Transforming Energy Networks via Peer-to-Peer Energy Trading

The potential of game-theoretic approaches

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Peer-to-peer (P2P) energy trading has emerged as a next-generation energy-management mechanism for the smart grid that enables each prosumer (i.e., an energy consumer who also produces electricity) of the network to participate in energy trading with other prosumers and the grid. This poses a significant challenge in terms of modeling the decision-making process of the participants' conflicting interests and motivating prosumers to participate in energy trading and cooperate, if necessary, in achieving different energy-management goals. Therefore, such a decision-making process needs to be built on solid mathematical and signal processing principles that can ensure an efficient operation of the electric power grid.

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This article provides an overview of the use of game-theoretic approaches for P2P energy trading as a feasible and effective means of energy management. Various game- and auction-theoretic approaches are discussed by following a systematic classification to provide information on the importance of game theory for smart energy research. This article also focuses on the key features of P2P energy trading and gives an introduction to an existing P2P testbed. Furthermore, the article gives specific game- and auction-theoretic models that have recently been used in P2P energy trading and discusses important findings arising from these approaches.

Motivation

In recent years, there has been an urgent pursuit of an alternative energy system in which energy production, transmission, distribution, and consumption can take place in an environmentally sustainable fashion. As a result, the development of smart, sustainable, and green solutions is becoming more significant, including the widespread deployment of distributed energy resources (DERs) at residences [1], the introduction of electric vehicles (EVs) [2], and the establishment of various smart energy services, e.g., demand response management [3], for the effective management of energy resources within the electricity grid. Consequently, different signal processing techniques, e.g., machine learning, artificial intelligence (AI) [4], and game theory [5], have been offered as solutions to consumers.

An important objective of using these signal processing techniques is to promote the use of renewable energy sources within the energy grid. For example, machine learning and AI have been used extensively to forecast the power generated from solar panels and wind turbines [6]. Due to this innovative use of signal processing tools as well as extensive rebates from local governments, a number of existing systems use DERs as the main or subsidiary source of energy. In particular, the global market for rooftop solar panels is booming; for instance, whereas the global market for rooftop solar panels was nearly US$30 billion in 2016, it is expected to grow by 11% over the next six years [7]. Meanwhile, the shift toward solar is being complemented by an increase in residential energy storage system adoptions, whose ability to deliver energy is predicted to grow from roughly 95 MW in 2016 to more than 3,700 MW by 2025 [7].

If properly utilized, these energy sources at the edge of the grid can help manage demand more efficiently; however, this will only happen if the owners of these power-generating assets are fully incorporated into the energy market [7]. To this end, a feed-in-tariff (FiT) scheme is a suitable model that engages customers to participate in energy trading. In an FiT, as shown in Figure 1(a), prosumers with DERs, such as rooftop solar panels, sell their excess solar energy only to the grid and can buy energy from the grid in case of any energy deficiency. However, due to the significant disparity between the buying and selling prices per unit of energy, the benefit to prosumers for participating in energy trading is not significant enough. As a result, some of the FiT techniques have been discontinued [8], making it increasingly important to create new energy markets that allow small-scale participants (users) to actively trade energy with one another in real time and facilitate a sustainable and reliable balance between the generation and consumption of energy within the community [9].

As such, P2P energy trading is being considered as a potential tool to promote the use of DERs within the energy grid [9]. The main objective of P2P sharing is to break the centralized infrastructure of the electricity grid by allowing the direct communication and supply of energy between various prosumers with DERs within the energy system, as shown in Figure 1(b). This enables interested consumers to buy renewable energy at a cheaper rate from a peer (or neighbor) with excess renewable energy (e.g., from rooftop solar), thereby reducing those consumers' dependence on the grid or a central supplier [10]. The development of such P2P energy trading has the potential to substantially benefit prosumers in terms of earning revenues, reducing electricity costs, and lowering their dependency on the grid. An example of such P2P technology in real energy systems can be found in the recent development of the Brooklyn Microgrid Project (BMP) [9].

In energy trading, the direct involvement of the users with one another and with the grid makes P2P systems unique when compared to existing FiT schemes. The system poses the challenge of modeling the decision-making process of each participant for the greater benefit of the entire energy network while taking into account human factors, e.g., rationality, motivation, and environmental friendliness. Particularly, in settings where there are many users with conflicting interests participating, it would be challenging either to integrate such conflicting interests when designing the decision-making process of each participant or, if necessary, to motivate the users to cooperate with reducing costs, maximizing revenues, and pursuing renewable energy objectives. Hence, such trading needs to be built on signal processing methods that can take such a diverse set of constraints into consideration and deliver an energy-management solution that ensures the efficient and robust operation of heterogeneous and large-scale cyberphysical systems. In this context, and considering the interactive and conflicting nature of energy trading, game theory is a very effective tool for modeling the decision-making processes of the participants in P2P networks.

Game theory has been used extensively for the design and analysis of energy systems; however, due to the purpose and framework of P2P energy trading, existing schemes may not be suitable in this context. This is because 1) in P2P trading, the main objective is to encourage the participants to trade energy with one another and, thus, comprise a community of energy buyers and sellers without any (or nearly any) direct influence from the grid so that the price signal from the central power station may not affect the performance of the P2P trading the way it influences the scheduling and trading of energy in existing systems; and 2) while the energy-trading schemes in the smart grid have exploited various pricing schemes including real-time and time-of-use pricing, P2P trading will necessitate the incorporation of more innovative pricing schemes. For example, as an independent decision

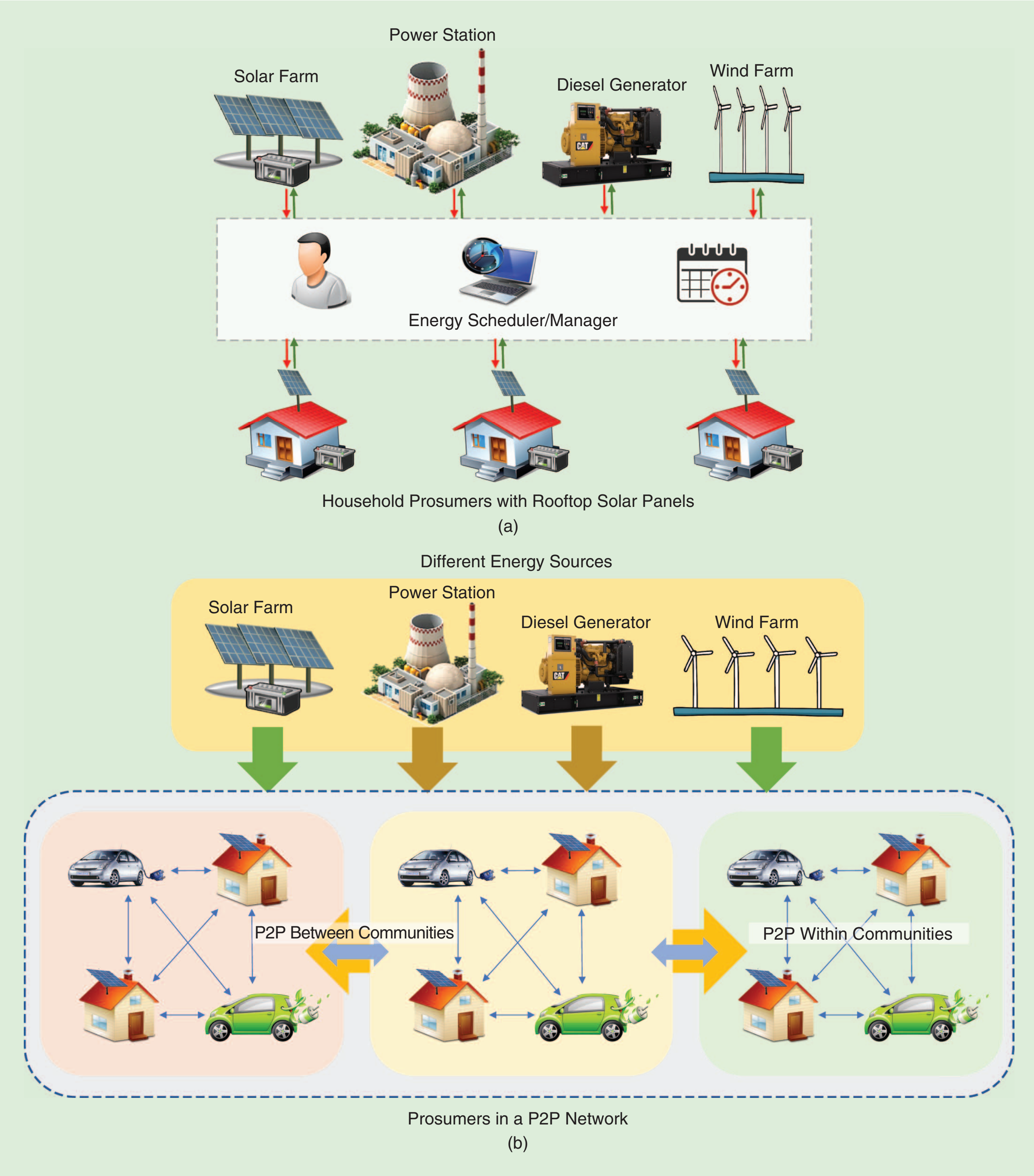

FIGURE 1. Renewable energy commodities currently trading in the emerging smart grid and P2P energy-trading schemes. (a) A traditional FiT scheme. (b) How a P2P energy-trading network may contribute to alleviate dependency on the main grid.

maker, a prosumer may intend to sell his or her surplus energy at different rates to different buyers within the network, necessitating the development of new pricing schemes. Finally, relaxing the presence of centralized management in the trading scheme subsequently creates a heightened emphasis on the security of energy-trading transactions between the participants of the P2P network.

In this context, novel and innovative applications of game-theoretic approaches will be necessary to design mechanisms for P2P energy trading. This article seeks to achieve this goal by

1) presenting an overview of various game- and auction-theoretic methods by following a systematic classification to provide information about the basic understanding and

importance of game theory and its extensive use in smart-energy research

2) focusing on basic P2P energy-trading techniques for integrating renewable energy sources into the grid by describing key features of such trading networks and providing a description of an existing testbed that has deployed P2P trading for managing energy
3) detailing some specific game- and auction-theoretic models that have been used for P2P energy trading and sharing some key results arising from those approaches, providing the reader with an understanding of game theory in the P2P energy-trading paradigm and its potential benefits.

This article can be used as a reference by both new and experienced researchers in the emerging field of smart grid research. Signal processing is part of a much larger smart grid context, and, in this article, we examine only the applications of various game- and auction-theoretic approaches for managing the trading between different entities within the energy network. This article, therefore, seeks to complement existing game-theoretic literature in guiding engineers to effectively design and manage the substantial energy generated by DERs across the overall network without compromising the stability of the grid and, thereby, to enable prosumers with conflicting interests to actively engage in energy trading with one another. Table 1 provides a summary of the pros and cons of game theory in addressing various challenges in energy systems as well as its similar application in other sectors.

Game theory for smart energy management

Within the context of energy management in smart grids, the applications of game- and auction-theoretic approaches are plentiful. On the one hand, noncooperative games have been used extensively to schedule energy-related activities and, subsequently, to trade surplus energy with buyers to earn revenue. On the other hand, the recent large-scale integration of alternative energy sources, e.g., EVs [11], solar arrays [12], and wind turbines [13], into the grid has exploited game theory to provide regulatory service for energy trading [14] and efficient home energy management [15]. In this section, we discuss the application of different game- and auction-theoretic approaches across EV domains, DERs and their storage domains, and service domains. We first provide a brief

Table 1. The advantages and limitations of using game theory for designing energy-management schemes.

Area	Focus	Brief Discussion
Energy management without P2P	Challenges	Designing management schemes based on the large amount of data from smart meters; modeling users' behavior; forecasting users' demand; forecasting the generation from renewable energy sources; modeling the interaction between the grid and customers; incentive design for increasing users' participation; improving grid stability in response to extensive renewable integration into the grid; and accommodation and coordination of EVs in the network.
	Advantages of game theory	A well-established, mathematically tractable, and proven optimization technique that can easily be integrated with other signal processing and data-driven techniques such as machine learning; is compatible with Internet of Things (IoT) devices; suitably captures the interactive nature of management problems and includes users' rational behavior in the modeling; and is applicable to any domain of energy networks including EV, residential, industrial, and commercial.
	Limitations of game theory	The practical deployment of game-theoretic models is limited and difficult to implement when it needs to directly involve human subjects in the optimization process. Furthermore, it is heavily dependent upon the performance of the communication network, which could potentially limit the performance of the process in case of a natural calamity or network congestion.
	Similar applications in sectors other than energy	These include financial modeling (allocation of investors' savings among financial assets); behavioral science (rationality of human behavior); computer science (testing boundaries of algorithms); resource management (water conflicts in a river basin); agriculture (irrigation strategies followed by stakeholders); and communication systems (channel allocation).
Energy management in P2P	Challenges	These include modeling user behavior; designing pricing schemes that help users to cooperate in the P2P network; managing the security and privacy of users; establishing strategy-proof transactions; maintaining trust between users without a centralized authority; reducing reliance upon the central grid, either partially or completely; managing network congestion when the number of users becomes large; stabilizing the system due to the increased penetration of renewables; and incorporating the central power station as a part of the P2P trading.
	Advantages of game theory	It can model users' behavior and their interactive trading with one another and easily integrate pricing and incentive design as a part of game framework development; potentially establish the trust between the users within the network and motivate them to cooperate via its game framework; and be incorporated with other signal processing techniques, such as fuzzy logic and machine learning.
	Limitations of game theory	The practical deployment of game-theoretic models is limited and difficult to implement when it needs to directly involve human subjects in the optimization process. However, there are recent applications of game theory (auction game) in pilot P2P projects, such as the BMP.
	Similar applications in sectors other than energy	These include banks (online financial transactions); IoT (device discovery and device control); health care (P2P help with patients who have chronic conditions); real estate (P2P lending); and finance (debt financing).

overview of the basic game-theoretic concept and a discussion of the different game- and auction-theoretic approaches that have been used to design various past energy-management schemes in the aforementioned three domains. It is important to note that, while the literature on game theory in energy management is extensive, only some of the key studies in each domain are discussed.

Basic game-theoretic concepts

Game theory is a mathematical and signal processing tool [16] that analyzes strategies in competitive situations where the outcome of a participant's choice of action depends on the actions of other participants. It can be divided into two main branches: noncooperative game theory and cooperative game theory.

Noncooperative games

A noncooperative game analyzes the strategic decision-making process of a number of independent players that have partially or totally conflicting interests in the outcome of a decision-making process influenced by their actions. Such games allow players to take necessary action, e.g., making optimal decisions, without any coordination or communication. Note that the term *noncooperative* does not mean that the players do not cooperate; rather, it refers to the fact that any cooperation that may arise in the noncooperative game must not be the result of either communication or coordination of strategic choices among the players [5].

In general, a noncooperative game can be divided into one of two categories: static or dynamic.

- *Static game*: In a static game, the players take action only once, either simultaneously or at different times. A static game can be defined in its strategic form as $\{\mathcal{N},(\mathbf{S}_n)_{n\in\mathcal{N}},(U_n)_{n\in\mathcal{N}}\}$, where $\mathcal{N}$ is the set of all of the participating players in the game and each player $n\in\mathcal{N}$ has a strategy set $\mathbf{S}_n$ from which it chooses an action $s_n\in\mathbf{S}_n$ to optimize its utility function U_n. The utility that a player n attains is affected by the choices of action $\mathbf{S}_{-n}$ of the players in the set $\mathcal{N}\setminus\{n\}$.
- *Dynamic game*: In contrast, players in a dynamic game act more than once and have some input regarding the choices of other players. In dynamic games, time plays a central role in the decision-making process of each player. Dynamic games can also be formulated as static games; however, there is a need for some additional information, including time and information sets, which are usually reflected in the utility functions.

For both static and dynamic noncooperative games, the players make their decisions either in a deterministic manner (pure strategies) or in a probabilistic manner (mixed strategies).

The most popular solution concept of the noncooperative game $\{\mathcal{N},(\mathbf{S}_n)_{n\in\mathcal{N}},(U_n)_{n\in\mathcal{N}}\}$ is the Nash equilibrium. A Nash equilibrium is a vector of actions $\mathbf{s}^*$ such that $U_n(\mathbf{s}^*)\geq U_n(s_n,\mathbf{s}^*_{-n}),\forall n\in\mathcal{N}$, where $\mathbf{s}=[s_n,\mathbf{s}_n]$. Thus, a Nash equilibrium refers to a stable state of a noncooperative game in which no player $n\in\mathcal{N}$ can improve its utility by unilaterally altering its action s_n from s_n^* when the actions of the other participating players $\mathcal{N}\setminus\{n\}$ are fixed at $\mathbf{s}^*_{-n}$. While a Nash equilibrium always exists in a noncooperative game with mixed strategies, the existence is not guaranteed in a game with pure strategies. Furthermore, a noncooperative game may also have multiple Nash equilibria, and, in such cases, it is important to select an efficient and desirable Nash equilibrium as the solution of the game.

Cooperative games

In contrast, with cooperative games, the focus is on how one can provide incentives to independent decision makers to act together as one entity to improve their position in the game. Essentially, both Nash bargaining and the coalitional game can be considered under the same umbrella of a cooperative game. Nash bargaining is the study of terms and conditions under which a number of players may agree to form a coalition, while coalitional games deal with the formation of coalitions [5]. In general, a coalitional game can be expressed by the pair $(\mathcal{N}_c,\nu)$, which involves a set of players $\mathcal{N}_c$ that seek to form cooperative groups. ν is the value function associated with each coalition $\mathcal{S}\subseteq\mathcal{N}_c$ and is expressed by a real number to quantify the value of the respective coalition. The most common form of a coalitional game is the characteristic form [17] in which the value of the coalition is determined by the members of that coalition, regardless of how the players in the coalition are structured. A coalitional game can be classified into one of three types: a canonical coalitional game, a coalition formation game, or a coalitional graph game.

- *A canonical coalitional game*: This game can be expressed with a transferable or nontransferrable utility. In this type, the formation of the grand coalition (i.e., the coalition of all of the players in the game) is never detrimental to the players, which pertains to the mathematical property known as *superadditivity*. The main objective of a canonical coalitional game is to study the properties and stability of the grand coalition, the gains resulting from the coalition, and the distribution of these gains in a fair manner to the players. The most commonly considered solution concept for the coalitional game is the core, which is directly related to the stability of the grand coalition. Essentially, the core is defined as the set of revenues x for which no coalition $\mathcal{S}\subset\mathcal{N}_c$ has any incentive to reject the grand coalition for the proposed revenue allocation x.
- *A coalition formation game*: In this game, the network structure and the cost of cooperation play a major role. In general, a coalition formation game is not superadditive, and, although forming a coalition brings gains to its members, the gains are limited by the cost associated with a coalition formation. As a result, the formation of a grand coalition is very rare; therefore, the objective of a static coalition formation game is to study the network coalitional structure. In a dynamic coalitional game, however, the game is subject to environmental changes, including a change in the number of players or a variation in network topology. Hence, the main objective is to analyze the formation of a coalitional structure through players' interactions and study the properties of the structure and its adaptability to environmental variations.

- *A coalitional graph game*: Communication between players within a coalition plays a significant role in coalitional games. In fact, in some scenarios, the underlying communication structures between players can have a major impact on the utility and other characteristics of the game [17]. The coalitional game that deals with the connectivity of communications between players is referred to as the *coalitional graph game* [17]. Here, the main objectives are to derive low-complexity distributed algorithms for players who wish to build a network graph (directed or undirected) and to study the properties (e.g., stability and efficiency) of the formed network graph.

Energy management in EV domains

EVs are becoming popular as a sustainable transport system, not only for their environmentally friendly features, but also for their capacities in assisting the energy grid via vehicle-to-grid (V2G) and grid-to-vehicle technologies. EVs, as independent entities, can participate in energy trading in the energy network either by coordinating their charging and discharging behavior to provide regulatory service to the grid [14] or by direct interaction with other traders within the network to negotiate trading and energy prices [11]. In this context, a brief overview of some game-theoretic approaches that have been studied in the literature to model energy trading by EVs is provided.

Since the EV market is growing rapidly around the world, both the grid and EV owners will benefit if the flexible demand of EV charging can be properly managed [18]. This has been approached by devising new scheduling techniques for the charging and discharging of EVs in [15], [18], and [19], based on a noncooperative Nash game. For example, a day-ahead EV charging schedule is proposed in [18], which considers the impact of electricity prices as well as the possible actions of other EVs. The unique Nash equilibrium is determined through quadratic programing, and the case studies are demonstrated using data from the Danish National Travel Surveys. Price competition between different EV charging stations with renewable power generators in [19] demonstrates that the interaction between the EV charging stations can be captured via a supermodular game and has a unique Nash equilibrium. Finally, a smart charging and discharging process for multiple EVs is designed in [15] to optimize the energy-consumption profile of a building. In the noncooperative energy-charging and discharging scheduling game, the players are the EVs and their strategies are the battery-charging and discharging schedules, with the utility function of each EV considered the negative total energy payment to the building. Each EV independently selects its best strategy to maximize the utility function, and all of the EVs update the building planner with their energy-charging and discharging schedules; the EV owners will have incentives to participate in the proposed game.

In recent studies, auction-based game-theoretic approaches, also known as *auction games* [20], have been used for studying coordination problems that arise from charging a population of EVs, the traded price negotiation between an electricity market and different EVs [21], and P2P electricity trading among EVs using the newly introduced blockchain methodology [22]. For instance, the authors in [20] use a progressive second-price auction mechanism to ensure that incentive compatibility holds for the auction game, and the efficient bid profile of the auction game is achieved through the use of the Nash equilibrium. In [21], a noncooperative game is formulated between storage units of EVs that are trading their stored energy; in the energy exchange market, between the storage units and the smart grid elements, the traded energy price is determined via an auction mechanism and allows at least one Nash equilibrium. An interesting blockchain-based auction mechanism is developed in [22], in which the authors propose a consortium method to detail the operation of localized P2P energy trading. The electricity pricing and the amount of traded energy among the EVs are administered by an iterative double-auction mechanism.

Another branch of game theory that has been exploited to design EV trading mechanisms is the coalitional game, which (as noted previously) is characterized by a set of players and a value function that quantifies the worth of a coalition. Examples of coalitional games in EV energy trading can be found in [23] and [24]. In [23], the authors propose a Bayesian coalition negotiation game as a means to perform energy management for EVs in the V2G environment. The game is used along with learning automata, wherein it is stationed on EVs that are assumed to be the players in the game. A Nash equilibrium is achieved in the game using convergence theory. In [24], the authors argue that leveraging the cooperation among EVs can enable grid stimulation of EV users to charge in load valleys and discharge in load peaks. As a result, the electricity load is well balanced, and the EV users achieve higher profits. The authors formulate the EV charging and discharging cooperation in the framework of a coalitional game and, in doing so, demonstrate that the EV users are more satisfied with the vehicle's battery status and their economic returns.

Hierarchical games, e.g., the Stackelberg game, are the most popular games used for designing energy-trading mechanisms for EVs. For instance, in [11], the authors study a static, noncooperative Stackelberg game to facilitate energy trading between a smart grid and EV groups, which is then extended to a time-varying case that can incorporate and handle slowly changing environments. The energy trading between the aggregation of EVs and fast-charging stations is modeled as a Stackelberg game to provide regulation reserves to the power grid [25]. In this study, EVs, as the followers in the game, can obtain a tradeoff between the benefits from energy consumption and reserves provision by choosing their charging and reserve strategies. A similar game is designed to capture the interaction between EVs and the charging system controller, while the game demonstrates a unique and robust optimal solution for poor communication channels [26]. A two-stage Stackelberg game is studied in [27] to address the problem of charging-station pricing and EV charging-station selection, in which the charging stations (leaders) announce their prices in stage one and the EVs (followers) make their selection of charging stations in stage two. A unique charging-station selection equilibrium always exists in stage two, and it depends on the charging stations' service capacities and the price difference. Similar examples of hierarchical and other games in the EV domain can be found in [28]–[31].

Energy management in DERs and storage domains

The widespread adoption of DERs in power systems can play a key role in creating a clean, reliable energy system with substantial environmental benefits. However, because energy production from these DERs is highly intermittent, their integration into the power system poses a significant challenge in maintaining the grid's stability. With suitable energy-storage and energy-management techniques, such intermittency can be addressed, and the benefits of using DERs can be increased significantly. We discuss some of the game-theoretic techniques that have been used for effective energy trading in DERs and storage domains.

The deployment of two-way communication enables interaction between the supply and demand sides of electricity networks and allows users to exploit Nash games to design energy-management schemes for DERs. In [32], for example, a game-theoretic approach is analyzed to minimize the individual energy costs to consumers by scheduling their future energy-consumption profiles. An instantaneous load-billing scheme is designed to effectively convince consumers to shift their time of peak consumption and to fairly charge the consumers for their energy purchases from the grid. With a view toward reducing the cost of energy trading within the grid, a day-ahead optimization process regulated by an independent central unit has been proposed in [33]. The existence of optimal strategies is proven, and, furthermore, the authors present a distributed algorithm to be run on the users' smart meters, which provides optimal energy-production and storage strategies while preserving user privacy and minimizing required central unit communication.

Auction games have been proposed for trading both storage space and renewable energy from DERs [34], [35]. In [34], the real-time implementation of a multiagent-based game-theoretic reverse auction model for microgrid market operations featuring conventional and renewable DERs is discussed. The proposed methodology was realistically implemented in a smart grid system at Florida International University, and the subsequent investigation shows that the proposed algorithm and the industrial hardware-based infrastructure are suitable for implementation in the existing electric utility grid. Meanwhile, the authors in [35] utilize an auction game to study the solution of joint-energy-storage ownership sharing between multiple shared facility controllers (SFCs) and those dwelling in a residential community. The auction process possesses both incentive-compatibility and individual-rationality properties and is also capable of enabling the residential units (RUs) to decide the fraction of their shared energy storage capacity with the SFCs of the community to assist in storing electricity.

Recently, coalitional games have also received attention for designing energy-trading mechanisms for users in residential areas that are equipped with DERs and storage devices. For example, in [36], a coalitional game is used to study the cooperation between small-scale DERs and energy users to enable the direct trading of energy without going through retailers. The asymptotic Shapley value is the core of the coalitional game so that no small-scale DERs or energy users have an incentive to abandon the coalition, which suggests the stable direct trading of energy for the proposed pricing scheme. Furthermore, numerous case studies demonstrate that the scheme is suitable for practical implementation. The authors in [37] focus on comprehensive economic power transactions of multiple microgrid networks with multiple agents; they design a three-stage algorithm based on a coalitional game strategy and include request, exchange, merge-and-split, and cooperative transaction stages. The developed algorithm enables microgrids to form coalitions where each microgrid can exchange power directly by paying a transmission fee.

Similar to EV domains, hierarchical games also have been used extensively for trading mechanisms in DERs and storage domains [1], [38]. (Due to constraints on the total number of references that can be cited, we are unable to provide an overview of all of them.) In [38], a distributed mechanism for energy trading among microgrids in a competitive market via a multileader, multifollower Stackelberg game is proposed. The game is formulated between different utility companies and end users (EUs) to maximize the revenue of each utility company and the payoff to each user, wherein the existence of a unique Stackelberg equilibrium is proven. The researchers also study the impact of a hacker who can manipulate the utility company's price information and discuss a scheme based on shared reserve power to improve the grid's reliability and ensure its dependability. A similar type of game in [1] is also designed, where the authors propose a three-party energy-trading mechanism within a smart grid community; in particular, a noncooperative Stackelberg game between the residential users and the SFCs is proposed to explore how both can benefit from received utility and the total cost reduction, respectively, from trading energy with each other and the grid. The maximum benefit to the SFCs, in terms of the reduction of total costs, is determined by the unique and strategy-proof Stackelberg equilibrium. Dynamic games have also been used in DERs and storage domains for energy management [39].

Energy management in service domains

Game-theoretic approaches have been exploited to provide services to the grid and consumers via the scheduling of energy-related activities by the users. These services include regulatory services, e.g., voltage and frequency regulation, demand response regulation, and services related to the sharing of resources, such as storage and designing incentives for users. In this context, we can explain how Nash, auction, coalition, and hierarchical games have been used to provide these services to energy users in EVs, DERs, and storage domains.

Nash games have mostly been used for providing demand response services to the grid. On the one hand, Nash games are sometimes exploited by the users to decide on the scheduling of their daily energy-related activities to participate in demand response [3], [18]. On the other hand, Nash games have also been played as a part of another game, such as a hierarchical game, to reach the desired solution. For instance, in [1] and [11], a Nash game was played by the followers as part of a Stackelberg game to reach an equilibrium solution. A Nash game has also been utilized in [14] to help develop a smart pricing policy and design a mechanism to achieve optimal frequency-regulation performance in a distributed fashion.

Applications of auction games can be found in designing services, e.g., storage sharing [35], demand response [21], and frequency regulation [40]. For example, in [40], the authors present a bidding behavior model and an auction architecture consisting of a central aggregator and networked-microgrid agents. The bidding behavioral states the microgrid agents are formalized for the belief updates and short-term policy determinations to maximize individual profits. A reverse auction model is then adopted to enable competitive negotiations between the central aggregator and the networked-microgrid agents. The auction and aggregation processes are implemented in a power-system control area to contribute to frequency control. Furthermore, auction games have also been employed by incentivizing users to participate in energy management [35].

Coalitional games, including both coalition formation games and canonical coalition games, have been effective in designing services for the energy sector. Demand response regulations in the EV domain have been implemented by using a coalition formation game [23]. In [36], the authors demonstrate how to incentivize energy users with small-scale energy power production units, e.g., rooftop solar panels, to directly trade energy with other users within a community instead of trading with the retailer. Moreover, the exploration of coalitional games for regulation service [24], wherein the authors design a coalition formation game to schedule the charging and discharging of EVs within a smart grid network so that the grid's stability is not compromised, has been discussed extensively.

Hierarchical games have covered nearly all of the aspects of service domains, and demand response regulations [1], [38], for example, show how hierarchical games, through the use of suitable incentives, can influence users to participate in energy trading. In [29], a hierarchical game is proposed to provide frequency regulation under a V2G scenario, i.e., a hierarchical Markov game is designed to coordinate the charging process of EVs. The Markov game optimizes the regulation capacity of the aggregator and, thus, strengthens its ability to bid for a more favorable frequency-regulation price (regulation service within a hierarchical game is also implemented in [25]). Furthermore, the application of a Stackelberg game to decide on a price for sharing energy storage devices can be found in [35] and [41].

As shown in Table 2, the application of game theory in energy trading and management is extensive. However, the discussion of its application in the field of P2P energy trading

Table 2. The importance and extensive use of game theory in smart energy domains.

Type	Domain	General Focus of the Study	Noncooperative Games	Cooperative Games
Smart energy networks without P2P	EV domains	It includes the coordinating and scheduling of charging and discharging EVs for optimizing energy-consumption profiles of buildings; reducing the queue size at charging stations; providing a mobile storage capability; peak load reduction; the efficient use of grid energy; and incentive design.	[11], [15], [18]–[22], [25]–[31]	[23], [24]
	DERs and storage domains	It includes scheduling household activities and managing energy dispatch from storage to reduce the volatility of renewable generation and improve the lifetime of storage. Furthermore, designing pricing schemes to coordinate the users' behavior toward efficient use of grid energy is studied.	[1], [32], [33], [34], [35], [38]	[36], [37]
	Service domains	It considers managing energy in EVs, DERs, and service domains; provides voltage and frequency regulation to the grid; and performs demand response. Furthermore, both static and mobile storage sharing as well as sharing of generated renewable energy with the grid are addressed.	[1], [3], [11], [14], [18], [21], [25], [29], [35], [40], [41]	[23], [24], [36]
Smart P2P energy network	EV domains	Energy trading among multiple EVs within the P2P network that ensures the security of transactions and protection of privacy is considered. The objective is to maximize the social welfare of the entire network, keep the trading with the grid at a minimum, and penalize EVs that do not abide by the rules.	[22], [44]	
	DERs and storage domains	Its intent is to design suitable pricing and revenue distribution schemes so that peers are interested in trading in P2P markets via a steady coalition. Furthermore, the large-scale participation of users and the trading mechanism including efficiency and fairness are considered.	[46]–[48]	[36]
	Service domains	It addresses the sharing of energy storage between different peers within the P2P network so that it maximizes the benefits to all users. The pricing of the auction is determined to ensure all of the participating entities are happy and have no incentive to leave the trade.	[35], [46], [47]	[36]

is limited, which could be because of the relatively recent emergence and exploration of P2P trading frameworks in energy domains.

Game theory for energy management in a P2P network

P2P energy networks

In a P2P network, the members, or peers of the network, share part of their own resources and information to facilitate certain applications. Each peer is both a provider and a receiver of resources and can directly communicate with other peers in the network without the intervention of any intermediate node [42]. This enables the network to be resilient in the face of failure of one or more peers and continue operating normally. Thus, new peers can be added and old ones can be replaced without altering the operational structure of the system. P2P energy networks, as shown in Figure 1(b), consist of a number of energy users, including both consumers and prosumers. Prosumers are equipped with small-scale DER units, such as rooftop solar panels or small wind turbines. The production of energy takes place within each house (or near each house) to reduce transmission losses and utilize cogeneration, if possible. If a prosumer has surplus energy, he or she can either store this energy in his or her storage device or distribute it among other peers within the network to avoid waste [42]. This empowers the users of the energy network to take control of the production and consumption of energy within the community without any central control authority (e.g., the grid [35]) and to potentially avoid using complex algorithms and technological equipment to negotiate pricing for the buying and selling of energy as well as its storage [42].

A P2P energy network consists of two main components: a virtual energy-trading platform and a physical energy network [9]. The virtual energy-trading platform provides the technical infrastructure for the local electricity market, and it must be based on a secured-information system, e.g., the blockchain-based architecture of the BMP, through which the transfer of all kinds of information takes place. To avoid discrimination, it needs to be implemented so that each peer has equal access; for example, the generation, demand, and consumption data of a peer are transferred from its smart meter to the virtual layer through a secured communication network. Then, buy and sell orders are created in the virtual layer based on information obtained from the smart meter, which are then sent to the appropriate market mechanism to facilitate energy trading. Once the matching of buy and sell orders is completed between different peers, the payment is carried out, and, subsequently, the exchange of energy takes place through the physical layer.

On the other hand, the physical energy network is the distribution grid, which is used for the physical transfer of energy among peers. This physical network could be the traditional distributed-grid network provided and maintained by the independent system operator or an additional, separate physical microgrid-distribution grid in conjunction with the traditional grid, which provides the network peers with the flexibility to be physically disconnected from the main grid in case of an emergency [9]. Note that the financial transactions that are carried out between different peers in the virtual platform have no influence on the physical delivery of electricity; rather, the payment can be thought of as the payment from the consumers to their producing prosumers within the P2P network for feeding the renewable generation into the distribution grid [9].

Key features of energy networks

An energy network should have seven key features that enable successful P2P energy trading [9], [43].

- *The market participants*: A clear definition of market participants as well as the purpose of the P2P energy trading must be established, and the form of energy that is traded in the market should be specified. P2P energy trading necessitates the existence of a sufficient number of market participants within the network, and a subgroup of the participants needs to have the capacity to produce energy. The purpose of P2P energy trading, i.e., increasing the use of renewable energy or reducing dependency on the main grid, affects the design of pricing schemes and the market mechanisms of the trading market. Furthermore, the form of energy traded in the market should be defined, i.e., whether the energy is traded in the form of electricity, heat, or a combination of both.
- *The grid connection*: For balancing the energy generation and consumption within the P2P energy-trading network, it is imperative that the connection points of the main grid be well-defined. At these connection points, it is possible to connect a smart meter to evaluate the performance of the P2P energy network, e.g., how much energy savings the participants can realize by not buying from the grid. If a physical microgrid-distribution network exists between the participants, it swiftly decouples itself from the main grid in case of an emergency. For island-mode operation, participants should have enough generation capacity to ensure the appropriate level of supply security and resiliency. However, if the P2P energy trading is only conducted over the existing traditional distribution network, such an island-mode operation is not possible.
- *The information system*: A high-performing information system is the heart of any P2P energy-trading network. This is necessary for 1) connecting all of the market participants for the purpose of energy trading, 2) providing the participants with a suitable market platform, 3) providing the participants with access to the market, and 4) monitoring the market operation. It is essential that every market participant has equal access to the market information without any interference. Examples of such information systems are blockchain-based smart contracts [22].
- *The market operation*: The market operation of P2P energy trading is facilitated by the information system, which consists of the market's allocation, payment rules, and a clearly defined bidding format. Its main purpose is to provide an

efficient energy-trading experience by matching the market participants' sell and buy orders in near real-time granularity. In market operations, the constraint of energy generation influences the thresholds of a maximum and minimum allocation of energy. Different market-time horizons can exist in the market operation (e.g., to cover various stages of the electricity market), and the market operation should be able to produce efficient allocations at every stage.

- *The pricing mechanism*: The objective of a pricing mechanism is to efficiently balance energy supply and demand, and it is implemented as a part of the market operation. Examples of pricing mechanisms include auctions with an individual or uniform clearing price. Pricing mechanisms for P2P energy trading have a significant difference compared to that of the traditional energy market. In particular, with traditional energy, a large part of energy prices consists of taxes and surcharges, whereas in a P2P trading market, taxes and surcharges are absent due to the zero marginal cost of renewable energy. Regardless, pricing needs to reflect the state of energy within the P2P energy network, e.g., a higher surplus should lower the price of P2P energy trading and vice versa.
- *The automatic energy-management system* (*AEMS*): The purpose of an AEMS is to secure the supply of energy for a market participant while implementing a specific bidding strategy. To do so, an AEMS has access to the real-time supply and demand information of its market participants, and, based on these data, an AEMS forecasts the generation and consumption profile and develops the bidding strategy. The AEMS of a rational user would always buy energy on the microgrid market when it falls below its maximum price limit. Individual agents' intelligent bidding strategies employ varying prices at different times and are expected to be a core components of active P2P energy markets in the future.
- *The regulation*: Regulation is a key feature of P2P energy trading, and it determines how these markets fit into the current energy policy, i.e., governmental rules decide what market design is allowed, how taxes and fees are distributed, and in which way the market is integrated into the traditional energy market and energy supply system. As a result, governments can either support P2P energy markets to accelerate the efficient utilization of renewable energy resources and to decrease environmental degeneration by regulatory changes, or they can discourage the implementation of such markets if these result in negative impacts on the current traditional energy system.

Brooklyn TransActive P2P project

Now, we focus on an existing pilot project on P2P energy trading built in Brooklyn, New York. This discussion of a real P2P energy network will provide the reader with an idea of how P2P energy trading is being envisioned for future energy markets. Local P2P energy trading, absent any utility involvement, is yet to be covered by regulations that decide how such markets fit into the current energy policy [9]. The choice of the BMP for this discussion is motivated by the breadth of the project as well as by the successful implementation of trading techniques shown in their recent pilot demonstration. The BMP consists of a microgrid market in Brooklyn, New York, and is run by LO3 Energy. The participants of the BMP are located across three distribution grids, including Brooklyn Borough Hall, Park Slope, and Bay Ridge. As shown in Figure 2, the BMP trading network consists of physical and virtual layers. In the physical layer, the BMP uses the traditional grid to supply physical energy flow; however, it also has a physical microgrid network among a limited number of housing blocks, which is comprised of 10×10 housing blocks that can be decoupled from the main grid in case of an emergency. The virtual layer, which is completely separated from the physical layer, is implemented on top of the existing physical grid infrastructure, provides the technical infrastructure for the local electricity market, and is based on a Tendermint protocol-based private blockchain called the *TransActive blockchain architecture* [9]. While each peer must have a blockchain account to participate in the P2P energy trading, a meter is installed in the house of each peer that communicates with the corresponding blockchain account and transfers energy generation and demand data from the TransActive meter.

The energy trading in the BMP is mostly done automatically by an AEMS and only requires several preferences of its market participants. The participants must use a mobile application (the BMG app), through which they can choose their preferences on the source of energy and price limits for the AEMS to conduct the energy trading. An example diagram of the mobile application is shown in Figure 3. Although the participants can change their preferences at any time, it is also possible for the participants to choose and set one preference for all future use without any further interaction with the mobile application. Once the preferences are submitted by the participants, the energy trading between two participants (one consumer and one prosumer) takes place following a step-by-step process [9].

- *Step 1*: The buy and sell orders of a consumer and a prosumer, respectively, are submitted to the market by their AEMSs. Any buy or sell order consists of a quantity and a price.
- *Step 2*: The market mechanism is a closed-order book with a time-discrete double auction in 15-min intervals. In the double auction, 1) consumers repeatedly bid up to their maximum price for their preferred energy sources, 2) prosumers bid the minimum price that they request for selling their generated energy on the market, 3) the highest bidder is allocated first and lower bidders are allocated following a merit-order dispatch, and, finally, 4) the last allocated bid price represents the market-clearing price for that particular time slot.
- *Step 3*: Consumers that cannot undercut the clearing price are supplied by other sources.
- *Step 4*: Financial transactions are carried out between the allocated market participants of that particular time slot according to predefined payment rules.

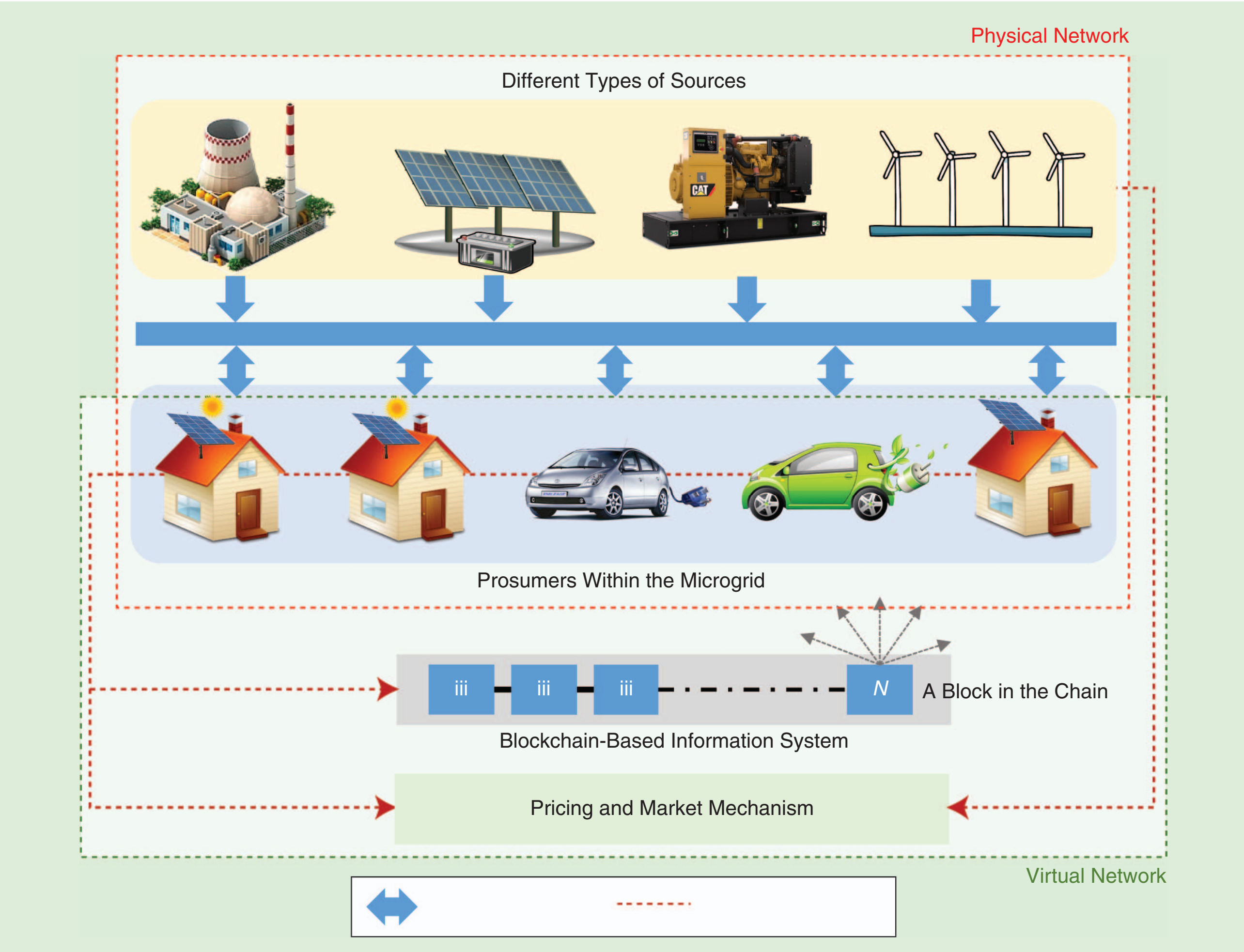

FIGURE 2. The topology of the BMP [9].

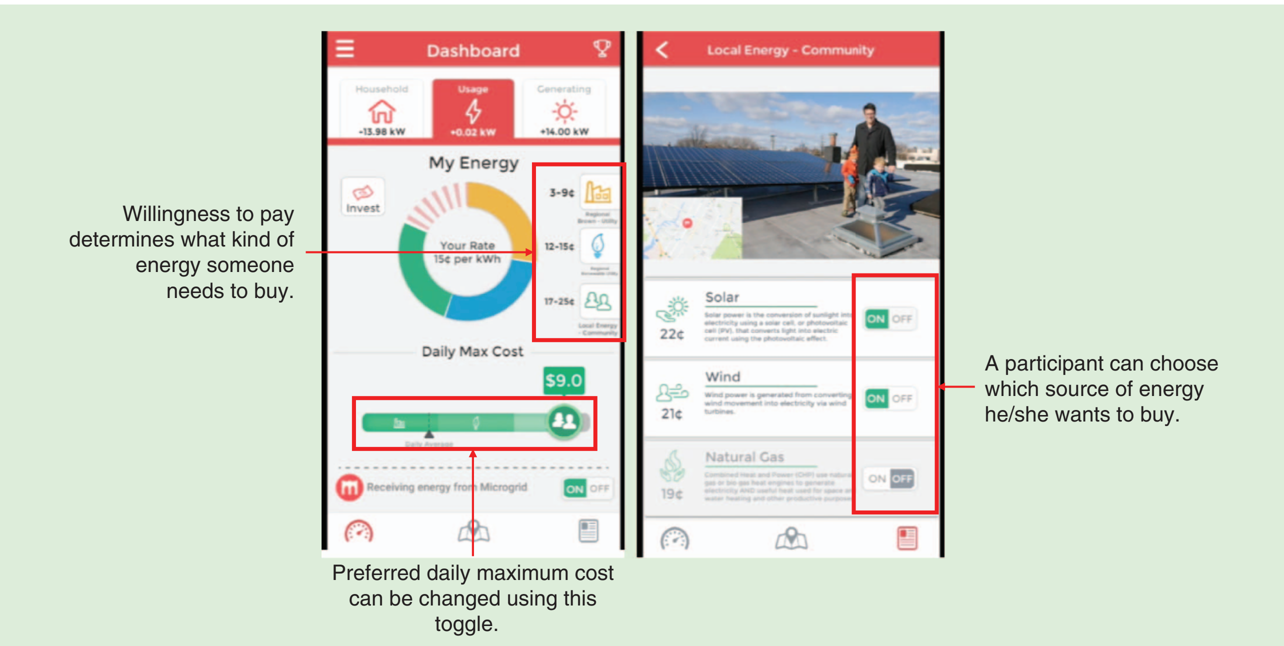

FIGURE 3. A screenshot of the mobile application used in the BMP. The BMP website: https://www.brooklyn.energy/support. (Image courtesy of LO3 Energy.)

- *Step 5*: Local trading is then realized in the virtual layer, and the transfer of funds is completed.
- *Step 6*: In the physical layer, and upon completion of the payment transaction, the prosumers feed their renewable energy into the distribution grid for the consumers to use. Note that prosumers may need to pay a subscription fee to the utility grid to use its network for P2P energy trading.

As we now have some idea of how a P2P energy network functions in practice, we detail some specific game-theoretic approaches that have been used for P2P energy trading in EV, DER and storage, and service domains. For each domain, we take a specific approach as an example and then explain, in detail, how the relevant game of that particular study is used to design the P2P trading scheme. Note that such explanations help the reader visualize how they may use such approaches to design games between different nodes in P2P networks to attain various energy-management objectives.

P2P energy trading in EV domains

P2P energy trading in EV domains has gained considerable attention, and studies are being conducted based on both game-theoretic and optimization approaches [22], [44], [45]. In this section, however, we focus on the study in [22], where an interesting exploration of auction games for P2P energy trading can be found in the EV domain. This study designs a P2P energy-trading technique among EVs in the smart grid via an auction game and ensures the security and privacy of the transactions by incorporating a consortium blockchain within the trading mechanism. Note that, to explore how an auction game is used in [22] for P2P energy trading in the EV domain, we will focus only on the use of an auction game for P2P trading and ignore the design of consortium blockchains in this discussion. The main objective of all of the EVs within the P2P energy network is to maximize the social welfare of the participants; the model for this localized P2P energy trading consists of three main components.

- *EVs*: The EVs play different roles in the proposed P2P electricity trading at charging stations, e.g., charging, discharging, and idling EVs. Each EV can choose its own role according to its current energy state and driving plan.
- *Local aggregators*: These are the energy brokers that provide access points for electricity and wireless communication services for EVs. Each charging EV sends a request for electricity demand to the nearest local aggregator. Then, the energy broker performs an assessment of local electricity demand and announces it to local EVs. In response, EVs with surplus electricity submit selling prices to the broker, who acts as an auctioneer, carrying out an iterative double auction among EVs, matching electricity-trading pairs.
- *Smart meter*: Each charging pole is equipped with a smart meter that calculates and records the amount of traded electricity in real time. The smart meter records are used by the charging EVs to pay the discharging EVs.

At each charging station, a local aggregator can communicate with any local EV to establish a real-time electricity-trading market and facilitate electricity trading between any charging EV and any discharging EV in the network. Each charging EV CV_i^n, which is connected to a local aggregator n, has a particular energy demand c_{ij}^n from the discharging EV DV_j^n connected to the same local aggregator. Meanwhile, d_{ji}^n is the amount of energy that a discharging EV DV_j^n supplies to CV_i^n in the local aggregator n. Due to the charging and discharging of c_{ij}^n and d_{ji}^n, the satisfaction and cost function of charging and discharging EVs, respectively, are given by [22]

$$U_i(\mathbf{C}_i^n) = w_i \ln(\eta \sum_{j=1}^{J} c_{ij}^n - c_i^{n,\min} + 1), \tag{1}$$

and

$$L_j(\mathbf{D}_j^n) = l_1 \sum_{i=1}^{I} (d_{ji}^n)^2 + l_2 \sum_{i=1}^{I} d_{ji}^n, \tag{2}$$

where η is the average charging efficiency from discharging EVs to CV_i^n and w_i is the charging willingness of CV_i^n in (1), and l_1 and l_2 are cost factors in (2); these satisfaction and cost functions refer to the benefits and costs in terms of real numbers that each charging and discharging EV can incur by participating in P2P energy trading and may vary with the changes in the parameters, e.g., energy price, charging willingness, and cost factors according to (1) and (2).

As mentioned previously, the purpose of this P2P trading is to maximize the social welfare of its participants. This is accomplished with the help of the local aggregator n by interacting with both the charging and discharging EVs to decide upon suitable charging and discharging energy vectors ($\mathbf{C}^n$ and $\mathbf{D}^n$) for trading. In doing so, as explained in [22], the local aggregator n that is working as an energy broker not only meets the demands of charging EVs but also maximizes electricity allocation efficiency. Accordingly, the overall objective function of the social welfare problem becomes the difference of (1) and (2) for the participating EV. For the social welfare maximization problem, it is crucial that the energy broker obtains true and complete information from all of the EVs' utility and cost functions. The complete information from each EV includes its current energy state, battery capacity, and so on; however, this is private information that EVs may not be willing to share with the energy broker. To address this issue, the designed mechanism must extract hidden information from the EVs.

In the context of an auction game, an auction mechanism is a part of the noncooperative game and is sufficient to elicit the hidden information in a real and competitive energy market; therefore, it is used in [22] to facilitate P2P energy trading among the EVs. A double-auction technique possesses the individually rational and weakly budget-balanced properties, which confirms that the participating EVs have bid truthfully according to privacy information and, at the same time, the energy broker does not lose money conducting the auction. The auction game in [22] is, therefore, adopted by following an iterative step-by-step process.

- *Step 1*: Each participating charging and discharging EV submits its bid price to the auctioneer.

- *Step 2*: Based on the received bid price vector of buying energy (i.e., bid price vectors from all charging EVs) and bid price vector of selling energy (i.e., bid price vectors from all discharging EVs), the auctioneer produces an optimal allocation of supply and demand energy vectors by following a predefined allocation policy and broadcasts them to the participating EVs.
- *Step 3*: According to the allocated energy vectors received from the auctioneer, each EV determines its optimal bid price, i.e., the optimal bid price for selling obtained by discharging EVs and the optimal bid price for buying obtained by charging EVs.
- *Step 4*: Each EV submits its optimal bid price to the auctioneer.
- *Step 5*: The auctioneer receives the vectors of optimal bid prices from both types of EVs and benchmarks them against predefined criteria to determine whether the optimal solution is achieved.
- *Step 6*: If the optimal solution is achieved, the auction game is completed and no further iteration is needed. Otherwise, the process reiterates from Step 2.

In the proposed auction process, the auctioneer monitors real-time localized P2P energy trading. When unexpected incidents happen (for example, a few EVs may leave suddenly from the scheduled trades), the auctioneer may restart the auction process, and a new energy-trading process is executed. However, in such cases, the abruptly disconnected EVs are held accountable and are made to pay a penalty for disconnecting. As shown in [22], the auction-based approach can obtain an efficient energy-allocation solution with optimal consideration of the participants' social welfare in the energy market without requiring the participants to completely share private information about their satisfaction and cost functions.

P2P energy trading in DER and storage domains

To illustrate the application of a game-theoretic approach for P2P energy trading in DER and storage domains, we will focus on the study in [36], in which the authors design a coalitional game to enable direct energy trading from one peer to another in the energy network. To do so, the customers in the network are divided into two types: 1) customers who are small-scale electricity suppliers and have renewable energy facilities (e.g., houses with rooftop solar panels) who can sell excess energy to the market for a monetary profit and 2) an EU who needs to buy energy to conduct energy-related activities. The amount of electricity supply and energy demand varies across time and may differ for each entity. While the customers can trade their respective energy surpluses in the traditional market with retailers, the energy trading in the P2P market could be more beneficial for both the EUs and small-scale electricity suppliers [36]. This is mainly because there is a significant difference between the wholesale price p_{wp} (i.e., the selling price per unit of energy) and retail price p_{rp} (i.e., the purchase price per unit of energy) in the traditional electricity market, and $p_{\mathrm{rp}} > p_{\mathrm{wp}}$. Hence, the monetary benefit that a customer may gain in terms of either obtaining revenue or reducing cost is very low. In P2P energy trading, on the other hand, the trading price p_{p2p} is set between the wholesale price and the retail price, i.e., $p_{\mathrm{wp}} \le p_{\mathrm{p2p}} \le p_{\mathrm{rp}}$. In [36], such a choice of price is beneficial to both the small-scale sellers and the EUs.

The coalitional game formed between the small-scale electricity suppliers and the EUs is a canonical coalitional game with transferable utility, and the price p_{p2p} for P2P energy trading is determined by an asymptotic Shapley value [17]. The canonical coalition game is formally defined by the pair $(\mathcal{N}_c, \nu)$, where $\mathcal{N}_c$ is the union of the set $\mathcal{N}_s$ of small-scale electricity suppliers and the set $\mathcal{N}_u$ of EUs and, as described in the "Game Theory for Smart Energy Management" section, ν is a real number that refers to the total benefit that all game participants realize by forming the coalition. Since the value function ν depends on the net surplus and deficient energy of the coalition, all coalition participants primarily trade their energy among themselves with a price p_{p2p}. If there is net surplus from the coalition, it is sold in the retail market at a rate of p_{wp} per unit of energy and bought at a price p_{rp} per unit if there is net deficiency. Thus, $\nu = (p_{\mathrm{wp}} \times \text{net surplus}) - (p_{\mathrm{wp}} \times \text{net deficiency})$.

To effectively perform P2P energy trading, a coalition needs to satisfy three properties.

- *Superadditivity:* The formation of a grant coalition must be beneficial for all participating coalition customers, i.e., it is always more beneficial for the small-scale electricity suppliers and the EUs to trade P2P, rather than to trade in the traditional market. Thus, both parties are interested in maximizing the total revenue of the coalition. To accomplish this, however, the value function ν needs to be superadditive [36], which means that the total benefit that a set of small-scale electricity suppliers and EUs acquired by forming the grand coalition is at least equal to the total benefit that they achieve by trading separately.
- *The core*: There should be a fair distribution of total revenue among all coalition customers. In P2P energy trading, this allocation of revenue can be done by suitably adjusting the trading price p_{p2p} so that no subgroup of customers can obtain more revenue by deviating from the P2P trade. The feasible allocation of this revenue among participants is known as the *core of a coalition*, and, if the core of a coalition is nonempty, no group of users has any incentive to leave that coalition. It is shown in [36] that there is a nonempty core for the coalition when $p_{\mathrm{rp}} > p_{\mathrm{wp}}$.
- *Stability*: When all of the customers receive their respective revenues that are at the core, no one wants to leave the coalition, which, in turn, makes the coalition stable. All of the network customers, therefore, continue to participate in P2P energy trading.

The derivation of the fair distribution of revenue is complex and could be computationally expensive. There are a number of mechanisms that can be used to determine a fair revenue distribution, such as Shapley value, nucleolus, and proportional fairness. In this study, p_{p2p} is derived according to the Shapley value. This concept is based on the three key axioms of efficiency, symmetry, and balanced contribution and are measurements of the contributions made by each customer participating in P2P energy trading. By allocating revenue to each customer according to its Shapley value, the revenue of the P2P energy trading is divided fairly. This is due to the fact that what each customer obtains corresponds to his or her contributions to P2P energy trading.

However, as the number of customers within a coalition grows, the number of computations required to determine the Shapley value of each customer increases prohibitively. Revenue distribution is conducted using an asymptotic Shapley value because the derived value lies within the core of the coalition game [36]. Consequently, and according to the third property mentioned previously, the coalition remains stable even for a large number of customers. The proposed P2P energy-trading scheme, therefore, is suitable for adoption by an energy network consisting of many customers.

The adopted canonical coalition game to design P2P energy trading in DERs and storage domains can be summarized in the following steps.

- *Step 1*: Choose or design a system model that is suitable to incorporate P2P energy trading.
- *Step 2*: Design a value function that captures the benefit of the coalition and determines whether the value function possesses the property of superadditivity.
- *Step 3*: Investigate the existence of the core in the coalitional game.
- *Step 4*: If the core is nonempty, design a suitable revenue distribution mechanism that lies at the core, resulting in stability.
- *Step 5*: Ensure that the design of a revenue distribution technique can accommodate a large number of customers, which confirms the practicality of the model's implementation [46]–[48].

P2P energy trading in service domains

Finally, we discuss the application of game theory in P2P energy trading for service domains. In [35], the authors propose an interesting integration of an auction game with a Stackelberg game to provide demand response services to the network users by sharing energy storage devices. In particular, this research explores the solution of joint-energy-storage sharing among multiple RUs and shared SFCs within a community by enabling the RUs to decide on the fraction of their energy-storage capacity that they may share with the SFCs of the community to assist them in storing electricity, e.g., for fulfilling the demand of various shared facilities. To do so, a modified auction game is designed that captures the interaction between the SFCs and the RUs to determine the allocation of storage spaces shared by the RUs. The auction price, on the other hand, is determined by a noncooperative Stackelberg game formulated between the RUs and the auctioneer.

To design the scheme, as shown in Figure 4, a smart community is used that consists of a large number of RUs that can be individual homes, a large number of homes connected via an aggregator, or a number of SFCs that provide energy services, such as managing elevators, corridor lights, water pumps, and heat pumps for the common facilities in the community. Each SFC and RU has its own energy-production capacity and storage devices. In the P2P network designed in [35], each SFC, which has larger energy-generation capacity, may sometimes need larger storage space to store extra generation, and it can share storage space with the community residential users

FIGURE 4. A demonstration of the system model of P2P energy trading in the service domain.

who have relatively small amounts of generation and storage capacity. To facilitate this sharing (or leasing) of storage spaces between multiple SFCs and RUs, the designed modified auction process consist of three rules, including determination, payment, and allocation rules.

The objective of the determination rule is to determine the set of SFCs and RUs that can effectively participate in the auction scheme to establish the payment and shared storage amount. This is executed in a step-by-step fashion, and the number of participating SFCs and RUs is influenced by their respective bidding prices, the number of storage spaces that the SFCs want to share, and the RUs agreed upon to lease, respectively, as well as the Vickrey price. Once the number of participating entities is determined, a payment rule is executed to determine the auction price.

An auction process where no participant has any motivation to cheat is referred to as an *incentive-compatible auction*.

In a payment rule, the proposed technique in [35] varies from the Vickrey auction and is named the *modified auction scheme*. In a Vickrey auction, the auction price for sharing the storage spaces would be the second-highest reservation price. However, since this second-highest price might not be considered beneficial by all RUs participating in the auction scheme, the auction price would need to be increased. On the other hand, if the auction price is set to the maximum bidding price, the price could be detrimental for some of the participating SFCs. To make the auction scheme attractive and beneficial for all participating RUs and, at the same time, cost-effective for all of the SFCs, a Stackelberg game is played by the RUs and the auctioneer, who decides the auction price to maximize the average cost savings to the SFCs and satisfies their need for storage space. The RUs choose which storage-space vector they would like to put into the market for sharing to maximize their benefits. In the Stackelberg game, there is always a unique solution to the game; therefore, a unique auction price can be derived, which all RUs and SFCs agree upon to be the equilibrium price for energy storage sharing between them. Also, at this auction price, no participants have an incentive to deviate from the auction process.

Once the auction price is established, the allocation of storage spaces from the RUs to the SFCs is conducted based on an allocation rule. According to this rule, if the total requirement of the SFCs is either greater than or equal to the total the supply from the RUs, then all of the offered storage spaces are shared by the SFCs. However, if the supply is greater than the requirement, the participating RUs need to tolerate the burden of oversupply, i.e., the monetary loss in cases when the supply of storage becomes larger than the total requirement of storage spaces by the SFCs. In [35], two allocation processes are considered for the distribution of this burden: proportional and equal allocation.

- *Proportional allocation*: Here, the burden of oversupply is shared among the RUs based on their respective reservation prices during the auction process. An RU that asked for a higher reservation price will endure a greater burden when compared to other units with a lower reservation price.
- *Equal allocation*: In an equal allocation, however, the burden is distributed equally among all of the participating RUs. The auction process is concluded with the completion of this process.

Note that, once an auction process is executed, there is always a possibility that the owners of the storage spaces, i.e., RUs, might cheat and withhold the amount of storage that they agreed to put into the market during the auction. However, auction schemes that possess the property of incentive compatibility are protected from such cheating. An auction process where no participant has any motivation to cheat is referred to as an *incentive-compatible auction*. When the participants of an auction are satisfied with the allocation and payment that they have received and have no incentive to cheat, the term *individual rationality* is applicable. It is shown in [35] that the Stackelberg game based on payment and proportional allocation rules render the proposed modified auction for P2P trading individually rational. The scheme is further extended to a time-varying case, which also possesses all of the properties of the static case.

Based on this discussion, the overall exploration of a modified auction scheme in the proposed storage sharing in the P2P trading network can be summarized in four steps.

- *Step 1*: The RUs and SFCs that can participate in the proposed auction are identified by following the determination rule.
- *Step 2*: The auction price is determined based on a Stackelberg game-based payment rule, which determines that the derived auction price is unique, and all of the RUs and SFCs agree between them on that price for sharing energy storage spaces.
- *Step 3*: The allocation of storage space between the SFCs are conducted based on the allocation rule; this burden of oversupply, however, is distributed among the participating RUs using either an equal or proportional allocation scheme.
- *Step 4*: The proposed auction scheme is shown to be incentive compatible and, thus, removes any incentive for participants to cheat during the auction process (this property also holds when the auction scheme is extended to a time-varying case).

From previous discussions in the "Game Theory for Smart Energy Management" and "Game Theory for Energy Management in P2P Networks" sections, the difference between the game-theoretic applications in existing energy-management studies and in P2P energy networks is obvious. In existing energy management, the focus is not primarily on energy trading between users; instead, the focus is on cooperation and competition between users to achieve an objective, which also significantly involves the main grid. Conversely, in a P2P network, the participants also work together to achieve the desired objective with minimal (or no) interaction with the grid, as shown in Table 2.

Outcomes of game-theoretic applications in a P2P energy network

In the "Game Theory for Energy Management in P2P Networks" section, we provided detailed descriptions of very specific game-theoretic applications in P2P energy trading by discussing three different studies in detail: EV, DER and storage, and service domains. In this section, our main purpose is to examine some interesting results from those studies and show how P2P trading outperforms some existing approaches. On the one hand, these results demonstrate the importance of P2P energy-trading schemes in achieving greater cost reduction and utility maximization of energy entities within the network. On the other hand, these results also show the effectiveness of using game theory to enable it to achieve those benefits.

EV domains

To demonstrate how game theory can be used to design P2P energy trading in EV domains, we discuss an auction game [22]. We show how the game-theoretic approach is beneficial for both the buyers and sellers of energy within the considered P2P network, based on two results from [22] and shown in Figure 5. Note that this performance is evaluated based on a real data set taken in an urban area of Texas. The latitude of the observed area is from 30.256° to 30.276° N, and the longitude is from −97.76° to −97.725° W. The observed area is approximately 2.22×3.88 km^2, including 58 parking lots. The battery capacity of the EVs is set to 24 kWh, and the minimum and maximum of electricity demand for charging EVs is assumed to be 5–10 kWh and 12–18 kWh, respectively. The maximum supply of electricity for discharging EVs is considered to be 10–20 kWh.

Figure 5 illustrates the performance comparison between the proposed P2P model in [22] and a hybrid energy-trading model [49], in which energy buyers can trade electricity with local energy sellers and with the smart grid. In [22], unlike the hybrid model, the focus is on localized P2P electricity trading between charging EVs (i.e., energy buyers) and discharging EVs (i.e., energy sellers) with 90% electricity transmission efficiency, in contrast to the high-energy transmission losses between the smart grid and energy buyers and sellers in a hybrid model resulting in a low transmission efficiency of 70%. Figure 5(a) shows that, when the sell-out price of the smart grid for energy buyers is smaller than that of local discharging EVs, the energy buyers obtain greater benefits by following a hybrid energy-trading model because of the lower average buying price. However, because of high transmission losses, the average amount of transmitted electricity from both energy sellers and the smart grid is higher than that of the P2P scheme to meet the same requirement. If the sell-out price of the smart grid is too high, the energy buyers will buy electricity from local energy sellers instead of the smart grid in the hybrid model; thus, they retain the same benefits as the P2P scheme. Similar results can also be found in Figure 5(b).

Although the average selling price increases with the increased buy-back price given by the smart grid, the available electricity for energy buyers decreases because of higher energy losses during electricity transmission. Therefore, compared with the trading model in [49], the proposed P2P model in [22] has lower energy loss and a higher electricity utilization

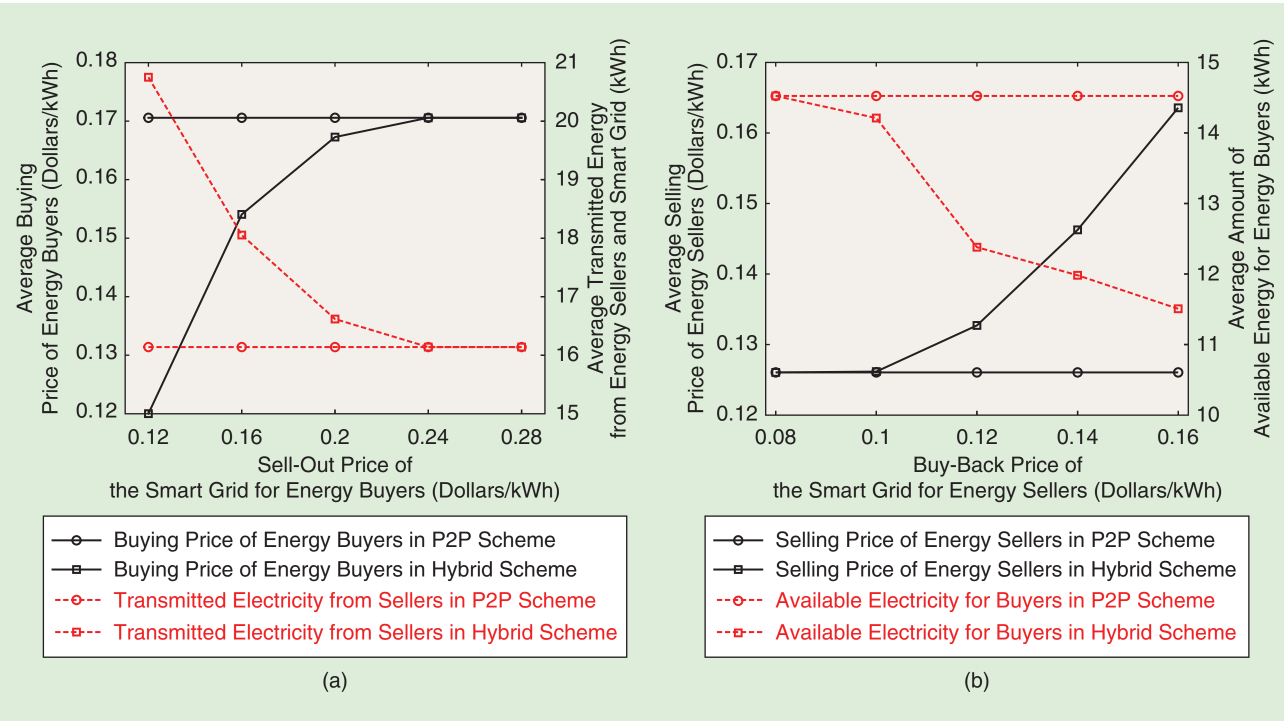

FIGURE 5. An illustration [22] showing how the benefits of energy trading in P2P and hybrid models are influenced in terms of pricing and energy utilization. (a) The average buying price and transmitted electricity for EVs and (b) the average selling price and transmitted electricity for EVs.

efficiency from the system's perspective. Reasonable assumptions can be made based on the results in Figure 5.

- For both cases in Figure 5(a) and (b), P2P energy trading is beneficial in terms of increasing systems' energy efficiency, which is mainly due to lower transmission loss compared to the hybrid network.
- In Figure 5(a), EVs would be interested in participating in P2P trading only when the sell-out price of the smart grid is very high because buyers are always motivated to buy from a source of energy that offers a lower price per unit of energy [1]. Therefore, to effectively establish this type of P2P trading scheme in the EV domain, the average buying price, which is US$0.17/kWh on average in the P2P network, must be revised to a lower value to compete with the hybrid market. Nevertheless, the proposed P2P scheme is still able to attract EVs at periods of peak loads when the electricity price is, in general, very high.
- Due to a lower average selling price, EVs may sell within a P2P network during times when the price of the hybrid network is also low. However, as the selling price increases in the hybrid network, more EVs would become interested in selling to the smart grid instead of in the P2P network. Therefore, similar to the case in Figure 5(a), the selling price in a P2P network should be chosen carefully. One example of suitable pricing for P2P networks could be a midrate pricing scheme [50].

DER and storage domains

In this section, we demonstrate how the P2P energy-trading scheme can be beneficial in terms of earning revenue for both the network buyers and sellers. In particular, we discuss some results from [36], in which the household load profiles are constructed from the individual load profiles of home appliances. Each appliance has different rates of power consumption and a different probability of being activated during each hour of the day so that the load profile has various statistical characteristics (e.g., means and variances) over time. The authors use an appliance load profile, which considers various appliances such as a stove, a dishwasher, a refrigerator, and lighting. They then scale the load profile so that the average daily electricity usage of households is similar to that of households in North Carolina.

As for the generation profile of small-scale energy supplies, solar and wind generation data profiles are used. For solar-generated electricity, the authors use the hourly electricity generation data that was measured at Elizabeth City State University, North Carolina, in June 2012. The data set was obtained from the Cooperative Networks For Renewable Resource Measurements website of the National Renewable Energy Laboratory (NREL) [51]. The generation profile of the solar generators is then scaled by assuming that the size of the solar panels is 6.45 m^2. For electricity generated by wind turbines, the Eastern Wind Sources data set is used, which is also available at the NREL. The generation profile of the wind turbines is scaled by assuming that the capacity of the wind turbines is 5 kW.

In Figure 6, we demonstrate two outcomes from [36]. Figure 6(a) shows the monthly revenue of individual EUs and small-scale energy suppliers who participate in P2P energy trading. In this figure, it is assumed that all of the energy suppliers have either solar generators or wind turbines and that the monthly revenue of energy suppliers and EUs participating in P2P trading can reach up to US$80 and US$62, respectively. However, as shown in [36], the monthly electricity bill of a household without P2P trading reaches as high as US$110, and, therefore, each EU can save up to 60% of its monthly electricity bill by participating in P2P energy trading. Another phenomenon that we observe in Figure 6(a) is that the monthly revenue of an energy supplier eventually decreases with an increase in the number of suppliers (this is mainly because of the characteristics of the P2P market as explained in [9]). As the number of small-scale energy suppliers increases in the market, the amount

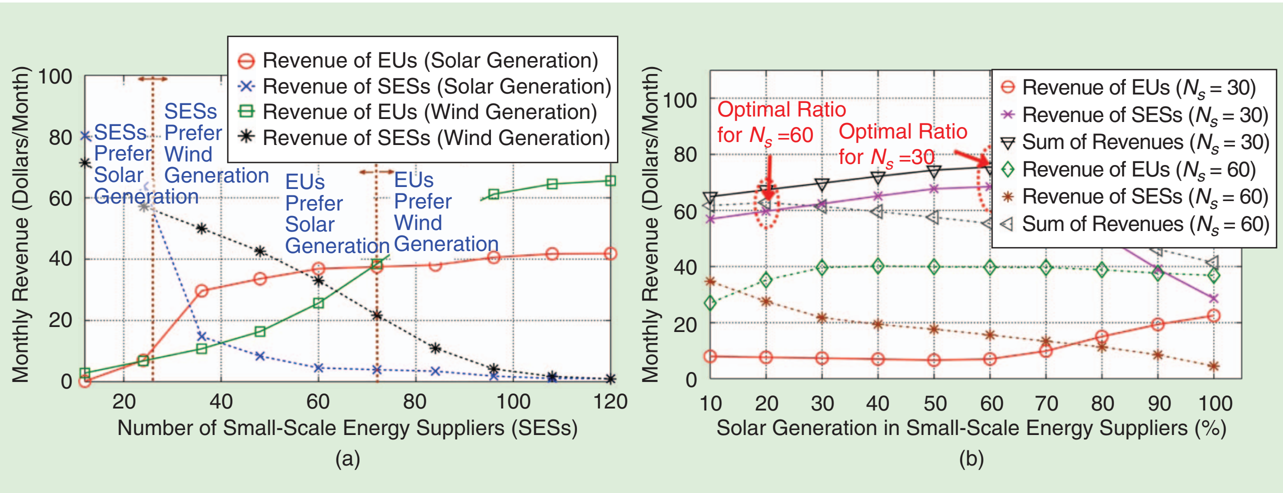

FIGURE 6. An illustration [36] showing how P2P energy trading may bring benefits to both EUs and small-scale energy suppliers in terms of monetary revenue per month. (a) The effect of a number of small-scale energy suppliers on the monthly revenue of various EUs and energy suppliers and (b) the effect of a percentage of solar generation on the monthly revenue of various EUs and energy suppliers.

of available energy for sale increases, leading to a drop in the trading price and decreasing the suppliers' revenue.

Moreover, Figure 6(a) shows how different kinds of generated energy may affect the monthly revenue of the suppliers and EUs. Such a scenario refers to the case in which participants are able to choose the type of generation they would like to use for trading, as observed in the BMP. We demonstrate in Figure 6(a) that, when the number of suppliers is lower than 24, the buyers and sellers both prefer solar generation over wind generation because of its higher monthly revenue. Similarly, both parties prefer wind generation when the number of energy suppliers is larger than 72. However, if the number of energy suppliers is between 24 and 72, EUs prefer solar generation, whereas energy suppliers prefer wind generation. Therefore, in this case, the mixed usage of wind generators and solar generators is advisable.

Figure 6(b) demonstrates the monthly monetary profit of EUs and energy suppliers for different percentages of solar generators used by energy suppliers. According to this figure, an optimal percentage of solar generators exists that maximizes the total revenue of EUs and energy suppliers. For example, when the number of suppliers is 30, the total revenue is maximized when 60% of all of the suppliers are solar generators. It can also be seen from Figure 6(b) that the optimal percentage of solar generators approaches zero as the number of energy suppliers increases, which is supported by the findings in Figure 6(a).

Based on the results in the DER and storage domain, as discussed previously, we can summarize our insights accordingly.

- Participant cooperation within a P2P energy network is always beneficial because it provides a platform for trading energy without involving the main grid pricing scheme, which is not as attractive as the P2P scheme [36]. Note that this may also be affected by how the pricing scheme is designed.
- When the number of energy suppliers in the market becomes very large, the revenue to the energy suppliers reduces, subsequently increasing the revenue of the P2P energy-trading network EUs.
- Depending on the number of energy suppliers within the market, the different percentage mixture of solar and wind generations would be optimal for the energy suppliers to maximize their revenue from the energy trading.

Service domains

Finally, in this section, we will discuss and illustrate some of the findings of a game-theoretic approach in the service domain, based on [35]. In this study, the authors consider a number of RUs at different blocks who are interested in allowing the SFCs of the community to jointly share their energy storage devices and provide demand response services in the P2P energy-trading market. When there is a large number of RUs and SFCs in the system, the reservation and bidding prices will vary significantly. Each RU is assumed to be a group between five and 25 households, where each household is equipped with a 25-kWh capacity storage device. The required electricity storage for each SFC is assumed to be within the range of 100–500 kWh. The required storage space for sharing could be different if the participants' usage patterns change, and, since the type of energy storage (and its associated costs) used by different RUs can vary significantly, the choices of reservation prices to share their storage space with the SFCs can fluctuate considerably as well.

Note that, once all of the participating RUs offer their free storage space to the auction market, they are distributed according to the allocation rule described in the "P2P Energy Trading in Service Domains" section. Figure 7 investigates how the average utility of each RU varies as the total storage amount required by the SFCs changes. In this case, the total energy storage requirements of the SFCs are assumed to be 100, 150, 200, 250, 300, 350, 400, 450, 500, 550, and 600. Generally speaking, the average utility cost for each resident initially increases with the increased requirements of the SFCs and eventually becomes saturated, resulting in a stable value (Figure 7). This is because, as the required amount of storage space increases, the RU can share more of its reserved energy storage that it put into the market with the SFCs at the determined auction price; hence, its utility costs increase. However, each RU has a particular fixed storage amount that it can put on the market to share,

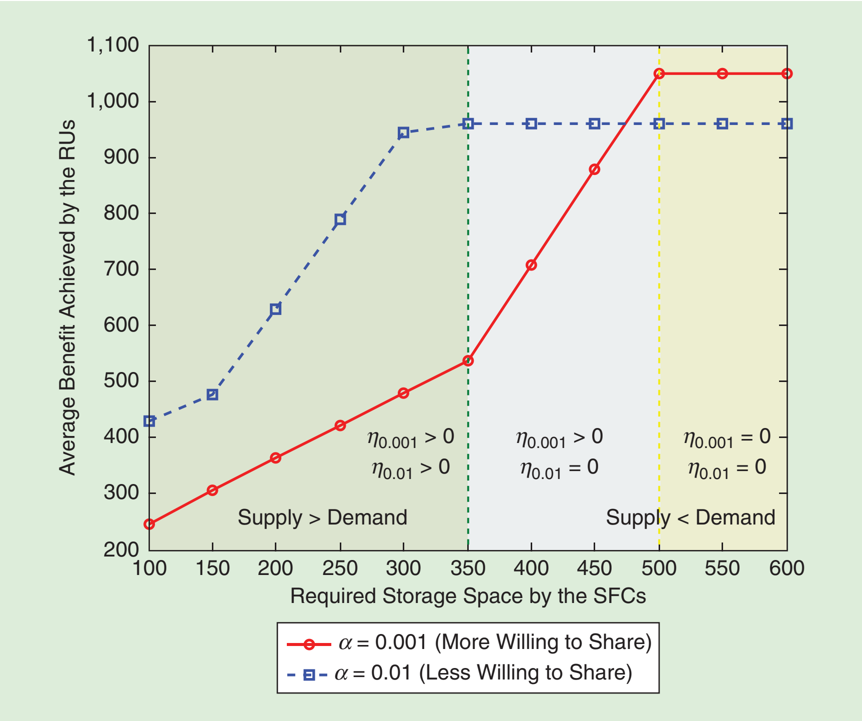

FIGURE 7. An illustration showing how the average benefit received by an RU may differ across various storage demands of the SFCs within the P2P energy network [35].

and, consequently, once the shared storage amount reaches its maximum, even with an increase in the requirements of the SFCs, the RU cannot share more. Therefore, its utility becomes stable without any further increment.

Another interesting observation from Figure 7 is that the designed P2P storage-sharing scheme favors the RUs with higher reluctance parameters more than when the storage requirements of the SFCs are relatively lower, and vice versa. Here, the reluctance parameter, which is denoted by α in Figure 7, refers to the measured willingness of sharing storage for each RU; a lower value of α indicates a higher willingness to share. The variation of benefits received from different reluctance parameters is dictated by the burden of storage-space oversupply. If reluctance is lower, an RU would be interested in putting a higher amount of storage into the market to share. However, if the total amount of energy storage required by the SFCs is lower, it would place a higher burden on the respective RU. As a result, the relative utility of the auction is lower. If the requirement of the SFCs is higher, the sharing brings significant benefits to the RUs, as seen in Figure 7. On the other hand, with higher reluctance, RUs tend to share lower amounts of storage, which enables them to endure a lower burden in case of lower demands from the SFCs; this, consequently, enhances the amount of utility received. If the requirement is higher from the SFCs, their utility reduces when compared to the RUs with lower reluctance parameters.

> **Energy-management research on P2P networks is relatively new, and, currently, all of the developments of P2P energy-trading platforms are in a pilot phase.**

In Table 3, the average utilities that each RU can receive from sharing its storage space with the SFCs by adopting P2P trading are shown and compared with the existing equal distribution (ED), and FiT schemes. Table 3 shows that, as the amount of energy storage required by the SFCs increases, the average utility achieved per RU also increases for all of the cases. Also, in all of the cases studied, the P2P storage-sharing scheme shows a considerable performance improvement when compared to both ED and FiT schemes. Particularly, an interesting trend of performance improvement can be observed if we compare the performance of the proposed scheme with the ED and FiT performances for each of the energy storage requirements. For instance, the performance of the P2P scheme is higher as the requirement for the storage increases from 200 to 350. However, the improvement is relatively less significant as the storage requirement switches from 400 to 450. This is because the amount of storage shared by each participating RU is influenced by its reluctance parameter, e.g., even if the demand of the SFCs could be larger, the RU may choose not to share more of its storage spaces if its reluctance is limited.

The RUs in this study increase their shares of energy storage as the requirement for the SFCs increases, which, in turn, produces higher revenue. Once the available storage spaces from the RUs reach a saturation point, the increase in demand, i.e., from 400 to 450, does not affect their shares. As a result, their performance improvement is not as noticeable as in the previous four cases. For all of the cases considered, the auction process performs better than the ED scheme with an average performance improvement of 34.76%, clearly showing the value of the proposed methodology. The performance improvement with respect to the FiT scheme, which is 34.34% on average, is due to the difference between the determined auction price and the price per unit of energy.

To this end, and based on the results in this section, several key insights can be summarized.

- As shown in Figure 7, if the total required energy storage of the SFCs is smaller, RUs with higher reluctance are more beneficial, and vice versa. This illustrates the fact that even RUs with a high unwillingness to share their storage space can benefit the system SFCs if their required storage is small.
- For a higher storage requirement, SFCs would receive more benefits from having RUs with lower reluctances since they would be interested in sharing more to achieve higher average utilities.
- Energy storage sharing in the P2P trading market is more beneficial for the RUs compared to the sharing done by following both ED and FiT schemes.

Conclusions

In this article, we have provided an overview of the potential of game-theoretic approaches for energy management in P2P networks. First, we have highlighted the extensive use of game-theoretic approaches in the smart energy domain and divided the discussion into three domains, including EV, DER and storage, and service domains. Then, we have expanded

Table 3. The improvement of the average benefits obtained by the RUs in a P2P sharing scheme in comparison to ED and FiT schemes [35].

Required storage space by SFCs	200	250	300	350	400	450
Average net benefits to RUs for an ED scheme	536.52	581.85	624.52	669.85	715.19	757.85
Average net benefits to RUs for an FiT scheme	537.83	583.16	626.83	673.16	717.50	759.16
Average net benefits to RUs for a P2P scheme	629.82	789.82	944.26	960.09	960.09	960.09
Percentage improvement compared to an ED scheme	17.4	35.74	51.19	43.32	34.24	26.68
Percentage improvement compared to an FiT scheme	17.1	35.43	50.63	42.61	33.81	26.46

our focus to recent game-theoretic energy-management models that have been proposed and implemented in P2P energy networks. Here, instead of providing an overview, we have given a detailed discussion of a specific game-theoretic approach in each of the domains of a P2P network. The purpose has been to present how different game-theoretic models can be designed to solve energy-trading problems in the P2P energy network and what the key criteria or properties are that need to be considered during the implementation. Finally, we have shown some interesting results from the game-theoretic models, and we have discussed and summarized the interpretation of those outcomes for a better understanding of participants' behavior in P2P energy management.

Energy-management research for P2P networks is relatively new, and, currently, all of the developments of P2P energy-trading platforms are in a pilot phase. Hence, much work is yet to be done before the integration of P2P energy trading into the current energy system. In this context, game theory may play a significant role in future research endeavors.

- *A consumer-centric model*: The design of the P2P energy-trading schemes need to be consumer-centric, i.e., consumers must benefit from participating in P2P energy trading. Note that some recent energy-trading models and pilot projects have been discontinued as they were not accepted by consumers. To avoid this, the users' interests and benefits must be taken into consideration. One potential way to do this is to explore cooperative games to demonstrate that users can always benefit from cooperating. For instance, a user may choose to be a part of the entire network (i.e., the grand coalition in a canonical coalition game) or dynamically change its position to a different small coalition (coalition formation game) to come to an agreement with other network peers for energy trading.
- *The demonstrated benefit to the grid*: In most of the current P2P energy-trading pilot projects, the physical transfer of energy takes place through the distribution network, which is set up by the traditional grid [9]. Hence, expecting that P2P energy trading will completely exclude the grid from any energy-related activities with local consumers could be impractical, since trading, itself, is conducted using the grid's assets. One way to address this problem is to demonstrate that P2P energy trading is also beneficial for the grid and that a grid may also participate in P2P energy trading if necessary. This will also help the regulatory board to understand the importance of P2P energy trading to both the grid and the local users, paving the way for this new approach to be approved as a part of the energy system. The Stackelberg game, where the grid can participate either as a leader or a follower depending on the context of the model and can interact with other users to decide on various energy-trading parameters across different times, could be an ideal candidate to model this trading.
- *High security and low computational complexity*: Due to the reduced involvement of a centralized authority in P2P trading, the security and privacy of participants is a critical issue. In P2P networks, an EU (buyer) does not want to reveal his/her identity during a transaction with a seller, whereas the seller does not want the buyer to misuse the traded energy, e.g., for illegal purposes. Therefore, there is a strong need for an energy-trading distribution mechanism in P2P networks that does not pose security and privacy threats to the sellers and EUs, respectively. The advancement of blockchain technology has solved this problem. A blockchain is a continuously growing list of records, called *blocks*, that are linked and secured using cryptography. Most of the current pilot projects on P2P energy trading in the United States, Europe, and Australia are based on blockchain-based information platforms. Hence, how to integrate blockchain with game theory is a potential future research direction of significant importance. However, using blockchains for privacy protection in P2P trading may require high computational power; therefore, the integration of blockchain with game theory needs to consider this particular stipulation with care and design trading mechanisms that are efficient and have lower computational complexity to provide users with the desired services.
- *Energy trading with incomplete information*: Incomplete information can be defined as a lack of information concerning the real-time demand of prosumers and P2P trading prices because of a problem in the network, e.g., a packet loss in the communication network. Such incomplete information can potentially damage the performance of the P2P energy-trading technique, creating the need to design energy-management solutions that can properly handle such scenarios. One promising way to address this is to design an energy-trading mechanism for a P2P network with incomplete game information. One example is the Bayesian game, where the solution is a Bayesian Nash equilibrium.
- *The incorporation of physical laws in the game model*: An important aspect that governs the power flows and couples DERs and aggregators on the physical network is Kirchhoff's laws, which are not properly modeled in most studies. The presence of physical laws may greatly complicate energy-trading analysis and has a significant impact on how the market should be designed and operated. The idea of how to incorporate the impact of Kirchhoff's laws into the game-theoretic model for P2P energy trading needs considerable attention. One solution could be to include a common constraint between the players of the game (similar to what is done in a generalized Nash game) that will be influenced by Kirchhoff's laws. Regardless, in-depth investigation is required to decide how to introduce such a common coupling constraint.

The potential application of game-theoretic approaches in P2P energy trading and their subsequent implications for the participating users is significant. The purpose of this article has been to put a small drop in that large vessel by showing the importance of game theory for such networks by demonstrating what it is capable of and how it has been used so far, as well as to provide the reader with some ideas on how they might contribute to this emerging energy domain.

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References
[1] W. Tushar, B. Chai, C. Yuen, D. B. Smith, K. L. Wood, Z. Yang, and H. V. Poor, “Three-party energy management with distributed energy resources in smart grid,” *IEEE Trans. Ind. Electron.*, vol. 62, no. 4, pp. 2487–2498, Apr. 2015.

[2] L. Gan, U. Topcu, and S. H. Low, “Optimal decentralized protocol for electric vehicle charging,” *IEEE Trans. Power Syst.*, vol. 28, no. 2, pp. 940–951, May 2013.

[3] A. H. Mohsenian-Rad, V. W. S. Wong, J. Jatskevich, R. Schober, and A. Leon-Garcia, “Autonomous demand-side management based on game-theoretic energy consumption scheduling for the future smart grid,” *IEEE Trans. Smart Grid*, vol. 1, no. 3, pp. 320–331, Dec. 2010.

[4] B. K. Bose, “Artificial intelligence techniques in smart grid and renewable energy systems—Some example applications,” *Proc. IEEE*, vol. 105, no. 11, pp. 2262–2273, Nov. 2017.

[5] W. Saad, Z. Han, H. V. Poor, and T. Başar, "Game-theoretic methods for the smart grid: An overview of microgrid systems, demand-side management, and smart grid communications," *IEEE Signal Process. Mag.*, vol. 29, no. 5, pp. 86–105, Sept. 2012.

[6] C. Voyant, G. Notton, S. Kalogirou, M.-L. Nivet, C. Paoli, F. Motte, and A. Fouilloy, "Machine learning methods for solar radiation forecasting: A review," *Renewable Energy*, vol. 105, pp. 569–582, May 2017.

[7] M. E. Peck and D. Wagman, "Energy trading for fun and profit buy your neighbor's rooftop solar power or sell your own—It'll all be on a blockchain," *IEEE Spectr.*, vol. 54, no. 10, pp. 56–61, Oct. 2017.

[8] T. Nelson, P. Simshauser, and J. Nelson. (2012, Feb.). Queensland solar feed-in tariffs and the merit-order effect: Economic benefit, or regressive taxation and wealth transfers? AGL Appl. Economic Policy Res. New South Wales, Victoria, Australia. [Online]. Available: http://aglblog.com.au/wp-content/uploads/2012/03/No-30-QLD-FiT-II-FINAL1.pdf

[9] E. Mengelkamp, J. Gärttner, K. Rock, S. Kessler, L. Orsini, and C. Weinhardt, "Designing microgrid energy markets—A case study: The Brooklyn microgrid," *Appl. Energy*, vol. 210, pp. 870–880, Jan 2018.

[10] Peer-to-peer rental: The rise of the sharing economy. *The Economist*. Mar. 2013. [Online]. Available: http://www.economist.com/news/leaders/21573104-internet-everything-hire-rise-sharing-economy

[11] W. Tushar, W. Saad, H. V. Poor, and D. B. Smith, "Economics of electric vehicle charging: A game theoretic approach," *IEEE Trans. Smart Grid*, vol. 3, no. 4, pp. 1767–1778, Dec. 2012.

[12] W. Tushar, C. Yuen, D. B. Smith, and H. V. Poor, "Price discrimination for energy trading in smart grid: A game theoretic approach," *IEEE Trans. Smart Grid*, vol. 8, no. 4, pp. 1790–1801, July 2017.

[13] M. Marzband, M. Javadi, J. L. Domínguez-García, and M. M. Moghaddam, "Non-cooperative game theory based energy management systems for energy district in the retail market considering DER uncertainties," *IET Generation, Transmission Distribution*, vol. 10, no. 12, pp. 2999–3009, Sept. 2016.

[14] C. Wu, H. Mohsenian-Rad, and J. Huang, "Vehicle-to-aggregator interaction game," *IEEE Trans. Smart Grid*, vol. 3, no. 1, pp. 434–442, Mar. 2012.

[15] H. K. Nguyen and J. B. Song, "Optimal charging and discharging for multiple PHEVs with demand side management in vehicle-to-building," *J. Commun. Netw.*, vol. 14, no. 6, pp. 662–671, Dec. 2012.

[16] G. Bacci, S. Lasaulce, W. Saad, and L. Sanguinetti, "Game theory for networks—A tutorial on game-theoretic tools for emerging signal processing applications," *IEEE Signal Process. Mag.*, vol. 33, no. 1, pp. 94–119, Jan. 2016.

[17] W. Saad, Z. Han, M. Debbah, A. Hjørungnes, and T. Başar, "Coalitional game theory for communication networks," *IEEE Signal Process. Mag.*, vol. 26, no. 5, pp. 77–97, Sept. 2009.

[18] Z. Liu, Q. Wu, S. Huang, L. Wang, M. Shahidehpour, and Y. Xue, "Optimal day-ahead charging scheduling of electric vehicles through an aggregative game model," *IEEE Trans. Smart Grid*, 2017. doi: 10.1109/TSG.2017.2682340.

[19] W. Lee, L. Xiang, R. Schober, and V. W. S. Wong, "Electric vehicle charging stations with renewable power generators: A game theoretical analysis," *IEEE Trans. Smart Grid*, vol. 6, no. 2, pp. 608–617, Mar. 2015.

[20] S. Zou, Z. Ma, X. Liu, and I. Hiskens, "An efficient game for coordinating electric vehicle charging," *IEEE Trans. Autom. Control*, vol. 62, no. 5, pp. 2374–2389, May 2017.

[21] Y. Wang, W. Saad, Z. Han, H. V. Poor, and T. Başar, "A game-theoretic approach to energy trading in the smart grid," *IEEE Trans. Smart Grid*, vol. 5, no. 3, pp. 1439–1450, May 2014.

[22] J. Kang, R. Yu, X. Huang, S. Maharjan, Y. Zhang, and E. Hossain, "Enabling localized peer-to-peer electricity trading among plug-in hybrid electric vehicles using consortium blockchains," *IEEE Trans. Ind. Informat.*, vol. 13, no. 6, pp. 3154–3164, Dec. 2017.

[23] N. Kumar, S. Misra, N. Chilamkurti, J. H. Lee, and J. J. P. C. Rodrigues, "Bayesian coalition negotiation game as a utility for secure energy management in a vehicles-to-grid environment," *IEEE Trans. Dependable Secure Comput.*, vol. 13, no. 1, pp. 133–145, Jan. 2016.

[24] R. Yu, J. Ding, W. Zhong, Y. Liu, and S. Xie, "PHEV charging and discharging cooperation in V2G networks: A coalition game approach," *IEEE Internet Things J.*, vol. 1, no. 6, pp. 578–589, Dec. 2014.

[25] T. Zhao, Y. Li, X. Pan, P. Wang, and J. Zhang, "Real-time optimal energy and reserve management of electric vehicle fast charging station: Hierarchical game approach," *IEEE Trans. Smart Grid*, 2017. doi: 10.1109/TSG.2017.2687522.

[26] R. Wang, G. Xiao, and P. Wang, "Hybrid centralized-decentralized (HCD) charging control of electric vehicles," *IEEE Trans. Veh. Technol.*, vol. 66, no. 8, pp. 6728–6741, Aug. 2017.

[27] W. Yuan, J. Huang, and Y. J. A. Zhang, "Competitive charging station pricing for plug-in electric vehicles," *IEEE Trans. Smart Grid*, vol. 8, no. 2, pp. 627–639, Mar. 2017.

[28] H. Yang, X. Xie, and A. V. Vasilakos, "Noncooperative and cooperative optimization of electric vehicle charging under demand uncertainty: A robust stackelberg game," *IEEE Trans. Veh. Technol.*, vol. 65, no. 3, pp. 1043–1058, Mar. 2016.

[29] J. Tan and L. Wang, "A game-theoretic framework for vehicle-to-grid frequency regulation considering smart charging mechanism," *IEEE Trans. Smart Grid*, vol. 8, no. 5, pp. 2358–2369, Sept. 2017.

[30] A. Mondal and S. Misra, "Game-theoretic energy trading network topology control for electric vehicles in mobile smart grid," *IET Netw.*, vol. 4, no. 4, pp. 220–228, 2015.

[31] Z. Zhu, S. Lambotharan, W. H. Chin, and Z. Fan, "A mean field game theoretic approach to electric vehicles charging," *IEEE Access*, vol. 4, pp. 3501–3510, June 2016.

[32] H. Chen, Y. Li, R. H. Y. Louie, and B. Vucetic, "Autonomous demand side management based on energy consumption scheduling and instantaneous load billing: An aggregative game approach," *IEEE Trans. Smart Grid*, vol. 5, no. 4, pp. 1744–1754, July 2014.

[33] I. Atzeni, L. G. Ordòñez, G. Scutari, D. P. Palomar, and J. R. Fonollosa, "Demand-side management via distributed energy generation and storage optimization," *IEEE Trans. Smart Grid*, vol. 4, no. 2, pp. 866–876, June 2013.

[34] M. H. Cintuglu, H. Martin, and O. A. Mohammed, "Real-time implementation of multiagent-based game theory reverse auction model for microgrid market operation," *IEEE Trans. Smart Grid*, vol. 6, no. 2, pp. 1064–1072, Mar. 2015.

[35] W. Tushar, B. Chai, C. Yuen, S. Huang, D. B. Smith, H. V. Poor, and Z. Yang, "Energy storage sharing in smart grid: A modified auction-based approach," *IEEE Trans. Smart Grid*, vol. 7, no. 3, pp. 1462–1475, May 2016.

[36] W. Lee, L. Xiang, R. Schober, and V. W. S. Wong, "Direct electricity trading in smart grid: A coalitional game analysis," *IEEE J. Sel. Areas Commun.*, vol. 32, no. 7, pp. 1398–1411, July 2014.

[37] J. Ni and Q. Ai, "Economic power transaction using coalitional game strategy in micro-grids," *IET Generation, Transmission Distribution*, vol. 10, no. 1, pp. 10–18, Jan. 2016.

[38] S. Maharjan, Q. Zhu, Y. Zhang, S. Gjessing, and T. Başar, "Dependable demand response management in the smart grid: A Stackelberg game approach," *IEEE Trans. Smart Grid*, vol. 4, no. 1, pp. 120–132, Mar. 2013.

[39] E. Mojica-Nava, C. A. Macana, and N. Quijano, "Dynamic population games for optimal dispatch on hierarchical microgrid control," *IEEE Trans. Syst., Man, Cybern., Syst.*, vol. 44, no. 3, pp. 306–317, Mar. 2014.

[40] M. H. Cintuglu and O. A. Mohammed, "Behavior modeling and auction architecture of networked microgrids for frequency support," *IEEE Trans. Ind. Informat.*, vol. 13, no. 4, pp. 1772–1782, Aug. 2017.

[41] Q. Zhu and T. Başar, "A multi-resolution large population game framework for smart grid demand response management," in *Proc. 5th Int. Conf. NETwork Games, COntrol and OPtimization (NetGCooP)*, Oct. 2011, pp. 1–8.

[42] C. Giotitsas, A. Pazaitis, and V. Kostakis, "A peer-to-peer approach to energy production," *Technol. Soc.*, vol. 42, pp. 28–38, Aug. 2015.

[43] D. Ilic, P. G. D. Silva, S. Karnouskos, and M. Griesemer, "An energy market for trading electricity in smart grid neighbourhoods," in *Proc. IEEE Int. Conf. Digital Ecosystems and Technologies (DEST)*, July 2012, pp. 1–6.

[44] W. Saad, Z. Han, H. V. Poor, and T. Başar, "A noncooperative game for double auction-based energy trading between PHEVs and distribution grids," in *Proc. IEEE Int. Conf. Smart Grid Communications (SmartGridComm)*, Oct. 2011, pp. 267–272.

[45] R. Alvaro-Hermana, J. Fraile-Ardanuy, P. J. Zufiria, L. Knapen, and D. Janssens, "Peer to peer energy trading with electric vehicles," *IEEE Intell. Transp. Syst. Mag.*, vol. 8, no. 3, pp. 33–44, 2016.

[46] P. Samadi, V. W. S. Wong, and R. Schober, "Load scheduling and power trading in systems with high penetration of renewable energy resources," *IEEE Trans. Smart Grid*, vol. 7, no. 4, pp. 1802–1812, July 2016.

[47] D. Kalathil, C. Wu, K. Poolla, and P. Varaiya, "The sharing economy for the electricity storage," *IEEE Trans. Smart Grid*, 2017. doi: 10.1109/TSG.2017.2748519.

[48] C. Zhang, J. Wu, M. Cheng, Y. Zhou, and C. Long, "A bidding system for peer-to-peer energy trading in a gridconnected microgrid," *Energy Procedia*, vol. 103, pp. 147–152, Dec. 2016.

[49] Y. Wu, X. Tan, L. Qian, D. H. K. Tsang, W. Z. Song, and L. Yu, "Optimal pricing and energy scheduling for hybrid energy trading market in future smart grid," *IEEE Trans. Ind. Informat.*, vol. 11, no. 6, pp. 1585–1596, Dec. 2015.

[50] C. Long, J. Wu, C. Zhang, L. Thomas, M. Cheng, and N. Jenkins, "Peer-to-peer energy trading in a community microgrid," in *Proc. IEEE PES General Meeting*, July 2017, pp. 1–5.

[51] CONFRRM. (2012). Elizabeth City State University, Elizabeth City, North Carolina. RReDC. [Online]. Available: http://rredc.nrel.gov/solar/new_data/confrrm/ec/

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