tariffs. This competition can drive down energy costs and increase affordability for consumers. LEMs potentially enhance grid resiliency by enabling localized energy production and consumption. During power grid outages or disruptions, communities within LEMs can continue to operate independently, relying on local energy resources. This promotes energy security and reduces vulnerability to external factors. LEMs foster innovation and entrepreneurship in the energy sector. They encourage the development of new business models, technologies, and services, such as P2P energy trading platforms, virtual power plants, and smart energy management systems. These innovations can unlock new opportunities, drive economic growth, and accelerate the energy transition. The relationships between LEM benefits and corresponding beneficial stakeholders and LEM challenges and potential affected stakeholders are represented in Figure 7. LEMs often require supportive regulatory frameworks and policies to facilitate their adoption and operation. Existing regulations may not adequately accommodate decentralized energy generation, energy trading, and grid interactions, and the lack of well-defined rules and standards can hinder market development and create uncertainties for participants. Establishing LEMs involves integrating various stakeholders, including energy producers, consumers, aggregators, and system operators. Ensuring seamless interoperability between different market participants and their systems can be complex, especially when dealing with diverse technologies, data formats, and communication protocols. LEMs rely heavily on data collection, management, and sharing among stakeholders, with the volume and complexity of data increasing as more devices, sensors, and systems are integrated into the market. Ensuring secure and reliable data communication, protecting consumer privacy, and addressing cybersecurity risks become critical considerations in LEM design and operation. LEMs should strive for inclusive participation, enabling all stakeholders, including residential consumers, businesses, and communities, to actively engage. However, barriers such as high transaction costs, lack of awareness, and limited financial resources can impede broad participation, preventing the full potential of LEMs from being realized.

2.3. LEM Market Platforms and Projects

Recently, a significant number of projects have been initiated to effectively harness the true potential of the LEM. German companies such as Lumenaza GmbH and Sonnen GmbH pioneered concepts allowing locally produced energy to be bought and sold at the residential level, empowering market players to actively and decisively manage their energy procurement. The introduction of BCT has further enhanced this potential, enabling real-time market platforms without the need for a central intermediary. As an emerging technology, BCT offers new prospects for decentralized markets, allowing energy consumers to make informed decisions regarding energy trades and transactions based on accurate information and predictive analytics to maximize rewards. In this work, LEM projects are categorized into two domains: real-time BCT projects (aggregator platforms) and local market flexibility projects (market platforms). Table 2 summarizes the LEM platforms and projects, and a few selected projects from both real-time aggregator platforms and local market flexibility platforms are briefly discussed.

Table 2. LEM market projects and platforms at global level.

LEM Projects	Market Platforms	Ownership	Stakeholder Countries	Period	Services	Time Frame	Market Mechanism	Pricing Mechanism
Real-time blockchain technology projects (Aggregator platforms).	Brooklyn Microgrid [60]	LO3 Energy	NYC, USA	2016	Technical infrastructure, load-balancing services	Real-time	P2P auction	Pay-as-bid
	Quartierstrom Community Microgrid [61]	Swiss Federal Office of Energy	Walenstadt, Switzerland	2019–2020	Flexible local tariff balancing	Real-time	P2P double auction	Pay-as-bid
	LAMP [62]	IISM	Landau, Germany	2017–2019	Active participation, price preferences	Real-time	Double auction	Pay-as-bid
	Equigy [63]	Swissgrid, TenneT NL, and Terna	Germany, Italy, Switzerland, Netherlands	2020–2021	Aggregators balancing services	Real-time	Single buyer	Corresponding TSOs regulation
	Tiko [64]	TIKO	Switzerland, Austria, Belgium, France	2014–to date	Load-balancing services	Real-time	Ancillary services	Market rules of TSO-balancing services

Table 2. *Cont.*

LEM Projects	Market Platforms	Ownership	Stakeholder Countries	Period	Services	Time Frame	Market Mechanism	Pricing Mechanism
Local market flexibility projects (Market platforms)	Enera [65]	EPEX SPOT (TSO), Avacon Netz (DSO)	Germany	2018–2020	Congestion management services	Intraday	Two-way market	Pay-as-bid
	GOPACS [66]	Tennet T (TSO), Liander, Enexis (DSOs)	Netherlands	2019–to date	Grid congestion	Intraday	Two-way market	Pay-as-bid
	Picloflex [67]	Piclo	United Kingdom	2019–to date	Congestion management services	Day-ahead	Auction single buyer	Pay-as-bid
	Nodes [68]	Nord Pool	Norway, Germany	2018–to date	Congestion management services	Intraday	Two-way market	Pay-as-bid
	EcoGrid 2.0 [69]	Nord Pool	Bornholm, Denmark	2020	Trading flexibility and capacity limitation	Day-ahead	Double-sided auction	Bid-market clearing
	Interflex [70]	Dutch and French DSOs	Czech Republic, France, Germany	2017–2019	Congestion management services	Day-ahead	Single-buyer market	Pay-as-bid
	FLEXIMAR [71]	VTT Technical Research Centre of Finland	Finland	2019–2020	Energy flexibility	Day-ahead	Two-way market	First come first served
	CoordiNet [72]	Greece: IPTO, HEDNO; Spain: REE, i-DE; Sweden: E. ON, Vattenfall	Greece, Spain, Sweden	2019–2023	Congestion management services	Intraday	One-sided market	Pay-as-clear and Pay-as-bid
	InteGrid [73]	DSOs and TSOs of owner countries	Portugal, Slovenia, Sweden	2017–2020	Decentralized flexibility	Intraday	Decentralized single-buyer markets	Pay-as-bid
	GOFLEX [74]	Local energy suppliers, DSOs	Switzerland, Germany, Cyprus	2017–2020	Automatic trading flexibility	Intraday	Single-buyer market	Market-based
	IREMEL [75]	Iberian Electricity Market Operator	Spain	2019–to date	Congestion management services	Intraday	Two-way market	Pay-as-bid or Pay-as-clear

The Brooklyn Microgrid Project [76] was the first worldwide real-time BCT-enabled LEM network based on a virtual community and physical microgrid platform. The virtual community platform deals with the technical infrastructure using BCT and a physical microgrid platform for load-balancing services, as it is uncoupled from the traditional grid operated by ISO to aggregate the demand and supply and balance the loads through DSO. The Quartierstrom community microgrid project [77] stands as a tangible instance of a prosumer-centric LEM implemented in Walenstadt, Switzerland, utilizing a BCT-based P2P approach. This initiative involved the active participation of 37 households, with 25 of them classified as consumers and the remaining 12 as prosumers equipped with ESSs. In this project, community members with the same voltage or grid level were offered a reduced tariff for grid usage. The Landau Microgrid Project (LAMP) [78] represents a practical example of an LEM in action, involving the participation of 20 household residents in Landau, Germany. This project was designed to scrutinize the energy consumption behavior, acceptance, and engagement of German households in an LEM facilitated by blockchain technology. LAMP offers market participants the opportunity to purchase locally generated electricity at prices aligned with their own valuation. Likewise, Equigy [79] is a European TSO-based BCT initiative that promotes the active participation of households in generating flexibility from decentralized systems through blockchain technology. The Equigy project also provides congestion management services for DSOs. Among the array of flexible market platforms, Enera is a German initiative aimed at attaining supply–demand flexibility to address congestion challenges faced by DSOs [80]. The Enera project involves a series of actions, including bid collection, settlement, market clearing, aggregation activities, network impact assessments, and flexibility activation. GOPACS (Grid Operators Platform for Congestion Solutions) is a Dutch platform that offers congestion management at all voltage levels to provide flexibility for TSO/DSO coordination [81]. GOPACS is a two-way platform where DSOs and TSOs are flexibility buyers and residential, industrial, and energy companies are flexibility sellers. Picloflex is a UK-based marketplace that operates the system efficiently by offering benchmark flexibility services to DSOs and reducing grid costs [82]. Based on locational information, the DSOs declare their flexibility needs and monitor the available resources. Nodes platform is owned by Nord Pool, which aims to stabilize grid operation through achieving network operators' flexibility and improving congestion services.

Danish-based EcoGrid 2.0 [83] is a local flexibility market project in which 800 household participants play their role by offering flexibility services to DSOs and TSOs through demand response (DR) programs. The capacity limitation service and baseline flexibility service are the two enablers for the DSOs. These services can be either scheduled at a predetermined time or conditional services activated manually by the DSOs. Tiko is a Switzerland-based aggregator platform [84] to aggregate flexibility in the form of primary and secondary balancing services to the Swiss TSO. This platform is restricted to only operate in low-voltage DSO grids. Interflex is a demonstration project that focuses on how distribution grid challenges can be solved by using the flexibility services of DSOs.

Upon reviewing these LEM projects, a common theme is observed, with the majority focusing on enhanced digitalization, demand flexibility, load-balancing services, and congestion management services. At the community level, these services are often facilitated by DSOs, serving as intermediaries between the transmission system and end-consumers connected to the distribution grid. Additionally, efforts are made towards energy trading mechanisms, preferences in trading prices, and trading flexibility through the utilization of BCT. In the following section, a deeper exploration into LEMs is provided, examining the intricacies of energy trading mechanisms and their diversity.

3. Energy Trading in Local Energy Market

In the recent energy trading literature of LEMs, three types of market platforms have been reported widely: P2P, community-operated (CO), and transactive energy (TE), which offer new mechanisms and models for energy trading locally. In P2P markets, direct dealing of energy trading between the market's participating players without any intermediary is executed to provide price incentives to the participants for engaging them in energy trade markets. In CO markets, co-located energy prosumers/consumers effectively trade their surplus/deficit energy within the defined community group. Grid services are the main target of TE markets to balance supply and demand in an autonomous way using price signals [85]. Although these LEM platforms lack consensus on their meaning, and there are differences between the market types, trading mechanisms, size variability, and operational scales, these can still be used interchangeably in some forms. The scope, modeling assumptions, objectives, and market mechanism were the major attributes studied in [86]. A P2P energy trading using a cooperative game theory with a priority-based approach in LEC was proposed in [87]. The prosumer participation mechanism and market flexibility framework in P2P energy trading was proposed in [88]. In [89], user preferences in a community-based LEM were defined using auction-based clearing approaches. In [90], community formation and multi-level energy trading networks were proposed in LEMs. A decentralized decision-making approach under uncertainty in a community-based energy market design was proposed in [91]. By adopting varying prices and competitiveness of LEMs, a path toward a fully TE system was proposed in [92]. A comprehensive review was presented in [93] to link the future of TE with LEMs. Table 3 illustrates the wealth of literature available for characterizing various market stakeholders, system components, and the primary and secondary purposes of P2P, CO, and TE market trading platforms when applied across different application domains. In P2P and CO markets, DSOs and prosumers are the major stakeholders. The DSO organizes the LEM and is responsible for distributing and managing the energy from different generation resources to market participants, whereas prosumers sell excess energy to consumers for financial reward and to balance system resources and needs. Energy cost and welfare maximization have proven to be the major purposes of these energy trading platforms.

Table 3. Classification of market stakeholders and system components in LEM energy trading platforms.

Ref.	Trading Platform	Market Stakeholders	System Components	Primary Purpose	Secondary Purpose
[94]	P2P	DSO, prosumers	PV, BESS	Energy cost	Welfare maximization
[95]	P2P	Prosumers, retailers	PV, BESS	Financial reward	Welfare maximization
[96]	P2P	WEM, P2P platform agent, prosumers	PV, BESS	Financial reward	Welfare maximization
[97]	P2P	DSO, prosumers, market agents	PV, BESS	Self-consumption	User preferences
[98]	P2P	DSO, prosumers, consumers	PV, BESS, EVs	Financial reward	User preferences
[99]	CO	DSO, community manager, prosumers	PV, BESS	Self-consumption	Fair cost distribution
[100]	CO	DSO, community manager, prosumers	PV, community BESS	Price transparency and fairness	Self-consumption
[101]	CO	DSO, prosumers	PV, auxiliary heating, BESS	Community preferences	Renewable energy adoption
[102]	CO	DSO, community manager	Controllable appliances, PV, BESS	Energy efficiency	Energy independence and resilience
[103]	CO	Community manager, prosumers, TSO	PV, BESS, EVs	Energy affordability	Energy equity
[93]	TE	Consumer, prosumers, grid operators	PV, wind turbines, large-scale storage	Grid constraints	Resilience and flexibility
[104]	TE	DERs, traditional generators, consumers	Combined heat and power	Ancillary services	Grid constraints
[105]	TE	Hydropower plants, geothermal plants	PV, wind, energy storage systems	Grid imbalance	Energy-balancing services
[106]	TE	Energy service providers, prosumers	Smart meters, blockchain	Ancillary services	Market efficiency
[107]	TE	DERs, energy service providers	Distributed ledger technologies	Transparent and auditable transactions	Energy traceability and sustainability

To analyze these trading platforms in more detail, different operational, financial, and constraint-based characteristics of P2P, CO, and TE in an LEM need to be explored further. The application areas and corresponding characteristics of P2P-, CO-, and TE-based LEMs, considering multiple factors, including network type, geographical aspects, market design, financial aspects, participation, network topology, and trading mechanisms, are summarized in Table 4. From Table 4, it can be concluded that P2P-, CO-, and TE-based energy trading platforms exhibit valuable cross-combinational characteristics. Unlike P2P and TE markets, a more limited body of literature specifically analyzes the CO market, focusing on community and locality aspects within energy markets. Moreover, P2P and CO markets primarily offer financial incentives to market participants, while TE markets are primarily oriented toward grid-related services.

Table 4. Characteristics of P2P-, CO-, and TE-based energy trading in LEM.

Category	Characteristics	P2P	CO	TE
Network type	Centralized			[108]
	Decentralized	[109,110]		
	Distributed			[111–113]
Topographical	Transaction area	[114,115]		[116,117]
	Energy/bidding zone	[118–120]	[121,122]	[123]
Market design	Competitive market structure	[124]	[125]	[126,127]
	Retailer	[128,129]		[130]
	Whole seller	[131]		[132]
Financial aspects	Price signals and economic incentive	[133,134]	[135]	[136–138]
	Trading contracts	[139,140]	[141]	[142]
Market services	Supply–demand balancing	[143,144]		[145,146]
	Grid stability and system efficiency			[147,148]
	Demand-side response	[149]	[150,151]	[152]
Network topology	Mesh structure	[153]		[154]
	Hybrid structure			[155,156]
Technology	Blockchain	[157,158]	[159,160]	[161]
	Artificial intelligence	--------------	[162]	[163,164]
	Internet of Things	[165,166]	[167]	
Participation	Small-scale participants	[168,169]		
	Participants within the same community		[170,171]	[172]
Market transactions	Trading of surplus energy	[173]	[174]	[175]
	Trading preferences	[176,177]		[178]
	Welfare maximization	[179]	[89,180]	[181,182]
Transaction timeframe	Real-time	[183,184]		[185]
	Intraday	[186]		[187]
	Day ahead	[188,189]		[190]
Trading mechanism	With intermediary	[191,192]		
	Without intermediary	[193,194]	[195]	
Constraints based	Physical network constraint	[196,197]		[198]
	Privacy and Security			[199,200]
	Risk of participation		[201]	[202]

In terms of operational scope, TE markets exhibit a broader range of operations, spanning various scales within the energy system, whereas P2P and CO markets are predominantly centered on smaller-scale energy users. Regarding network types, P2P and TE markets emphasize grid operations and typological configurations. Technological adoption and usage have demonstrated diverse applications and valued characteristics across these energy trading platforms. Given the intricacies of energy trading, involving the exchange of electricity, gas, and other energy products, comprehensive information and data are necessary for informed strategic decision-making. In this regard, blockchain technology (BCT) and machine learning (ML) are gaining interest in energy trading platforms, especially in LEMs, to help market participants make informed and correct decisions.

4. Machine Learning in Energy Trading

4.1. Machine Learning Techniques and Models

Energy trading is a complex and dynamic process and is primarily challenging due to the need for accurate information to make precise decisions regarding energy sharing, selling, or trading [203]. These decisions depend on various criteria, such as the number of participants, energy quantities, time horizons, and pricing. Decision-making strategies can be broadly categorized into mathematical models and learning models. Within learning models, approaches can be divided into sequential decision-making tasks and data-driven tasks. Recently, data-driven approaches, particularly machine learning (ML), a subset of artificial intelligence (AI), have demonstrated promising capabilities in addressing energy trading challenges in LEMs. ML employs a range of search and optimization algorithms and statistical models to execute tasks by recognizing patterns and analyzing data sets. As a learning method, ML assists energy traders in making informed decisions based on extensive data sets and identifying patterns that may be difficult or impossible for humans to detect. A significant application of ML in energy trading is predictive modeling, where energy traders use ML to forecast energy prices, demand, and supply based on historical data and relevant information [204]. By analyzing these predictions, traders can identify opportunities to buy or sell energy at optimal prices. Additionally, ML plays a crucial role in portfolio optimization, enabling traders to enhance their energy asset portfolios by considering factors such as pricing trends, weather patterns, and production data [205] to pinpoint the most profitable investment opportunities.

ML algorithms can also be used to make real-time decisions about energy trading based on incoming data from different sources, which helps energy traders respond immediately to varying market conditions and take advantage of emerging opportunities. Furthermore, ML can be applied to develop automated trading systems capable of executing trades in response to real-time market conditions and predefined rules. This feature empowers energy traders to execute quicker and more precise transactions, simultaneously mitigating the risk associated with human errors. Based on the reviewed literature, ML can be broadly classified into four distinct types: supervised, semi-supervised, unsupervised, and RL. Figure 8 categorizes these ML models as they relate to their application within the context of the LEM.

"Learning with a teacher" is the best representation of supervised learning, in which the model learns from a set of training data provided by a specific internal or external knowledgeable teacher in a supervised form [206]. The training data are based on both the applied input labels and desired outputs, which can effectively map and predict the updated output associated with the corresponding inputs. The model weights are updated iteratively to minimize the mean variation in predictions and labels. Regression and classification are the two major variants of supervised learning to predict the value of the dependent attribute from the attribute variables [207]. In the regression approach, the dependent attribute is numerical, and continuous output is returned, while for classification, the dependent attribute is categorical, and a discrete value is returned. "Learning without a teacher" is the true reflection of an unsupervised learning approach, where patterns are inferred from unlabeled data, and the output data are presented without any inputs; this relates to a self-organization approach to capturing unknown data patterns. Association and clustering are the two major variants of unsupervised learning which try to connect, associate, and cluster the unlabeled data pattern together based on similarities [208].

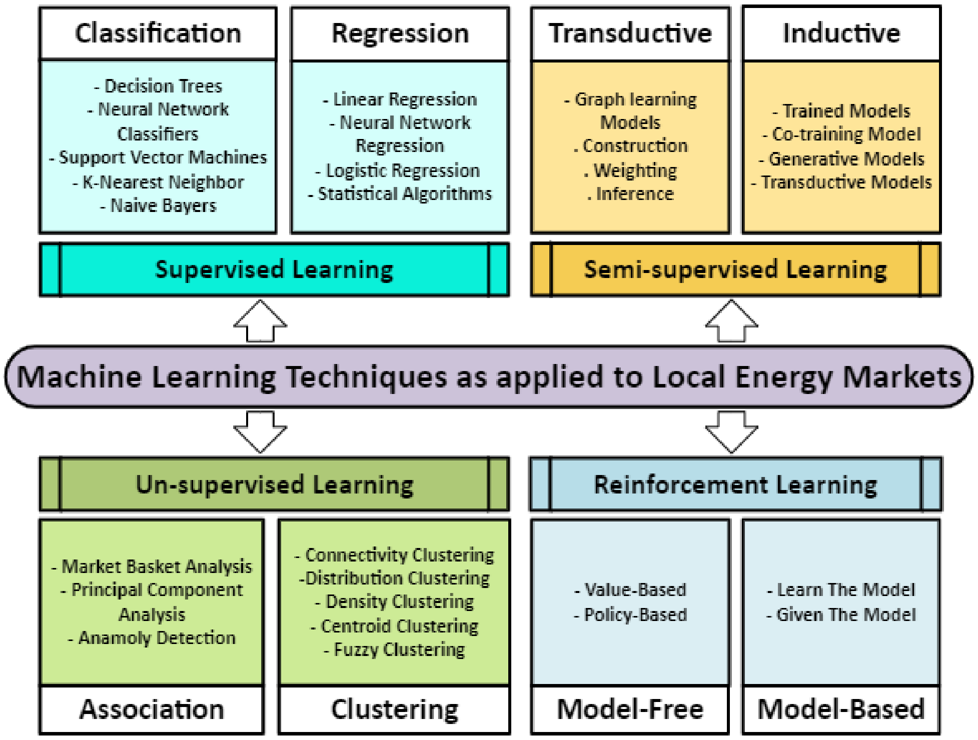

Figure 8. ML models as applied to LEM.

Both supervised and unsupervised learning have limitations in terms of insufficient labeled data and unpredicted clustering, respectively. The theme behind semi-supervision learning is to utilize the data points in an adaptive way considering whether the data are labeled or not. For labeled data points, model weights are updated using the traditional supervision mechanism, and for unlabeled data points, the difference in predictions is minimized between other training data sets. Transductive and inductive are the two variants of semi-supervised learning. Transductive produces labels only for the available unlabeled data, whereas inductive not only produces labels for unlabeled data but also produces a classifier. RL serves as a classic example of learning in sequential decision-making scenarios [209], where no direct supervisor or labeled input–output data are necessary; rather, the quality of actions or decisions is determined solely on the resulting rewards, indicating their effectiveness or ineffectiveness. In RL, the learning agent or player directly interacts within a variable condition in a dynamic environment and attempts to improve the overall position and maximize the collective return or rewards to achieve specific goals by learning strategies, agent, environment, reward, and action components [210].

In this review paper, while all ML techniques have been surveyed, particular emphasis has been placed on RL within the LEM research community. Figure 9 categorizes the reviewed papers by different ML techniques, revealing that a significant majority (around 64%) employ RL algorithms, surpassing the use of other ML techniques. These papers demonstrate a broad range of applications and mechanisms for ML in energy markets. Further insights into the distribution of the reviewed papers, categorized by LSEM and LEMs as per market applications, are presented in Figures 10 and 11, respectively. These figures indicate substantial work in load forecasting and tariff structuring, with some noteworthy contributions to energy trading. However, most research is concentrated on the WEM and REMs. Despite numerous studies focusing on optimizing various aspects of local energy trading, there is limited research specifically targeting LEM optimization for energy trading and community social welfare through advanced learning algorithms, particularly state-of-the-art ML and RL techniques. Utilizing RL in energy trading within LEMs has the potential to empower community prosumers and DSOs to enhance social welfare and optimize resources more effectively.

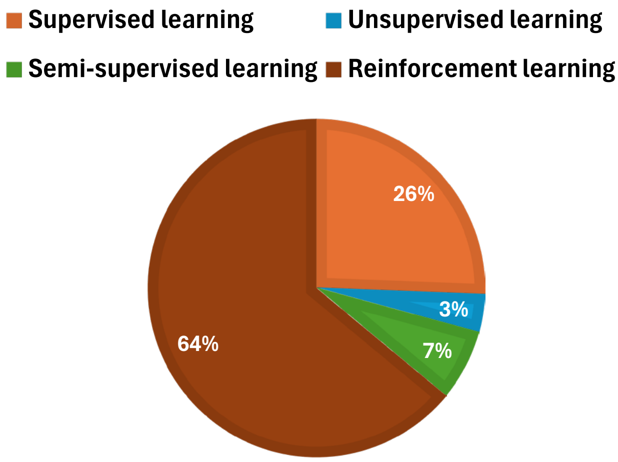

Figure 9. Number of papers reviewed as per ML technique in percentage.

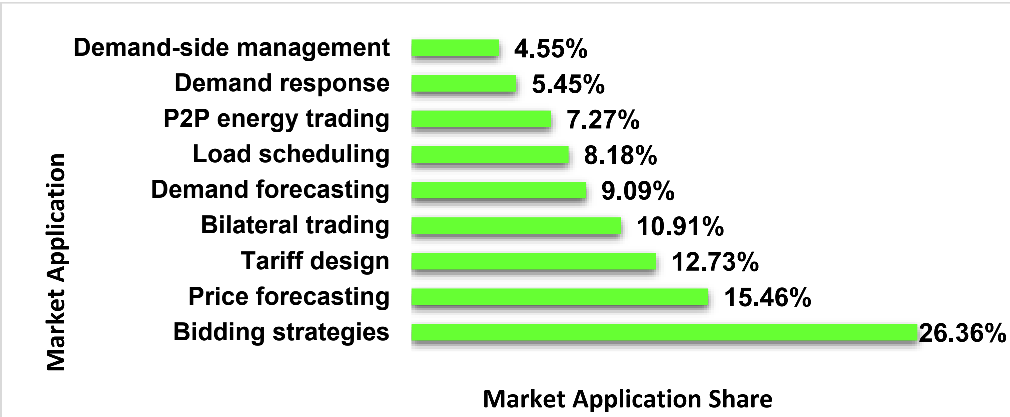

Figure 10. Share of reviewed literature related to market applications in large-scale energy market.

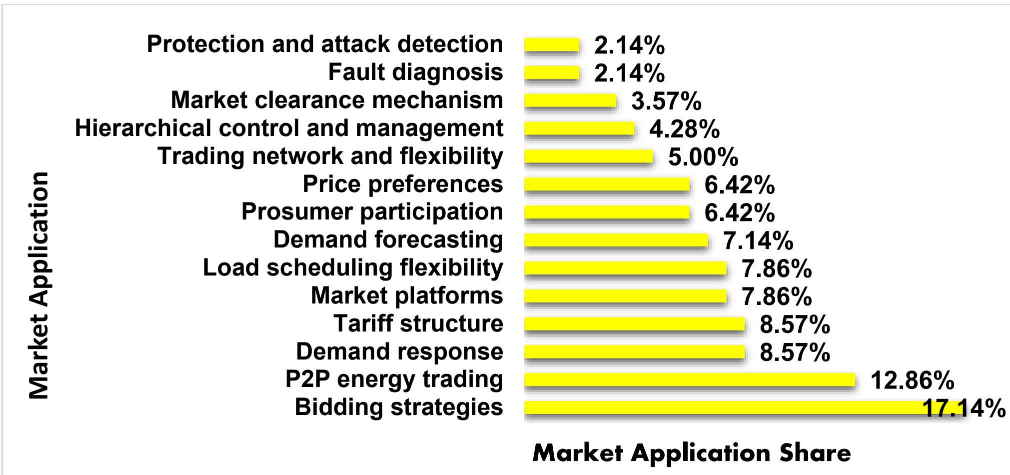

Figure 11. Share of reviewed literature related to market applications in LEM.

4.2. RL Approaches and Algorithms

RL, as an ML strategy, can be harnessed to address energy trading-related challenges by optimizing the decisions made by participants or agents in dynamic and uncertain environments. Practically, the game player/agent(s) need to select an action from a set of possible actions. The chosen action is based on the agent's policy and strategy. The agent updates the policy without a value function, improving with each learning step by adjusting weights. The basic RL model, including policy evaluation and reward, is illustrated in Figure 12.

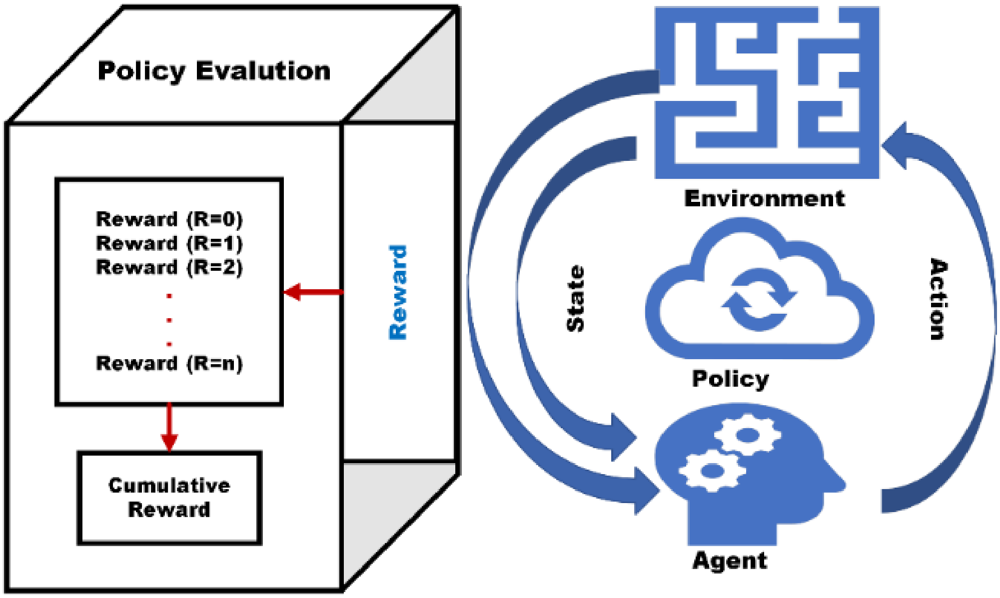

Figure 12. RL model with the policy evaluation and reward.

The core concept of RL is to learn a policy that maximizes the cumulative reward [211]. The agent or game player observes the current state of the environment, takes an action, and receives a reward based on the outcome of that action. The agent then uses this feedback to update its policy and maximize its expected cumulative reward. The RL approach proves effective, particularly when the goal is to sustain equilibrium in energy trading games across various computations and when assessing financial payouts within an environment characterized by incomplete information [212]. Nevertheless, the RL approach encounters challenges in energy trading games when prosumers opt to keep their strategies hidden from trading partners and competitors, adopting a non-cooperative stance. Additionally, the distribution of payoffs is often not discussed, finalized, or shared in advance. RL algorithms are strategic trade-offs between exploring new actions and exploiting those actions that are optimal in the specific domain. RL algorithms constantly adapt to a changing environment, which makes exploration an important consideration. Thus, RL is an equilibrium between exploration and exploitation. In RL, learning is normally classified based on the model-based and model-free algorithms. Figure 13 illustratively shows the classification of RL algorithms.

Model-based RL draws on control theory, assumptions, and approximations, which can result in a complex framework [213]. This approach learns optimal behavior indirectly by utilizing an internal environmental model, employing search or planning techniques, and subsequently executing a sequence of appropriate actions while observing the resulting transitions and outcomes, including the next state and the immediate action reward function. Model-free RL algorithms do not estimate the transition probability model and action reward function strategies [214]. These algorithms use a trial-and-error approach to learn directly from the state/action values or policies to achieve optimal performance but without using estimation, approximation, or real-world models. These algorithms are adaptable, trajectable, linear, and broader in learning domains, but are still simple and faster [215]. In this work, more focus will be given to model-free RL algorithms specially used for energy trading applications in the LEM domain. The two major variants of model-free learning approaches are value-based and policy-based. In value-based learning, the players learn from trajectory sampling of the same environment by updating and improving the action (Q) value for the action-value function at each defined iteration until it optimally converges [216]. Q-learning (action(s)) is the most popular example that learns from another policy. Fitted learning and deep Q-learning (multiple actions) are the two major variants of Q-learning. In the Q-learning approach, the learning agent chooses the activities based on state–action values.

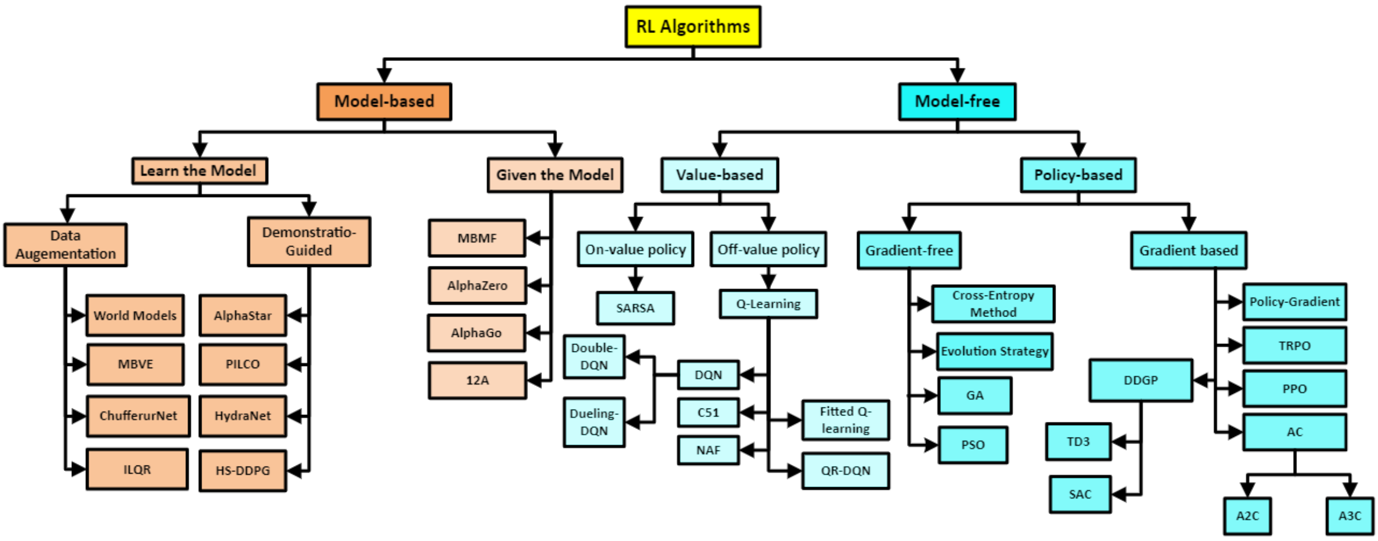

Figure 13. Classification of RL algorithms. A2C: advantage actor-critic, A3C: asynchronous A2C, DDPG: deep deterministic policy gradients, DPG: deterministic policy gradients, HER: hindsight experience replay, HS-DDPG: hot start deep deterministic policy gradient, ILQR: iterative linear quadratic regulator, MBFM: modified Bessel function model, MBVE: model-based value estimation, NAF: normalized advantage function, PG: policy gradient, PILCO: probabilistic inference for learn control, POMDP: partially observable Markov decision process, PPO: proximal policy optimization, PSO: particle swarm optimization, QR-DQN: distributional reinforcement learning with quantile regression, SARSA: state–action–reward–state–action, TD: temporal difference, TD3: twin delayed deep deterministic policy gradients, TRPO: trust region policy optimization.

After every learning step, all the Q-action values are updated using the Bellman equation; this means the action of learning is dependent on any value function. To define and determine the optimum action at a required state, all the Q-values must be initialized at the input state. This approach appears practical when the number of input states or actions is limited, but it becomes highly impractical for scenarios with many action states or when dealing with extended periods involving a community of states. The deep Q-network (DQN) algorithm is a modified form of Q-learning built on neural network approximations of the Q-function. The double DQN and dueling DQN are the two extensions of DQN to improve the original design of the Q-function. The double DQN solves the issue of overestimation of the value function, as happens in DQN algorithms, whereas dueling DQN approximates the Q-function by decoupling the value function. In cases involving a larger set of state–action pairs or a continuous approach, policy-based learning becomes a preferred strategy. This method involves the direct learning of a policy through a parameterized function, where policy weights are updated and optimized incrementally at each step. The policy value is calculated iteratively, improving it until convergence is achieved through gradient ascent. Policy-based methods learn the stochastic policies, and they are effective in continuous action spaces. On-policy and off-policy are the two variants of policy-based learning.

In off-policy learning, algorithms assess and improve a different policy from the selected action. Soft critic actor (SAC) is an example of off-policy learning, where parallel learning, continuous exploration, and learning from demonstration is possible. In on-policy learning, algorithms assess and improve the same policy from selected action. RL is an example of off-policy learning. In RL, where there is no need for any value function for the learning agent to update the learning policy, policy-based learning is more suited for a type of problem that requires continuous state space. In policy-based learning, the weights of the policy are updated and improved at each step.

4.3. Machine Learning Solution Strategies

Machine learning (ML) strategies in energy trading focus on leveraging advanced algorithms to predict market behaviors, optimize trading decisions, and adapt to dynamic environments. Regardless of the market configurations, data-driven algorithms, especially ML and RL, have shown broader suitability for energy trading applications to study, analyze, and optimize market participant behavior in an LEM. The energy transactions within an LEM result in higher levels of self-consumption, as LEC members can be in a good position to make more informed decisions about their energy trades. Concerning data privacy and security, by using BCT, energy transactions can be more secure and transparent. Table 5 summarizes the RL algorithms used for energy transactions in different applications of LEM. Table 5 confirms that quite a few RL algorithms have been used for different LEM applications and energy trading scenarios, enabling more efficient, flexible, and adaptive energy transactions among different entities. The states, actions, and rewards are the key considerations in RL algorithms, and they vary depending on the context and goals of the energy trading system. Table 6 offers a comprehensive overview of potential factors to be considered in RL-based energy trading systems. The "state" encompasses all pertinent information about the energy trading system at a given moment, including variables like current energy demand and supply, battery storage levels, prevailing energy prices, weather conditions, and other factors influencing decision-making. The "action" represents the feasible choices available to the RL agent in response to the current state, such as energy buying or selling, adjusting generation, or storing energy. The "reward function" plays a pivotal role in guiding the RL agent toward favorable decisions, and in an energy trading context, it should be crafted to optimize system performance, accounting for variables like energy cost, profit from sales, and other pertinent objectives, be it profit maximization, cost reduction, or grid stability maintenance.

In Table 7, various RL algorithms are analyzed based on multi-dimensional parameters, i.e., objectives, type of agent, whether value- or policy-based, type of policy, type of state space, type of action space, and action selection. Q-learning updates the learning through Bellman's equation and Bellman's backup; thus, it operates only in discrete state and action spaces. The SARSA algorithm is specifically suited for solving Markov decision processes in sequential decision-making problems. SARSA is an on-policy learning algorithm that directly estimates the Q-values for the current policy that is being used for exploration and exploitation. The AC and SAC networks can make a more accurate value prediction for the current policy, as they utilize a value and policy combination approach, but since in on-policy algorithms the prior transitions cannot be employed more frequently to update the policy network, the AC and SAC networks may suffer from poor sampling efficiency. The TD algorithms update their value function estimates based on incomplete experiences using bootstrapped estimates of future states' values rather than waiting for the outcome of an episode. This bootstrapping allows them to learn online and incrementally from partial episodes.

Table 5. Application strategies for energy transactions in different RL algorithms.

Application	RL Algorithm
Bidding strategies [217]	SARSA
Pricing mechanism [218]	DDPG
Price optimization [219]	Deep double Q-learning
Bidding strategies [220]	SAC
P2P energy trading [221]	Fuzzy Q-learning
Bidding strategies [222]	DDPG
Bidding strategies, P2P energy trading [223]	Actor-critic
P2P energy trading [224]	Q-learning
P2P energy trading [225]	DQN
P2P energy transaction [226]	Q-learning
Demand response [227]	Q-learning
Bidding strategies [228]	DQN
Energy prices [229]	TD3
Demand response, bidding strategies [230]	Q-learning
Trading strategies [231]	DQN
Energy price optimization [232]	TRPO

Table 6. RL algorithm based on state, action, and reward functionality in energy trading.

Ref.	RL Algorithm	State	Action	Reward
[233]	Q-learning, SARSA	Current energy supply and demand	Buy/sell energy	Profit/loss from energy trading
[234]	Q-learning, DQN, DDPG	Energy market prices	Adjust energy production	Cost savings/penalties
[235]	Fitted Q-iteration	Battery SoC	Charge/discharge battery	Profit from battery usage
[236]	DQN, DDPG	Weather conditions	Modify energy generation	Increased renewable energy use
[237]	PG, A3C	Historical energy consumption	Optimize energy trading strategy	Improved performance
[238]	Q-learning, SARSA	Market demand and supply trends	Adjust energy trading volume	Higher market share
[239]	DQN, SAC	Competitor actions and strategies	Modify energy pricing	Increased market competitiveness
[240]	DDPG, SAC	Grid condition and balancing services	Change trading strategy	Grid-balancing services, cost reduction
[241]	PPO	Energy market regulations and policies	Comply with regulations or exploit loopholes	Avoid penalties or take advantage of incentives
[242]	SAC, DQN, TD3, PPO	Customer demand patterns and preferences	Offer tailored energy products or services	Increased customer satisfaction or retention
[243]	Q-learning	Market trends and competitor behavior	Adjust pricing or marketing strategies	Increased market share or competitive advantage
[244]	Q-learning, DQN, PPO	Energy storage capacity and charging/discharging rates	Control energy storage systems	Efficient utilization and optimal charging and discharging

Table 7. Summary of RL algorithms based on single agent type, policy, state space, action space, and action selection.

Ref.	RL Algorithms	Objectives	Agent Learning Method	Learning Updates	Value/Policy	Policy	Policy Type	State Space	Action Space	Action Selection
[245]	Q-learning	Energy trading	TD learning	Bellman equation	Value	OFF	Deterministic	Discrete	Discrete	Epsilon-greedy strategy
[246]	DQN	Social welfare maximization	Neural network	Bellman equation	Value	OFF	Deterministic	Continuous	Discrete	Epsilon-greedy strategy
[247]	SARSA	Maximizing reward	TD learning	SARSA algorithm's	Policy	ON	Stochastic	Continuous	Continuous	Epsilon-greedy strategy
[248]	AC	Demand flexibility	Gradient ascent	A2C algorithm	Policy+ Value	N/A	Stochastic	Continuous	Discrete or continuous	Tree search
[249]	SAC	Demand flexibility	Gradient descent	Entropy regularization method	Policy+ Value	N/A	Stochastic	Continuous	Discrete or continuous	Gaussian distribution
[250]	TD	Optimal pricing strategies	Bootstrapping approach	Monte Carlo methods	Value	OFF	Stochastic	Continuous	Discrete	Epsilon-greedy strategy
[251]	PPO	Energy trading	Gradient descent	Monte Carlo estimation	Policy	ON	Stochastic	Continuous	Discrete or continuous	Probability distribution
[252]	TRPO	Energy trading	Monte Carlo estimation	Neural networks	Policy	ON	Stochastic	Continuous	Discrete or continuous	Probability distribution
[253]	PG	Portfolio optimization	Gradient ascent	Monte Carlo algorithm	Policy	ON	Stochastic	Continuous	Discrete or continuous	Tree search
[254]	DPG	Energy cost reduction	Neural networks	Bellman equation	Policy	ON	Deterministic	Continuous	Continuous	Decision tree
[255]	DDGP	Energy market participants	Deep neural network	Bellman equation	Policy	ON	Deterministic	Continuous	Continuous	Decision tree

The policy optimization approaches mostly operate in continuous state and action spaces to find an optimal policy for an agent to maximize its cumulative reward in an environment. PPO is a state-of-the-art policy optimization algorithm trust region approach to ensure that the policy updates stay within a safe region to prevent large policy changes. PPO offers the best sample efficiency and good convergence properties. TRPO algorithm uses a similar trust region approach to ensure that policy updates are not too aggressive. It offers more stability and ensures that the policy changes are gradual. DDPG is a policy optimization algorithm specifically designed for continuous action spaces. It uses an AC architecture with a deterministic policy, which is suitable for problems with continuous action spaces.

In RL algorithms, the action space represents the set of possible actions that an agent can take in each state. It can be discrete or continuous, depending on the nature of the problem. Discrete action spaces consist of a finite number of actions, while continuous action spaces are characterized by a range of possible action values. In deterministic policy function, all the actions remain the same until the policy changes from the set of environment state to the set of actions. A stochastic policy function is a conditional probability distribution from the set of states to the set of actions. As an action selection mechanism, the epsilon-greedy policy selects the action with the highest Q-value most of the time (greedy exploitation), but with a small probability epsilon, it chooses a random action (exploration). The tree search approach represents various scenarios, decision points, or states in a problem-solving domain. A decision tree strategy uses decision structures for problem-solving and decision-making tasks. Decision trees can be used for both classification and regression tasks. They are particularly useful for tasks that involve making a sequence of decisions based on multiple attributes or features. The SoftMax policy assigns probabilities to each action based on their respective Q-values.

5. Conclusions and Future Directions

The energy sector is undergoing a significant transformation, characterized by an increasing focus on decentralization and the adoption of RES. LEMs are emerging as a promising solution to optimize energy distribution within small-scale communities. The energy trading environment in LEMs is susceptible to uncertainties stemming from renewable energy generation and is highly complex due to market dynamics, energy trade price diversity, consumer behavior, interaction, and trading cooperation mechanisms between market participants. In this review paper, initially, different LEM market platforms and projects were investigated and classified into real-time technology-based aggregator platform projects and local market flexibility platform projects. Real-time aggregator platform projects aimed to leverage BCT capabilities and smart contracts to enable transparent tracking of energy transactions, real-time energy trading, data management, and analytics to foster renewable energy adoption at the community level. Local market flexibility platform projects targeted the DERs and demand-side flexibility into the LEM, market facilitation, improved grid management, ancillary services, load balancing, and network planning and development.

Our exploration of RL, as a subset of ML, within the context of LEMs has also led to several key findings through an analysis of the literature and various research studies. First and foremost, the dynamic nature of LEMs necessitates flexible decision-making. RL algorithms have demonstrated their capacity to adapt actions effectively in response to changing market dynamics, enabling game players/agents to learn and select optimal actions. We have surveyed various aspects of RL in energy trading, encompassing predictive and analytical approaches within LEMs to enhance decision-making and optimize energy trading strategies. RL methods have shown promise in handling uncertainties by learning from the environment, enabling market players and agents to make informed decisions through the exploration of different strategies and ultimately enhancing rewards. In conclusion, this comprehensive review underscores the considerable potential of RL in optimizing energy trading within LEMs, thereby improving overall market efficiency. The RL techniques also showcased adaptability, robustness, and a capacity to thrive in complex and uncertain environments.

Our research has further highlighted that the implementation of LEMs is accompanied by a host of challenges. These challenges include but are not limited to price volatility, demand fluctuations, efficient resource allocation, effective auction and pricing mechanisms, participant interaction and preferences, flexibility, selection of appropriate learning algorithms, real-world implementation, data efficiency, data quality, and scalability. Addressing these challenges is imperative for the successful and widespread adoption of LEMs and necessitates future research efforts and collaborations between academia, industry stakeholders, and policymakers.

In the future, the effectiveness of different market structures and regulatory frameworks for LEMs needs to be investigated further to rationalize their role in competitive markets, increase market participation, and ensure fair competition. Researchers may also investigate the potential integration of smart contracts to automate energy trading processes. In addition, more transparent, secure, and verifiable energy transactions for LEMs will require more involvement with BCT and distributed ledger technologies. Privacy and security challenges associated with the increasing amount of data generated in LEMs are another area that needs to be focused on. For seamless communication and collaboration between different market participants and technologies, standardization and interoperability are the obligatory requirements.

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Abbreviations

A2C	Advantage actor-critic
A3C	Asynchronous advantage actor-critic
AI	Artificial intelligence
ANN	Artificial neural network
BCT	Blockchain technology
BRL	Batch reinforcement learning
BRP	Balance responsible party
CEM	Competitive energy market
CO	Community-operated
DDPG	Deep deterministic policy gradients
DER	Distributed energy resources
DG	Distributed generators
DPG	Deterministic policy gradients
DQN	Deep Q network
DSO	Distribution system operator
ESS	Energy storage systems
ETPA	Energy Trading Platform Amsterdam
EV	Electric vehicle
FSP	Flexible service providers
GA	Genetic algorithms
GOPACS	Grid Operators Platform for Congestion Solutions
HER	Hindsight experience replay
HS-DDPG	Hot start deep deterministic policy gradient
IISM	Institute of Information Systems and Marketing
IoT	Internet of Things
ILQR	Iterative linear quadratic regulator
LAMP	Landau Microgrid Project
LEC	Local energy community
LEM	Local energy market
LES	Local energy system
LSEM	Large-scale energy markets
MBFM	Modified Bessel function model
MBVE	Model-based value estimation
MDP	Markov decision process
MG	Microgrid
MGM	Microgrid market
ML	Machine learning
NAF	Normalized advantage function
P2P	Peer-to-peer
PG	Policy gradient
PILCO	Probabilistic inference for learn control
POMDP	Partially observable Markov decision process
PPO	Proximal policy optimization
PSO	Particle swarm optimization
Q	Action
QR-DQN	Distributional reinforcement learning with quantile regression
REM	Retail electricity market
RES	Renewable energy sources
RL	Reinforcement learning
SAC	Soft critic actor
SAM	Strategic assessment model
SARSA	State–action–reward–state–action
SFOE	Swiss Federal Office of Energy
SoC	State of charge
SM	Smart meter

TSO	Transmission system operator
TD	Temporal difference
TD3	Twin delayed deep deterministic policy gradients
TE	Transactive energy
TRPO	Trust region policy optimization
TSO	Transmission system operator
WEM	Wholesale electricity market

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