Peer-to-Peer Energy Sharing: A New Business Model Towards a Low-Carbon Future

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Abstract—The development of distributed generation technology is endowing consumers the ability to produce energy and transforming them into “prosumers”. This transformation shall improve energy efficiency and pave the way to a low-carbon future. However, it also exerts critical challenges on system operations, such as the wasted backups for volatile renewable generation and the difficulty to predict behavior of prosumers with conflicting interests and privacy concerns. An emerging business model to tackle these challenges is peer-to-peer energy sharing, whose concepts, structures, applications, models, and designs are thoroughly reviewed in this paper, with an outlook of future research to better realize its potentials.

Index Terms—energy sharing, peer-to-peer energy trading, business model, mechanism design

I. INTRODUCTION

Global warming and climate change are urging governments, industry, and academia to build a low carbon society [1]. Meanwhile, the development of economy and technology makes energy demand grow rapidly with diversifying usage scenarios [2]. This dilemma of less carbon versus more energy motivates researchers, engineers, and policy-makers to restructure a more sustainable and affordable energy landscape.

A pivotal piece of the puzzle assembling such a landscape is the proliferation of distributed energy resources (DERs) such as small wind turbines, rooftop solar photovoltaic (PV) panels, and energy storage [3]. Over 81,000 distributed wind turbines with more than 1GW total capacity were installed in the U.S. during 2003 to 2007 [4]. Global residential PV panels increased from 3.7GW in 2004 to 150GW in 2014 [5]. Worldwide battery storage capacity is expected to grow from 2GW in 2017 to 235GW in 2030 [6]. These low-carbon technologies demonstrate great potential in relieving environmental pressure, yet accompanied by nontrivial challenges.

First, the engagement of DERs still relies heavily on policies at this stage. Indeed, deceleration of DER installation has been observed in regions with declining financial supports. For instance, U.K. cut its subsidy for PV adoption by 80% from 2017 to 2018 [7]. The global storage market shrank by nearly zero costs, they can thus offer competitive prices to incentivize demand-side flexibility for backup dismissal and efficiency improvement. To unlock this opportunity, the grid operation shall be migrated from a vertically structured market, which co-optimizes renewable energy sources, responsive loads, and other DERs without subsidy and without jeopardizing system reliability.

What inspires such a market design is the emerging sharing economy in other sectors, which is motivated by similar needs to enhance resource utilization and facilitated by advanced information and communication technologies [9]. The widespread deployment of those technologies (e.g., smart meters) also makes sharing economy ready for power and energy systems. In this context, we provide a comprehensive and in-depth review of energy sharing—the first of its kind to our knowledge—on its definition, application scenarios, business models, mechanism designs, and future research directions.

TABLE I compares topics discussed by this paper and previous literature reviews, including those for sharing economy in other sectors [10], [11], peer-to-peer energy trading [12]–[18], and transactive energy [19], [20]. These reviews adopt different terminologies for energy sharing in a broad sense, partly due to the fact that “sharing” has a variety of semantic meanings with different conceptual emphases, such as communicating (sharing information), acting together (sharing responsibility), or giving out (sharing a cake). Such ambiguity is intensified by the intangible feature of energy, which differs from tangible assets such as cars and houses in that one does not need physical access to a generator to use energy. As a result,
TABLE I
COMPARISON OF RELEVANT LITERATURE REVIEWS

| Our review                  | Application | Business model | Mechanism design | Market structure | Pilot project | Legal context |
|-----------------------------|-------------|----------------|------------------|------------------|---------------|--------------|
| Sharing economy in other sectors | ✓           | ✓              | ✓                | ✓                | ✓             | ✓            |
| [10]                        |             |                |                  |                  |               |              |
| [11]                        |             |                |                  |                  |               |              |
| Peer-to-peer energy trading  | ✓           | ✓              | ✓                | ✓                | ✓             | ✓            |
| [12]                        |             |                |                  |                  |               |              |
| [13]                        |             |                |                  |                  |               |              |
| [14]                        |             |                |                  |                  |               |              |
| [15]                        |             |                |                  |                  |               |              |
| [16]                        |             |                |                  |                  |               |              |
| [17]                        |             |                |                  |                  |               |              |
| [18]                        |             |                |                  |                  |               |              |
| Transactive energy          | ✓           | ✓              | ✓                | ✓                | ✓             | ✓            |
| [19]                        |             |                |                  |                  |               |              |
| [20]                        |             |                |                  |                  |               |              |

II. CONCEPTS AND APPLICATIONS

A. Definition and basic structures

The idea of sharing, initiated from rental markets, is not new, yet its concretization in the energy sector is only boosted after deployment of high-speed information and communication technologies that connect and settle transactions among participants in energy markets. Recent pilot projects have tested energy trading platforms at various geographical scales for different entities, e.g., Piclo [21] and P2P3M [22] in the U.K., TransActive Grid [23] in the U.S., and Enexa [24] in South Australia. A comparison of those pilot projects can be found in [25]. Moreover, index systems have been built to evaluate the performance of sharing platforms [25], [26].

Essentially, sharing means to utilize otherwise wasted resources or capabilities by transferring their ownership or separating their ownership from the right to use them, targeting a win-win situation across providers and consumers. Inheriting this concept, energy sharing can be defined as follows.

**Definition 1. Energy Sharing** refers to the business model to optimize energy system operation by acquiring, providing, or sharing access to facilities or energy, leveraging advanced information and communication technologies.

Market structures for energy sharing generally fall in three categories as shown in Fig. 2. A centralized market is vertically structured with communications and transactions managed centrally by the operator [27]. Specifically, the operator monitors the status of agents and computes energy prices. Upon receiving the prices, the agents determine and report to the operator their energy quantities to buy or sell. The operator then dispatches control signals to deliver these quantities. Most demand-side markets today lie in this category, in which pricing is a big challenge because of privacy concerns and small capacities of agents that make their behavior hard to observe. A distributed market settles transactions in a horizontal peer-to-peer (P2P) way. An operator still communicates with all the agents [28], but instead of directly trading with them, it indirectly influences transactions between them, e.g., by announcing incentive or regulation signals. In this way, the agents enjoy a high degree of autonomy in decision making, while preserving their privacy by disclosing limited information to the operator. In a decentralized market, the agents can communicate and trade between themselves without involving an operator [29]. This structure renders agents the highest levels of flexibility and privacy, but makes it difficult for agents to provide grid services as an aggregate or to maximize their social welfare, due to lack of coordination.

B. Applications

TABLE II categorizes common applications of energy sharing by objectives and scenarios.
Fig. 2. Typical market structures for energy sharing: (a) centralized, (b) distributed, (c) decentralized.

TABLE II
SUMMARY OF ENERGY SHARING APPLICATIONS

| Objectives         | Scenarios          | References |
|--------------------|--------------------|------------|
| Accommodate renewables | Solar              | [30]–[36] |
|                    | Wind               | [37]–[39]  |
|                    | Hydrogen           | [40]–[42]  |
| Enhance efficiency | Smart building     | [33], [43]–[45] |
|                    | Microgrid          | [28], [46]–[48] |
|                    | Integrated energy  | [40], [42], [49]–[51] |
| Reduce backups     | Battery            | [34], [35], [52]–[57] |
|                    | Electric vehicle   | [38], [40], [60] |

1) Accommodate renewable energy. Renewable generation from solar, wind, hydrogen, etc. can effectively mitigate carbon emissions. However, the intermittent and volatile nature of renewable sources makes it hard for prosumers to plan their energy purchase and usage and hence discourages them from investing in more renewables. This difficulty has motivated extensive studies on sharing renewable energy. For instance, a group of DERs can mutually cancel out variations in their power outputs to generate a steady aggregate output. In evenings with no sunshine and abundant wind, prosumers with wind turbines can share surplus generation to compensate for the energy shortage of those with PV panels [61]. For solar PV prosumers, prior work developed clustered sharing models [30], [31], [36], distributed pricing strategies [32], and resource allocation rules [33]. The performance of solar energy sharing can be further improved by controlling aggregated batteries [34], [35]. With wind power, an online algorithm was proposed to share energy in a cooperative residential community [37] and a P2P trading platform was built [38]. Wind energy producers can also trade with demand-response aggregators to co-schedule energy and reserves [39]. Moreover, energy sharing models were developed for aggregators with plug-in hybrid electric and hydrogen vehicles [40] and for interconnected microgrids with hydrogen energy storage [41]. The synergy of electricity, hydrogen, and heat networks was studied in [42].

2) Enhance operating efficiency. Energy sharing can improve the overall efficiency of a group of participants that have different cost or utility functions for their distributed generation, storage, or demand-response units. For example, in demand response, a customer can buy energy to compensate for its demand reduction from another customer that incurs a lower cost to reduce the same demand; both customers will gain benefit with a proper payment [46]. There are three typical scenarios of such efficiency improvement. The first is for smart buildings, e.g., via P2P energy trading among smart homes [43] and apartment buildings [33], coordinated energy-sharing control in a building cluster [44], and energy sharing between commercial buildings, electric vehicle (EV) charging stations, and the grid [45]. The second scenario is for microgrids, where optimal demand function bidding [28], [46] and blockchain technology [47] were used for energy sharing and simulations verified improved efficiency [48]. The third scenario is for multi-energy systems that integrate power, heat, hydrogen, et cetera [40], [42]. Transactive energy can support economic operations of multi-energy microgrids [49], building clusters [50], and energy internet [51].

3) Reduce reliance on backups. The waste of standby backups raised in Section I can be greatly reduced by energy sharing. Previous research on such backup reduction mainly focused on static batteries and EVs as mobile energy storage. The sharing economy brings in new business models for energy storage [52], [53], among which a representative is cloud storage [54]. Indeed, energy storage is commonly co-shared with PVs [34], [35], [56], resting on methods such as adaptive bidding [55]. Apart from scheduling, the sizes of batteries were also optimized [57]. For mobile storage, the potential of energy sharing was revealed by a case study in California [58]. Game-theoretic approaches were taken to price shared energy between the grid and EVs [59]. Blockchain technology can also facilitate energy sharing among EVs [60].

III. BUSINESS MODELS

A. Models by resource sharing modes

TABLE III summarizes four models by their modes of resource sharing, with examples from energy and other sectors.

1) Share possessed resources. Zipcar, Mobike, and Offo are good examples, which own the vehicles/bikes and track them through web/mobile platforms so that the sharing is essentially leasing [68]. A drawback of this model is the tremendous financial burden to acquire and maintain the resources to share. An alternative option is to allow each customer to buy such a resource and the company to coordinate them, but this model is hard to initiate due to the scale effect and cross-group externalities [69]. This drawback can be neutralized in energy sharing due to the convenience to access energy across
a network, without requiring customer possession of resources. For example, customers can first to invest in cloud storage, a shared pool of storage centrally controlled by the operator, to receive storage service when needed [54], [62].

2) Find new homes for used resources. Conventional means such as garage sales to trade used items are restricted by venues and occurrences. To facilitate cascaded utilization of goods, companies like eBay serve as intermediaries between owners and buyers instead of owning the inventory themselves. This model is implemented in energy systems, e.g., with batteries as the goods [63]. The performance of reused automotive batteries as stationary energy storage has been validated in Europe [64] and China [65], [66]. The common practice of replacing lithium-ion EV batteries with lower than 80% rated capacity is causing serious pollution, while allowing those batteries to participate in energy sharing markets can push forward the sustainable electrification of transportation [67].

3) Utilize underused resources. Successful sharing platforms Airbnb and Uber belong to this category. For instance, Airbnb brings together owners of vacant rooms and enables them to get cash by posting and renting rooms online. A key difference between the category above (e.g., eBay) and this category is that the former transfers ownership while the latter only temporarily leases the right of use. In energy systems, intermittency and uncertainty of renewable energy sources force them to be regularly underused to avoid supply-demand mismatch. Energy sharing can improve the utilization of renewable sources by smoothing out their uncertainties, e.g., for PVs [30]–[32] and other resources [37]. Note that this kind of sharing is often aided by batteries [33], [34].

4) Exploit resource abilities. Companies like TaskRabbit assist customers with routine work, e.g., home repair, to find someone better qualified to accomplish the work at a lower cost, so that both the customer and the worker can benefit with a proper payment. Similarly, in demand response programs, energy consumption of certain customers can be adjusted at lower disutilities than others, and hence they can perform excessive adjustments to share with those suffering higher disutilities and to reduce the social disutility [28], [46].

B. Models by flexibility characterizations

Energy sharing models can also be categorized by their flexibility characterizations as explained below. Consider agents \(i \in I := \{1, ..., I\}\). Let \(q_i\) denote the sharing quantity of agent \(i\) and let \(\theta_i\) denote its type. An agent \(i\) with \(q_i > 0\) (\(q_i < 0\)) buys (sells) energy from the market. The individual value of agent \(i\) is \(v_i(q, \theta_i)\), which may depend on all quantities \(q := (q_i, \forall i \in I)\). A general formulation of energy sharing is:

\[
\begin{align}
\max_{q_i, \forall i \in I} & \quad \sum_{i \in I} v_i(q, \theta_i) \\
\text{s.t.} & \quad \sum_{i \in I} q_i = 0 \\
& \quad q_i \in D_i \cap Q_i, \forall i \in I; \quad q \in \tilde{D}
\end{align}
\]

which aims to maximize the total value of all the agents. The sharing market is cleared when the total energy sold equals the total bought, i.e., \(|\|\|. The shared energy \(q_i\) is limited by individual constraint \(D_i\), such as capacity limit of local resources; network constraint \(\tilde{D}\) that couples the agents; and energy exchange limit \(Q_i\) depending on the sharing model adopted. The following discussion focuses on \(Q_i\) that characterizes flexibility of the corresponding model.

1) Fixed roles, sharing mediating assets. In this model, shared energy is mediated by certain assets between agents whose roles as sellers or buyers are determined exogenously and beforehand. For example, the sellers charge the cloud storage as a mediating asset, which is then discharged by the buyers [54], [62]. Flexibility set \(Q_i\) in this case becomes:

\[0 \leq q_i \leq Q_i, \forall i \in B; \quad -Q_i \leq q_i \leq 0, \forall i \in S\]

where \(B\) and \(S\) are the set of buyers and sellers, respectively, with \(I = B \cup S\). Constant \(Q_i\) aggregates the physical limits of mediating assets accessible by agent \(i\), e.g., accessible capacity and maximal charging or discharging rate of cloud storage.

2) Fixed roles, sharing local capacity. Energy may also be traded directly without a mediating asset. For instance, a prosumer with excessive renewable generation in real time may offer it, within local capacity of renewable sources, to one with unexpected demand [30]–[32]. In this case, \(Q_i\) is:

\[q_i \geq 0, \forall i \in B; \quad q_i \leq 0, \forall i \in S\]

Flexibility of this model is restricted by local capacity \(D_i\) but not any mediating asset. However, the agents are still pre-assigned into a seller set \(S\) or a buyer set \(B\).

3) Flexible roles. The two models above both pre-assign market roles and hence limit the flexibility of agents, partly due to the rigid feature of shared products. This is similar to the Airbnb model where sellers and buyers are divided by locations of houses. This spatial restriction is not stringent for energy that can flow in a network. This allows market roles
of energy prosumers to be endogenously determined, in which case \( Q_i = \mathbb{R} \) for all \( i \in \mathcal{I} \) does not impose additional limits. References [28], [46] designed this type of energy sharing mechanisms based on generalized demand function bidding.

As we can observe, the constraint sets \( Q_i \) are expanded and the flexibility is improved as we go through the three models above. Exploiting the flowability of energy, the last model demonstrates the best potential in utilizing flexible resources.

IV. MECHANISM DESIGNS

Despite the extensive research on general sharing economy [70], it is only recently that energy sharing research has grown, started with empirical studies or abstract models to demonstrate its advantages [61] and followed by mechanism designs that will be reviewed in this section. A good mechanism addresses both pricing and allocation issues to satisfy: 1) The market is cleared with energy supply and demand balanced and network constraints respected. 2) The profit is properly distributed to incentivize customer participation. 3) The mechanism can be implemented with simple rules, without requiring participants to disclose private information.

Let \( q = (q_i, \forall i \in \mathcal{I}) \) be the vector of sharing quantities and \( \mathcal{A}_i, \forall i \in \mathcal{I} \) the action sets of agents; let \( \theta_i \) be the type of agent \( i \), which is private information from a set \( \Theta_i \). Each agent’s total value \( \text{value}_{i}(s_{i}) \) consists of two parts: individual value \( \text{value}_{i}(q_i, \theta_i) \) and monetary transfer \( m_i \), where the latter satisfies \( \sum_{i=1}^{\mathcal{I}} m_i \leq 0 \). Let \( \mathcal{Y} = \{q, m_1, m_2, ..., m_i\} \) denote the market outcome. Then a mechanism can be defined as follows.

**Definition 2.** (Mechanism) Let \( L : \mathcal{A}_1 \times \mathcal{A}_2 \times ... \times \mathcal{A}_\mathcal{I} \rightarrow \mathcal{Y} \) be an outcome function. Then a mechanism \( \Gamma \) is a collection of \( \mathcal{A}_i, \forall i \in \mathcal{I} \) and \( g(\cdot) \). A pure strategy for agent \( i \in \mathcal{I} \) in mechanism \( \Gamma \) is a function \( S_i : \Theta_i \rightarrow \mathcal{A}_i \) that maps agent types into actions, under which agent \( i \) receives value \( \text{value}_{i}(s_{i}) \).

Generally, the mechanism designer has a certain goal \( J : \Theta \rightarrow \mathcal{Y}, \) e.g., social value maximization. However, since \( \theta_i \in \Theta_i \) is private to agent \( i \in \mathcal{I} \), the designer can only achieve the goal indirectly via a well-designed mechanism. The relationships between designer’s goal, mechanism, and market outcome are shown in Fig. 3.

![Fig. 3. Relationships between designer’s goal, mechanism, and outcome.](image1)

Existing energy sharing mechanisms can be divided into those based on **game-theoretic models** and **optimization models**. The former category includes cooperative and noncooperative games. Cooperative games rest on proper allocation of values, e.g., by Shapley value or nucleolus, to incentivize prosumers to form one or more coalitions, which align prosumer interests with social objectives such as minimizing the operational cost of a network or maximizing the total utility of prosumers. In contrast, noncooperative games focus on competition between individual prosumers. Commonly exploited noncooperative games for energy sharing are Stackelberg games in centralized markets, generalized Nash games in distributed markets, and multi-leader multi-follower games and Nash games in decentralized markets. The latter category includes those using distributed optimization methods and learning algorithms. TABLE IV compares these models.

A. Game-theoretic models

1) Cooperative game-based energy sharing

![Fig. 4. Cooperative game-based energy sharing.](image2)

As Fig. 4 shows, an allocation rule is designed based on cooperative game theory to achieve certain social objectives, and is implemented by the agents who form coalitions to optimize the value they will each receive. Specifically, let \( J \subseteq \mathcal{I} \) denote a coalition (subset) of agents. A game conducted in coalitions can be modeled with a characteristic function \( V : 2^\mathcal{I} \rightarrow \mathbb{R} \) that maps coalitions to values. If the game satisfies superadditivity defined below, then all the agents will cooperate to reach the maximal total value \( V(\mathcal{I}) = \sum_{I=1}^{\mathcal{I}} \text{value}_{i}(q_i, \theta_i) \).

**Definition 3.** (Superadditive Game) A game with characteristic function \( V \) is superadditive if \( V(J_1 \cup J_2) \geq V(J_1) + V(J_2) \) for all \( J_1 \subseteq \mathcal{I}, J_2 \subseteq \mathcal{I}, J_1 \cap J_2 = \emptyset \).

Let \( c := (c_i, \forall i \in \mathcal{I}) \) be a value allocation when all the agents collaborate as a grand coalition, from which no agent has the incentive to leave if \( \sum_i \text{value}_{i}(J) \geq \text{value}_{i}(\mathcal{I}) \) for all \( J \subseteq \mathcal{I} \). In this case, we say allocation \( c \) is in the core of the game.

There are two common approaches to the design of cooperative games. First, Shapley value distributes values to players according to their marginal contribution, i.e., for player \( i \):

\[
  c_i = \sum_{J \subseteq \mathcal{I}, i \in J} \frac{|J|!(|\mathcal{I}| - |J| - 1)!}{|J|!} (V(J \cup \{i\}) - V(J)).
\]

With Shapley value, incentives were designed for coalitional operation of networked energy-exchanging microgrids [71]. Reference [72] proposed a random sampling method to estimate the Shapley value of a P2P energy sharing game. Reference [73] compared a Shapley value-based P2P energy trading mechanism with the classical bill sharing, mid-market rate, and supply-demand ratio algorithms. A two-level reward allocation scheme was developed to deal with the computational complexity of Shapley value under a large number of agents [50]. Note that Shapley value, albeit a fair allocation, is not always in the core of a cooperative game.

Differently, the nucleolus is the set of element(s) in the core that minimizes the overall dissatisfaction of players in the grand coalition measured by the excessive values they
would receive should they form alternative (smaller) coalitions. Specifically, let $\le_{lex}$ be the lexicographical ordering of $\mathbb{R}^n$, i.e., for any $x, y \in \mathbb{R}^n$, there is $x \le_{lex} y$ if either $x = y$ or $\exists t \in [0, n]$ such that $x_t = y_t$, $\forall i \in [0, t]$ and $x_t < y_t$, $\forall i \in [t + 1, n]$. Denote by $C$ the set of all possible allocations in the grand coalition, and then the nucleolus is the set $\{c_1 \in C \mid e(c_1) \le_{lex} e(c_2), \forall c_2 \in C\}$, where $e(c)$ is the sequence of excesses $e(J, c) = V(J) - \sum_{i \in J} c_i$ over all the $2^J$ coalitions $J \subseteq I$. With the nucleolus, distributed energy storage units can form cost-minimizing coalitions [74]. A K-means clustering method was used to accelerate the nucleolus calculation [75].

To circumvent the possibly heavy computation of Shapley value and nucleolus, [76–79] adopted the Nash bargaining model. Ad hoc designs were also made for the sharing of energy storage [80] or among aggregator-managed agents [81].

The designs so far stick to budget balance, i.e., the sum of allocations equals the value of the coalition. An alternative to relax this balance is the Vickrey-Clarke-Groves (VCG) mechanism, which pays $m_i = \sum_{j \neq i} v_j(q(\theta), \theta_i) + h_i(v_{-i})$ to agent $i$, where the second term is a function of the (declared) values of agents other than $i$. As a result, every agent $i$ chooses its action to maximize $v_i(q(\theta)) + \sum_{j \neq i} v_j(q, \theta_j)$, namely the social value, as $h_i(v_{-i})$ does not depend on agent $i$'s action. The VCG mechanism is proved to be a truthful mechanism in that every agent will report its true value. It was used in [82] to limit power losses in P2P energy sharing.

Besides the advantage of achieving social optimality and the concern with computation burden, a serious drawback of cooperative games is that private information, such as value functions of the participants, needs to be disclosed.

### 2) Noncooperative game-based energy sharing

Four noncooperative game models are reviewed below.

### References

| References | Features | Structures | Advantages | Drawbacks | Game-theoretic model | Optimization model |
|-----------|----------|------------|------------|-----------|----------------------|-------------------|
| [50], [71]–[73], nucleusal [74], [75], Nash bargaining [76]–[79], others [80]–[82] | Need an allocation rule; agents act cooperatively considering their allocated values. | Distributed | Can achieve social optimum without a central coordinator; agents can freely choose to sell or buy. | Hard to maintain budget balance, design allocation rules, and protect privacy. | Cooperative game | Optimization model |
| [83]–[86], proofs [32], [87], algorithms [88]–[90] | The operator makes prices, followed by all the agents who decide sharing quantities. | Distributed | Can achieve social optimum while satisfying network constraints; budget is balanced. | Need to maintain budget balance, design allocation rules, and protected privacy. | Noncooperative game | Distributed / Decentralized |
| Applications [30], [31], proofs [32], [87], algorithms [88]–[90] | Agents make bids, and the operator returns prices and sharing quantities. | Distributed | Can achieve social optimum while satisfying network constraints; budget is balanced. | Need to maintain budget balance, design allocation rules, and protected privacy. | Noncooperative game | Distributed / Decentralized |
| [28]–[46], [91], 93–95, [55], [96]–[101] | Sellers make prices first, followed by buyers who decide sharing quantities. | Decentralized | Can run in an asynchronous manner; budget balanced; individual interests fulfilled. | Need to maintain budget balance, design allocation rules, and protected privacy. | Multi-leader multi-follower generalized Nash game | Distributed / Decentralized |
| [102]–[105], learning algorithms [106], [107] | Agents act separately as sellers or buyers; sharing quantities are first set and then prices. | Decentralized | Can run in an asynchronous manner; budget balanced; individual interests fulfilled. | Need to maintain budget balance, design allocation rules, and protected privacy. | Bilateral Nash game | Distributed / Decentralized |

### Table IV

| Summary of energy sharing mechanisms |
|--------------------------------------|
| **Game-theoretic model**             |
| **Cooperative** | **Noncooperative** | **Optimization** |
| Stackelberg game                    | Generalized Nash game | Multi-leader multi-follower generalized Nash game | Bilateral Nash game |

### Fig. 5

Energy sharing based on (a) a Stackelberg game, (b) a generalized Nash game, and (c) a multi-leader multi-follower game.

#### 2.1) Stackelberg game

A Stackelberg game adopts the centralized leader-follower structure in Fig. 5(a). The operator (leader) sets prices to optimize its objective such as profit; the agents follow the prices to decide sharing quantities to maximize their net utilities. Specifically, consider prices $p_i^b$ and $p_i^s$ to buy and sell, respectively, with the main grid. Then the operator solves:

$$\max_{\lambda^b, \lambda^s} \sum_{i \in B} \lambda^b_i q_i + \sum_{i \in S} \lambda^s_i q_i - p_i^b \sum_{i \in B} q_i - p_i^s \sum_{i \in S} q_i, \quad \sum_{i \in B} q_i \geq 0, \quad \sum_{i \in S} q_i < 0$$

and every agent $i \in I$ solves:

$$\max_{q_i} \left\{ v_i(q, \theta_i) - \lambda^i_i q_i \right\}, \quad i \in S$$

$$\max_{q_i} \left\{ v_i(q, \theta_i) - \lambda^b_i q_i \right\}, \quad i \in B$$
where $\lambda_i^a$ and $\lambda_i^b$ are the selling and buying prices of agent $i$. The operator in (2) maximizes its total revenue from the agents minus its net payment to the main grid, while each agent $i$ in (3) maximizes its utility minus its net payment to the operator. Besides numerous heuristics, a prevalent method to compute the market equilibrium is to replace every agent’s problem (3) with its optimality condition such as the Karush-Kuhn-Tucker (KKT) condition, which leads to a mixed-integer program.

Prior work along this line spans applications including microgrids with PVs [30], [31], demand response [83], multi-energy systems [84], multi-regional energy sharing [85], and two-stage robust energy sharing with uncertain generation and prices [86]. Theoretically, [32] proved existence and uniqueness of the Stackelberg equilibrium, and [87] further proved stability of the equilibrium under follower coalitions. Moreover, efficient algorithms have been developed to reach the market equilibrium. For instance, an online algorithm was designed based on Lyapunov method to maximize the self-sufficiency of prosumers and ensure the stability of nano-grid clusters [88]; a consensus-type distributed algorithm was developed in [89]; a Q-learning algorithm was developed by embedding the prediction of rooftop PV generation [90].

Besides the reliance on a central operator and the difficulty to decide optimal prices, a major limitation of the Stackelberg game is that prosumers are simply modeled as price-takers.

### 2.2 Generalized Nash game

In a generalized Nash game, the strategy set of an agent depends on the strategies of others. It adopts the distributed structure in Fig. 5(b), where every agent submits a bid considering other agents’ reactions, and then the platform clears the market. In particular, every agent $i \in \mathcal{I}$ maximizes $v_i(q(b), \theta_i) - \lambda_i(b)q(b)$, i.e., its utility $v_i$ minus its net payment $\lambda_i$ to the market, over its bid $b_i$. Upon receiving all the bids $b := (b_i, \forall i \in \mathcal{I})$, the platform decides prices $\lambda = (\lambda_i, \forall i \in \mathcal{I})$ and quantities $q = (q_i, \forall i \in \mathcal{I})$ to minimize a social cost $P(\lambda(b), q(b))$. Such a generalized Nash game boils down to an equilibrium problem with equilibrium constraints (EPEC).

Reference [91] modeled a distributed P2P energy market as a generalized Nash game and proved equivalence between its variational equilibria and social optima. Reference [40] proposed a generalized demand function bidding mechanism to attain a unique Nash equilibrium that approaches the social optimum with an increasing number of prosumers. Based on that, a practical bidding process to reach the generalized Nash equilibrium was developed in [28], with network power flow limits further incorporated in [92]. These mechanisms do not require complicated allocation rules or impose exogenous restriction on buyer and seller roles. However, they may suffer inefficiency due to the market power of some participants.

### 2.3 Multi-leader multi-follower game

In such a mechanism, the agents are predetermined as sellers or buyers and act in a distributed market as shown in Fig. 5(c). The sellers first announce prices taking into account buyer reactions, followed by the buyers who decide energy sharing quantities. Specifically, each seller $i \in \mathcal{S}$ solves:

$$\max_{\lambda_{ij}, j \in \mathcal{B}} v_i(- \sum_{j \in \mathcal{B}} q_{ij}(\lambda), \theta_i) + \sum_{j \in \mathcal{B}} \lambda_{ij} q_{ij}(\lambda)$$

and each buyer $j \in \mathcal{B}$ solves:

$$\max_{q_{ij}, i \in \mathcal{S}} v_i(q_{ij}(\lambda), \theta_j) - \sum_{i \in \mathcal{S}} \lambda_{ij} q_{ij}$$

where buyer $j \in \mathcal{B}$ purchases energy quantity $q_{ij}$ from seller $i \in \mathcal{S}$ at price $\lambda_{ij}$. A seller (buyer) aims to maximize its value plus (minus) its revenue (payment). Reference [93] modeled the dynamics of buyers selecting sellers as an evolutionary game. Reference [94] grouped physically separated prosumers into logical virtual microgrids and modeled their energy sharing as a multi-leader multi-follower game. Reference [95] designed an alternative procedure that buyers bid prices and sellers decide quantities. A major limitation of these mechanisms is the inflexibility of market roles of prosumers.

### 2.4 Bilateral Nash game

Such a mechanism has a similar structure to that in Fig. 5(c) but works in a quite different way. The pre-assigned sellers and buyers post their offers, and the sharing quantities are determined via matching or auctions. Then the bilateral prices or contracts are settled [108]. A key advantage of this mechanism is its compatibility with asynchronous actions, and a key challenge is to find matching results in a scalable way.

A bilateral contract network in forward and real-time markets was proposed in [96]. A P2P energy transaction matching algorithm was developed in [97] considering uncertainty and fairness of profit allocation. A negotiation algorithm settled an agreement among prosumers without prior knowledge about the preference of each other [98]. Reinforcement learning was used by an energy broker to match sellers and buyers [99]. Energy user behavior can be modeled using reinforcement learning with bounded regret and embedded into the mixed-integer linear program for seller-buyer matching [100]. Double auctions were also held for bilateral matching [55], [101].

### B. Optimization models

Optimization-based energy sharing mechanisms aim to reach social optimum. However, solving the social optimization in a centralized manner would compromise the privacy of participants. To address that, many studies interpreted dual variables of the social optimization as energy prices and carried out distributed iterative processes for energy sharing, which converge to socially optimal market equilibria.

The bidirectional energy exchange between EVs and roads was conducted with a privacy-preserving consensus algorithm [102]. Reference [103] further considered strategic choice of objective function parameters by the agents. Other approaches include the gradient algorithm [104] and the alternating direction method of multipliers [49], [105]. Besides, learning algorithms have gained popularity for energy sharing. A modified deep Q-network was applied to microgrids that share energy to maximize their total utility [106]. Multi-agent deep reinforcement learning aided energy sharing to realize a zero-energy community [107]. A disadvantage of optimization-based designs lies in the difficulty to reveal the underlying economic intuition and incentivize the agents to participate.

### V. Future Research

This section discusses three directions to explore about energy sharing, a promising concept that is still in its infancy.
A. Participants

1) Operators. Most existing work assumes only one operator in an energy sharing system. Market designs and pricing strategies with more than one competing operators require further investigation. Another critical issue is for an operator to attract customers and maintain their loyalty.

2) Prosumers. It is valuable to group the prosumers for better energy sharing outcomes. Despite the various clustering algorithms [109], most of them simply bundles prosumers with similar utility functions or load patterns which may not fully realize the potential of sharing. Especially, if the prosumers in a group are identical, sharing would not create much benefit. Besides clustering, the matching between prosumers [96] as well as prosumer’s bounded rationality that can be analyzed with the prospect theory [110], [112] are also crucial.

B. Energy, information, and value flows

1) Energy. The work so far has mainly concentrated on sharing electricity. As co-generation technologies are connecting multiple energy systems tighter than before, the sharing and conversion between multiple energy forms and the development of an integrated energy market will become inevitable.

2) Information. Energy sharing has mostly been studied under a symmetric information structure where the participants have full and equal knowledge about each other. However, asymmetric information is more common in reality [103], which may cause market failure if not handled properly. In particular, it deserves efforts to design mechanisms that can motivate participants to truthfully report their relevant information. Furthermore, when user data such as load profiles are needed for market operation, the information privacy and the value of information [113] are issues of great merit.

3) Value. Energy sharing markets today are mostly settled with financial support. It is worth the attempt to apply other paradigms, such as the credit score system for carbon and emission trading [114], to energy sharing.

C. Environment

The uncertainty of large-scale renewable generation is a key challenge for energy systems. Classical methods to overcome this challenge include stochastic, robust, and distributionally robust optimizations. Those methods often assume uncertainty scenarios or sets that are modeled exogenously. However, such uncertainty can actually depend on operating decisions. For example, the changing angle of a PV panel can influence its power output. This kind of decision-dependent uncertainty has not received adequate attention, partly due to its computational intractability that needs to be addressed in the future [115].

VI. CONCLUSION

This paper serves as a comprehensive survey of energy sharing from its basic structures, applications, business models, and market mechanisms. Its three typical structures are centralized, distributed, and decentralized. Applications of energy sharing can accommodate volatile renewable sources such as solar, wind, and hydrogen; enhance the operating efficiency of smart buildings, microgrids, and integrated energy systems; and relieve the reliance on energy storage backups. We reviewed business models of energy sharing from perspectives of resource sharing modes and flexibility levels. Market mechanisms were categorized into game-theoretic and optimization models. Finally, future research directions were discussed in terms of operators and prosumers; energy, information, and value flows; and uncertainty of the environment.

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