Renewable and Sustainable Energy Reviews 156 (2022) 111890

Contents lists available at ScienceDirect

Renewable and Sustainable Energy Reviews

journal homepage: www.elsevier.com/locate/rser

Market Mechanisms for Local Electricity Markets: A review of models, solution concepts and algorithmic techniques

Georgios Tsaousoglou [a,*,1], Juan S. Giraldo [b], Nikolaos G. Paterakis [a]

[a] Eindhoven University of Technology, Netherlands

[b] Mathematics of Operations Research group, University of Twente, Netherlands

ARTICLE INFO

Keywords:
Local Electricity Markets
Market Mechanisms
Demand Response
Smart Grid
Peer-To-Peer Energy Markets
Market Clearing
Distributed Energy Resources
Mechanism Design

ABSTRACT

The rapidly increasing penetration of distributed energy resources (DERs) calls for a hierarchical framework where aggregating entities handle the energy management decisions of small DERs and represent these DERs upstream. These energy management decisions are typically envisaged to be made via market-based frameworks, aspiring the so-called Local Electricity Markets (LEMs). A rich literature of studies models such LEMs adopting various modeling assumptions and proposes various Market Mechanisms towards making dispatch and pricing decisions. In this paper, we make a systematic presentation of a LEM formulation, elaborating on the cornerstone attributes of the market model, i.e. the Market Scope, the Modeling Assumptions, the Market Objective, and the Market Mechanism. We discuss the different market model choices and their implications and then focus on the prevailing approaches of Market Mechanisms. Finally, we classify the relevant literature based on the market model that it adopts and the proposed Market Mechanism, visualize the results and also discuss patterns and trends.

1. Introduction

Global decarbonization goals are currently triggering a series of fundamental changes in electricity systems. At the same time, market liberalization and bottom-up investments are envisaged as a catalytic driver towards fast and sustainable penetration of Renewable Energy Sources (RES). In the face of these transitions, electricity systems and markets are facing major challenges with respect to their design and operation. One major challenge relates to the uncertainty of RES output which comes in stark contrast to the (almost) deterministic dispatchability of traditional power plants. Notably, such uncertainty aggravates the need for corrective actions close to real-time. Such a need can be significantly costly, while it also brings over-provisioning measures (e.g. grid reinforcement) to secure the system's operation robustly. In this context, enhancing the system's flexibility comes as a new approach paradigm that replaces system over-provision.

Another major challenge is the increased presence of RES and other energy resources in low-voltage grids, which necessitates active energy management at the edge of the network. In particular, the safe operation of the distribution network needs to be ensured, while these Distributed Energy Resources (DERs) need to be integrated into the macroscopic network energy management (e.g. offer balancing services and bear balance responsibility). A computational barrier presents itself towards tracking globally efficient solutions in a system with high penetration of small DERs. The computational complexity is burdensome due to the large numbers of small resources (instead of a few bulk power plants), the increased amounts of uncertainty that they bring, as well as the non-convexities that stem from the distribution network flow constraints and from the DER models.

Towards accommodating these challenges, the pivotal drivers are reported to be the better use of networks and the safer and more secure operation through information and communication systems ([1] page 7). In the face of the above developments, a significant amount of work in the research literature is headed towards designing novel market frameworks towards efficient, scalable, and uncertainty-aware system operation.

The integration of DERs has motivated novel electricity markets that stem from a hierarchical market architecture where aggregating entities represent multiple DERs upstream. These aggregation schemes are of the general form illustrated in Fig. 1. In the architecture of Fig. 1, four types of actors/entities can be identified:

* Corresponding author.
E-mail address: g.tsaousoglou@tue.nl (G. Tsaousoglou).

1 Georgios Tsaousoglou received funding from the European Union's Horizon 2020 research and innovation programme under the Marie Skłodowska-Curie grant agreement No. 754462.

https://doi.org/10.1016/j.rser.2021.111890
Received 8 April 2021; Received in revised form 22 October 2021; Accepted 6 November 2021
Available online 3 December 2021

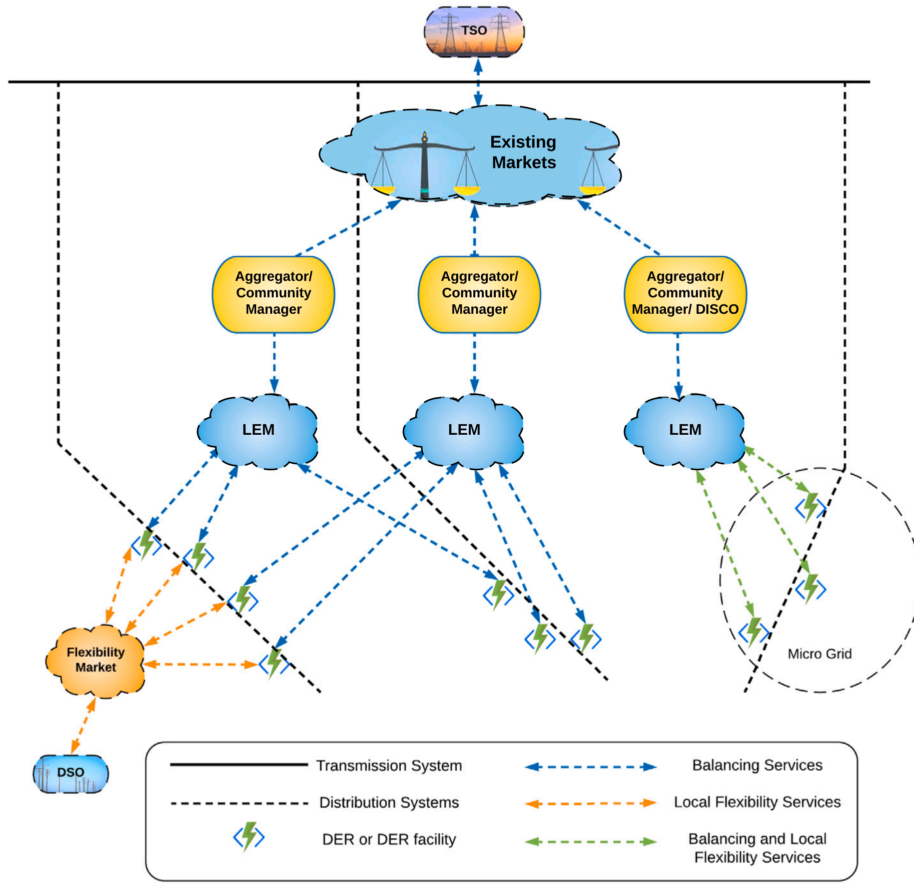

Fig. 1. Hierarchical Market Architectures and the Role of Local Electricity Markets.

- The Transmission System Operator (TSO) is the entity responsible for balancing the electricity system through operating the balancing market. In different regulation frameworks, this entity can also be called Independent System Operator.
- The Distribution System Operator (DSO) is the entity responsible for the safety of a particular distribution network. For this purpose, a DSO can acquire services from assets located in nodes of its own distribution network, through a flexibility market [2]. The regulatory framework that relates to the operation of relevant markets is still under development, and part of the literature refers to the Flexibility Market Operator as an entity that operates the flexibility market on behalf of the DSO [3].
- A DER or DER facility can be any asset, e.g., generator, storage, flexible load, or an assets' cluster, e.g., a building.
- The Aggregator is a central entity of the architecture since it is responsible for representing its portfolio assets upstream. An Aggregator participates in the balancing energy market by undertaking balance responsibility,[2] for its registered assets and aggregating their balancing services. The TSO instructs a balancing action (dispatch) to the Aggregator, and the latter needs to solicit the corresponding balancing energy from its registered assets, in order to implement the TSO's instruction. The Aggregator, thus, dispatches the assets in its portfolio, either via direct control or through a Market Mechanism, the scope of which is *local* i.e., only among assets registered with this Aggregator. Different entities can act as Aggregators, e.g. Demand Response Aggregator, Community Manager, Electricity Service Provider and more, also depending on the characteristics of the set of assets they represent.

Moreover, by referring to Fig. 1, four types of markets can be identified:

- Existing markets: These are the markets where Aggregators participate. These markets' role is to balance electricity supply and demand while also providing the TSO with the necessary frequency restoration reserves. The most representative of such markets is the real-time balancing market and the day-ahead spot market, while there are also intra-day and forward markets where participants trade among themselves in order to fix their position or hedge their risks.
- Flexibility Markets: These are the markets where DSOs acquire services from assets connected to their distribution system to ensure the operational safety of the distribution network. It is a relatively new proposition, and their design is an area of vibrant research [4]. Market models have been proposed for this use case as well [2].
- Local Electricity Markets (LEMs): In a LEM, the assets of an Aggregator trade with the Aggregator (or among each other) to decide each asset's dispatch, also depending on the position of the whole community/Aggregator. Such LEMs go by various names in the literature, e.g. "Transactive Energy" [5] or "Demand Side Management", while sometimes they are also called "flexibility markets", albeit they do not have to be local in the geographical sense, i.e. a community may encompass assets located in different distribution networks as seen in the left and middle LEMs

[2] In some systems (predominantly European) a party that undertakes balance responsibility is called a Balance Responsible Party (BRP) which is a more general term that includes not only Aggregators. For example, a big power plant can be the BRP of itself, an energy supplier is the BRP of its consumers even though it cannot interact and manage their consumption, etc.

of Fig. 1. Also, studies that propose peer-to-peer (P2P) market frameworks (e.g. [6]) usually refer to this type of markets. Finally, many studies propose LEMs (e.g. [7]) that try to maximize the community's self sufficiency by minimizing the exchange with the wholesale market. The motivation is that there is a price spread between the price for energy sold (e.g. feed-in-tariff) and the price for energy bought (e.g. retail price), which deems such trades unprofitable. A study of how this price spread affects the level of self-sufficiency is presented in [8].
- Hybrid LEMs and flexibility markets: A mixture of a LEM and a flexibility market is formed for the case where the assets constituting a particular distribution system also jointly participate in the existing markets, as in the LEM on the right of Fig. 1. In such a case, DSO constraints and balance responsibility are co-optimized. Under this perspective, a Microgrid can also be perceived as a community with an exclusively-defined geographical location. A Microgrid is usually deemed to be balance-responsible, i.e., the Microgrid operator is an Aggregator, also called a "Distribution Company - DISCO" sometimes.

Following the elaborations above, a generic framework is envisaged, where Aggregators and/or Community Managers participate in the existing markets, while each one runs an internal market[3] to further decide the dispatch of the parties that it represents. It is to these internal markets that the term "LEM" refers.

Literature review papers have addressed several aspects of LEMs. In [4], the concept of local flexibility markets is surveyed from a DSO point of view. [9,10] focus on energy communities, the former presenting different business models and offering policy insights, while the latter also discussing socio-economic aspects. [11] focuses on electric vehicles and reviews control algorithms for smart charging (centralized control, transactive control, time-of-use pricing). The authors in [12] adopt a methodology-oriented viewpoint by reviewing applications of artificial intelligence techniques in demand response contexts. [13] offers a broad, high-level view of different peer-to-peer markets use cases and discusses relevant pilot projects. Authors in [14] discuss engineering aspects of DERs, including a discussion on which types of DERs are suitable for which kinds of services (e.g. primary/secondary reserves etc.). In [15], the authors discuss the relevant literature from the perspective of the different coordination frameworks (e.g. uncoordinated, distributed Optimal Power Flow, peer-to-peer trading etc.), discussing technical implications but leaving market aspects aside. In [16,17], the authors present and compare different architectures (peer-to-peer, community-based, hybrid) of hierarchical prosumer-centric LEMs.

The studies above cover different aspects of DERs (e.g. engineering, policy, business, integration paradigms, scheduling and control algorithms). A subset of studies also discusses market architectures (e.g. peer-to-peer, community) and/or surveys market-based approaches (e.g. time-of-use pricing, transactive control). However, none of the above surveys discusses the different possibilities of Market Mechanisms and their algorithmic aspects. The design of Market Mechanisms for LEMs has attracted research stemming from different disciplines, including Economics, Computer Science, Optimization, and Algorithmic Game Theory.

In the LEM literature, each study makes some explicit or implicit modeling assumptions regarding how the market considered interacts with other markets. For example, many studies consider a set of DERs and assume that the electricity cost of the set's aggregated consumption takes a quadratic form. In such approaches (e.g. [18,19] and later studies of this research stream), the wholesale market is modeled simply by considering a clearing price dependent on the generation cost of the marginal generator. In a different example, [6] models a community of prosumers (i.e. DER-controlling facilities) that faces two different prices for drawing/injecting power from/to the grid. A third example is [20] that models a request for a consumption reduction from an "operator entity" to a set of Aggregators. Each Aggregator runs an internal market among its portfolio of households (i.e. assets) to draw the services it offers upstream. In [20], the existing markets are modeled simply by assuming an already cleared order for balancing energy down, and competing Aggregators.

In general, each study proposes Market Mechanisms for a certain use case by adopting certain assumptions. Depending on the modeling assumptions and the objectives adopted by each study, different Market Mechanisms (with various properties) have been proposed towards operating these markets. In view of such different mechanisms and various market scopes of the relevant studies in the power systems literature, there is a clear motivation for defining a systematic framework, within which most of the literature can fit and through which the applications and contributions of each paper are more clear. Therefore, in this paper we aspire to establish the relevant concepts of LEM Market Mechanisms in a clear, unified, and structured way so that the research community is headed towards a standardized framework instead of customized setups. We envision this paper as the first step in a three-step process towards taking LEMs to the next level. This process is envisioned as follows:

1. Establish a systematic framework (scope, modeling assumptions, objectives and relevant techniques) through which a LEM design can be classified and put into perspective with respect to other works while, by referring to this framework, a new study can communicate its scope and contributions more efficiently and clearly.
2. Establish standardized testbeds, with models and metrics that are relevant for real LEMs, where propositions can be evaluated and compared with respect to their performance.
3. Take the prevailing mechanisms to real LEM trials.

Thus, in reference to the first step above, in this paper we make the following contributions:

- Describe a systematic framework for studies that propose market models for LEMs by identifying and analyzing the distinct components that define a particular market model: Market Scope (participants, operator and products), Modeling Assumptions, Objective, Market Mechanism.
- Elaborate on the components of a Market Mechanism (Communication, Allocation rule, Payment rule), categorize the Market Mechanisms most typically used in LEMs into four families (Lagrangian, Game Theoretic, Data-driven, Heuristic) and describe the Communication, Allocation rule, Payment rule of each family.
- Present the main known results regarding the properties of each mechanism family, towards facilitating the understanding of what market models and modeling assumptions pair with each mechanism family.
- Classify the state of the art studies within the presented framework, and characterize each study based on its market model and the Market Mechanism that it proposes.
- Visualize the classification, revealing patterns, areas less researched and research gaps.

Future studies can be systematically classified among the existing literature by referring to this framework while communicating their scope and contributions more efficiently and clearly.

2. Market models

In a broad sense, an electricity market is a system that facilitates the exchange of electricity-related goods and services. By reviewing the

[3] The case of direct control, instead of an internal market, is represented by aggregating entities usually called Virtual Power Plants, and will not be analyzed further in this paper.

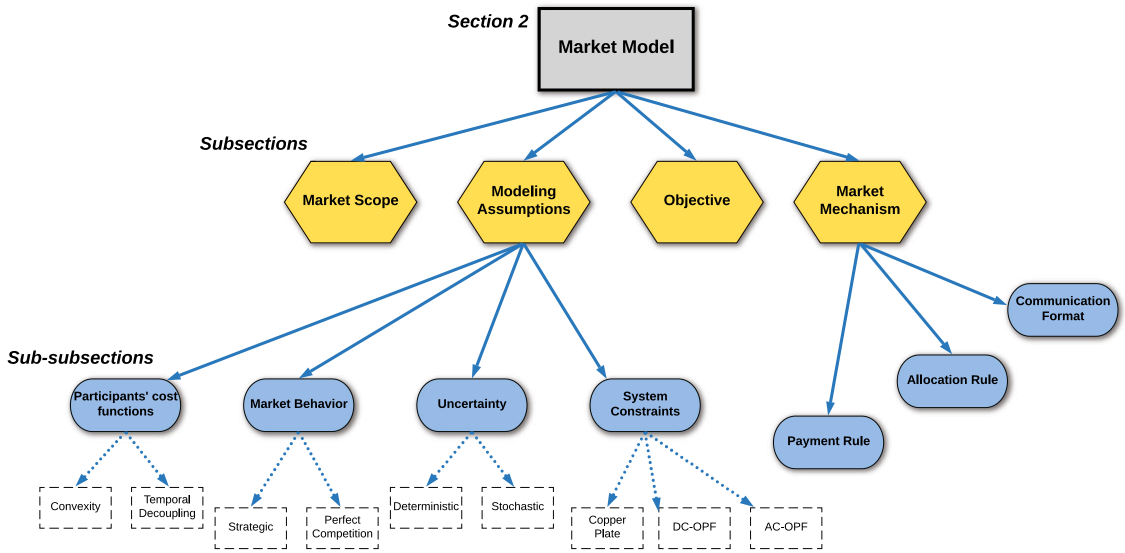

Fig. 2. Attributes of a Market Model/Structure of Section 2.

literature on studies that design and propose electricity Market Mechanisms, a set of common features can be identified towards defining a complete description of LEM design. Specifically, a properly defined electricity market design study needs to specify its scope with respect to at least four attributes:

- Market scope: This includes the set of market actors (eligible market participants and the market operator), as well as a set of standardized products that can be exchanged in the market.
- Modeling assumptions adopted by the study.
- Objective of the market designer.
- Definition of proposed Market Mechanism, including an *allocation rule*, a *payment rule* and a *communication model*.

In Fig. 2, these attributes are graphically demonstrated in yellow polygons. Modeling assumptions and Market Mechanisms are defined based on the further sub-attributes depicted in blue oval shapes. In this section, we elaborate on each of these components. In fact, the polygon-attributes of Fig. 2 also represent this section's subsections, two of which are further divided into the sub-subsections depicted by the oval sub-attributes. Finally, the dashed squares present some typical (but not comprehensive) examples of attribute choices used in the literature.

2.1. Market scope

The Market Operator is the entity responsible for carrying out the market procedures according to the designed Market Mechanism, while the set of market participants includes the entities that can participate in the market based on the market's scope and rules. For this paper's purposes, it is useful to assign a symbol N to denote the set of a market's participants. The set N generally consists of electricity producing/consuming facilities and assets, such as RES facilities, storage facilities and flexible or inflexible loads.

As an analogy, we refer to typical balancing markets. These are operated by the Transmission System Operator and the set of participants N consists of all registered entities capable of providing balancing services. However, LEMs may be subject to a more designated set of participants. For example, for a market where a DSO acquires services towards controlling the nodes' voltages or the lines' congestion of its distribution system [3], the set N consists exclusively of DERs located in that particular distribution network. Similarly, an Aggregator can run an internal market, designated for the DERs (or facilities) N that are registered to this Aggregator [20].

While energy, in the form of active power over time, is usually the main product of an electricity market, other products also exist. Energy reserve (of different types) is a product sold to the operator in order for the latter to have enough resources available for balancing the system or relieving congestion in real-time. Reactive power injection is another product [2], relevant to distribution systems, while some recent works have formulated markets for data [21], related to the forecasting accuracy of RES. In many electricity markets, several products are jointly cleared in a co-optimization problem (e.g. energy and reserve), so it is useful to define a set P of products $p \in P$ for a market.

Due to the natural necessity of energy systems to be balanced (i.e. supply has to equal demand at all times), an important property of an electricity market product is the time of delivery. Strictly speaking, energy in different timeslots could be conceived as different products since it has a different value for the participants. However, in this paper, we refer to the time of delivery explicitly by using a timeslot index $t \in T$. A special mention is in order for P2P market studies where the authors consider participants who have preferences over their trading partners, i.e., for participant $n \in N$, buying a product $p \in P$ from a participant $i \in N$ has different value than buying the same product from another participant $j \in N$ (e.g. because one seller is more reliable, more "green", geographically closer etc.). In market terms, we say that there is product differentiation among sellers [22].

2.2. Modeling assumptions

The outcome of the market is that each participant is allocated with certain quantities $b_{n,p,t}$ and $s_{n,p,t}$ of, respectively, buy or sell of product p at time t and is also charged/credited a payment amount π_n. Note that π_n depends on $b_{n,p,t}$ and $s_{n,p,t}$, and can be positive or negative (depending on whether n receives payments for selling products or makes payments for purchasing products). Let $\boldsymbol{x}_n = \{b_{n,p,t}, s_{n,p,t}\}_{p\in P,t\in T}$ denote the allocation (dispatch) of participant n for all products and all timeslots. We denote the combination of all the participants' dispatch as the market's allocation $\mathcal{A} = \{\boldsymbol{x}_n\}_{n\in N}$. Each participant $n \in N$ is characterized by a cost function $c_n(\boldsymbol{x}_n)$ which is a function of its allocation for all products and all timeslots. Again, the cost function $c_n(\boldsymbol{x}_n)$ can also take on negative values, indicating a benefit/utility/valuation from buying products. Finally, at least for LEMs, it is regarded that a participant cares only about its own allocation, i.e., the cost/utility function of n does not depend on the whole allocation $\mathcal{A}$ but only on $\boldsymbol{x}_n$.

In the rest of this subsection, we present four types of assumptions, based on which many studies in the literature can be categorized. Our motivation for doing that is that for any Market Mechanism proposed in the literature, it is important to consider (and state) under what modeling assumptions the mechanism's performance is guaranteed.

2.2.1. Assumptions on the participants' cost/utility functions and local operational constraints

A significant part of the literature assumes *convexity* of the participants' cost functions $c_n(\cdot)$, which greatly facilitates the functionality of the Market Mechanism or at least the analysis of it. A more subtle assumption refers to whether $c_n(\boldsymbol{x}_n)$ is temporally coupled. While this cost function is assumed separable over T by some studies, i.e.

$$c_n(\boldsymbol{x}_n) = \sum_{t\in T} c_{n,t}(x_{n,t}) \tag{1}$$

this is not generally the case. For example, the cost/utility of an electric vehicle may depend on the total energy accumulated until a certain deadline, the cost of a storage facility may depend on the total number of charge/discharge cycles, while a generator also bears start-up costs that couple its costs across time. All these considerations couple the participants' cost functions over the time horizon, which can sometimes incommode the solution of the market clearing problem.

In addition to its cost function, each participant bears a set of local operational constraints which define a feasible region $C_n \subseteq \mathbb{R}^{2|P||T|}$ for n's dispatch, such that $\boldsymbol{x}_n \in C_n$. For example, generators have certain ramp constraints that couple the dispatch between consecutive timeslots, batteries have certain constraints that describe the relationship between their dispatch and their state of charge. Moreover, flexible loads have a number of different constraints depending on the device models adopted. Similarly to the cost functions assumptions, whether assumptions on convexity and temporal-independence are adopted is of central importance when modeling a participant's local constraints as well.

2.2.2. Market behavior

The objective of a market participant is usually the maximization of its own payoff, which is comprised by the payment $\pi_n(\mathcal{A})$ that it receives/pays from/to the market, minus the cost/valuation $c_n(\boldsymbol{x}_n)$ that it suffers/gains for delivering/consuming the products assigned to it by the market's dispatch:

$$\max \ \left\{\pi_n(\mathcal{A}) - c_n(\boldsymbol{x}_n)\right\} \tag{2a}$$

$$\text{s.t. } \boldsymbol{x}_n \in C_n \tag{2b}$$

The control variables of participant n, through which it can pursue a good solution of problem (2a), are usually n's bids, the form of which depends on the market's communication model, analyzed in Section 2.4.1.

An important modeling assumption refers to the participants' information and market behavior. More specifically, many studies assume a *price-taking* or *myopic* market behavior where participants cannot unilaterally affect the market outcome due to their small size, lack of information, and/or lack of computational capabilities. This assumption is often called the "perfect competition" or simply "price-taking" assumption, and in many cases, it can facilitate the Market Mechanism's performance. A typical example is the family of Lagrangian decomposition methods, widely used as a Market Mechanism in LEMs (e.g. [6,7,23–25]), that guarantee an optimal allocation but only under the (sometimes implicit) assumption that no participant behaves strategically.

A participant i can behave strategically if it is aware of the Market Mechanism and also has some knowledge over the other participants' cost functions $c_j(\cdot)$ and constraints C_j, where $j \neq i$. Some studies have demonstrated the effect of strategic behavior on the market outcome [26], by using bi-level programming, where the cost functions and constraints of other participants as well as the Market Mechanism, are explicitly modeled in the lower level problem of the focal strategic player i.

In a different direction, some studies have demonstrated that even in cases where i is not aware of the Market Mechanism and/or $c_{j:j\neq i}(\cdot)$, $C_{j:j\neq i}$, it is still able to exhibit strategic behavior by having an Artificial Intelligence (AI) algorithm learn to optimize i's market position through i's bids. Such an example is [27], where Deep Reinforcement Learning was used. Such strategic aspects become increasingly relevant since intelligent agents, that make market participation decisions on behalf of participants, have already been proposed in the smart grid literature, e.g. [28,29].

In cases where the perfect competition assumption is relaxed, Game Theory is the formal framework for conducting market analysis, while Mechanism Design is the science of designing mechanisms for environments with strategic participants.

2.2.3. Uncertainty

Due to various operational constraints of market participants (ramps, start-up procedures etc.) a product p_t for timeslot t is typically traded not only in real-time but also in markets that take place ahead of delivery time t (e.g. in day-ahead markets). In such markets, the allocation is decided for a horizon T ahead. However, in reality, a participant never really has full observability ahead of time over its own cost function and constraints. This is well understood for RES generation facilities and demand response availability of loads, while it is also true for conventional generators since their operation also depends on unknown parameters such as the quality of the fuel or simply an unforeseen failure. Therefore, an important distinction needs to be made in the literature with respect to whether and how a study takes *uncertainty* into account.

In particular, the notion of a participant's cost function is generalized from $c_n(\boldsymbol{x}_n)$ to a parameterized function $\sum_{t\in T} c_{n,t}(x_{n,t}, \beta_{n,t}, q_t)$, where $\beta_{n,t}$ is an uncertain parameter (also called *disturbance* in the control literature) and q_t is the so-called *state* variable that captures all relevant past information (generally, past decisions and disturbances). The system model can be visualized as a tree graph with each level representing a timeslot and each node representing a system possible state. Thus, the dispatch decisions are generalized into state-dependent variables $x_{n,p,t,q}$. A rigid mathematical representation of such models for uncertainty can be found in [30]. In general, the state space grows exponentially in the number of participants, which is known as the *curse of dimensionality* of multi-agent systems. However, certain assumptions, that are usually valid in practice for power systems, can drastically sidestep this issue. The most important simplifying assumption in power systems is the one of *exogenous* uncertainty, i.e., the evolution of the uncertain parameters $\beta_{n,t}$ does not depend on the dispatch decisions.

For a typical example, consider that $\beta_{n,t}$ represents the local RES generation at n, t. Observe that participant's actual cost at t depends not only on its dispatch, but also on $\beta_{n,t}$. However, since RES available generation depends only on the weather conditions and not on the dispatch decisions, $\beta_{n,t+1}$ does not depend on $x_{n,t}$. Due to this property, one can avoid the need to represent all states $q \in Q$ and use only a number of representative scenarios $k \in K$ for the uncertainty realization instead. These representative scenarios can be defined by applying scenario reduction techniques. In this case, a scenario k captures a certain RES generation profile (i.e. the independent trajectory $\{\beta_{n,t}\}_{t\in T}$), and the (expected) cost function takes the stochastic form $c_n = \sum_{t\in T} \sum_{k\in K} c_{n,t}(x_{n,t}, \beta_{n,t,k}, q_t)$. Some representative studies that adopt this approach include [7,31], and [32]. The trivial case of $|K| = 1$ represents the point-forecast (or deterministic) approach (e.g. [33,34]), which in practice would necessitate (sometimes costly) re-dispatch actions close to real time. Another group of studies use robust optimization techniques (e.g. [35,36]) or information gap theory [37], to optimize the worst case scenario of the uncertainty realization.

Towards managing the computational complexity of stochastic programs, and especially for power system applications, relevant decomposition techniques are thoroughly analyzed in [38]. Another, increasingly adopted, approach is the so-called *learn-to-optimize* technique, where the dispatch problem for each scenario is solved offline, and the mapping from scenarios to optimal dispatch solutions is fed into a machine learning algorithm. The idea is that the agent learns to predict a good dispatch, online, once provided with an up-to-now uncertainty realization. An example of this approach can be found in [39] for a low-voltage distribution grid. In [40], the authors also use the partial derivatives of the dispatch optimization problem to train a sensitivity-informed neural network.

Nevertheless, the exogenous uncertainty assumption may no longer be valid in practice in LEMs of the near future, since more types distributed resources that do not satisfy this assumption become increasingly important. A characteristic example is the one of smart buildings that offer demand response capabilities. The thermal energy demand of buildings is an uncertain parameter that its evolution depends both on disturbances (e.g. outside temperature, user behavior, etc.) *and* on dispatch decisions. Many studies avoid the computational impasse of the general discrete-time dynamical system, described in the beginning of this subsection, by assuming a parameterized, physics-based thermal model for the building (e.g. [18,41]). However, this modeling approach is considered an oversimplification by recent studies, since constructing an accurate thermal model for each building is very challenging and also impractical [42]. Consequently, many recent studies turn towards Markov-based uncertainty models (e.g. [43]) and propose data-driven techniques (e.g. [44,45]).

2.2.4. System constraints

In contrast to the local constraints $\boldsymbol{x}_n \in C_n$ discussed in Section 2.2.1, system constraints involve more than one participant. Constraints that involve more than one participant are sometimes called "global", "complicating", "coupling" or "resource" constraints also depending on their nature. For the purposes of this paper, we use S to denote the whole set of system constraints, such that $\mathcal{A} \in S$, where $S \subseteq \mathbb{R}^{2|N||P||T|}$. System constraints in electricity systems include the supply–demand balance for all products (e.g. power and reserve), as well as a set of network (or "flow") constraints. Network constraints are a special kind of complicating constraints that are particularly relevant for electricity markets since actual product delivery is made through a physical electric grid, and therefore, it is subject to physical constraints of the grid, known as the power flow problem. Convexity is a central issue also in these constraints, and a comprehensive line of research is devoted towards proposing convex relaxations for the (inherently non-convex) set S.

Given these issues, another clear distinction can be made among studies regarding the model they adopt for incorporating the flow constraints. Indicatively, electricity markets that take place in the low-voltage network typically consider an AC power flow model, whereas for markets of the transmission network, a DC power flow model is generally deemed sufficient. Finally, another modeling choice is the so-called Power Transfer Distribution Factors (PTDFs) model [46] or some extension of it as in [47]. The authors in [48] provide a comprehensive review of different formulations for the optimal power flow problem, while authors in [49] compare different methods for its convexification as a second-order cone formulation, and in [50], authors compare different linear approximations for AC optimal power flow of three-phase distribution systems. Finally, many studies assume that the grid is over-provisioned enough, such that network constraints (e.g. voltage limits) are never violated and need not be modeled. This is commonly called a "copper-plate" assumption [51] which can simplify the mechanism. Nonetheless, such an assumption can lead to infeasible dispatch decisions [52], which need to be corrected *after* the market clears. This typically means that there will be inefficient re-dispatch actions, which sabotages the ostensible optimality of the Market Mechanism. In general, it must be highlighted that model simplifications, approximations, and assumptions inevitably mean diverging from reality. Hence, it is imperative for the modeler and user of such models to be aware of their accuracy/performance trade-off and limitations.

2.3. Objectives and solution concepts

In the vast majority of studies, the objective of the market designer is to find an optimal allocation $\mathcal{A}^*$ which maximizes the *Social Welfare* or, equivalently, minimizes the *System Cost*. Social Welfare is defined as the sum of all the participants' payoffs. In other words, the objective of the market is to maximize economic efficiency. At the same time, local and global constraints must be satisfied. Therefore, an abstract form of a standard Social Welfare maximization problem can be formulated as

$$\mathcal{A}^* = \operatorname{argmax} \left\{ \sum_{n\in N} \left(\pi_n(\mathcal{A}) - c_n(\boldsymbol{x}_n)\right) - c_0(\mathcal{A}) \right\} \tag{3a}$$

$$\text{s.t. } \boldsymbol{x}_n \in C_n, \quad \forall n \in N \tag{3b}$$

$$\mathcal{A} \in S. \tag{3c}$$

where c_0 is the cost of $\mathcal{A}$ for the market operator. In many studies the participants' payments are constrained to be $\sum_{n\in N} \pi_n(\mathcal{A}) = c_0(\mathcal{A})$. This is called a *strictly budget-balanced* market. Problem (3) maximizes the aggregated participants' payoffs, as those were defined in (2a). Notice, though, that for budget-balanced markets, all payments (paid by buyers/operator and received by sellers/operator) cancel out and, thus, (3) reduces to the following cost minimization problem

$$\mathcal{A}^* = \operatorname{argmin} \left\{ \sum_{n\in N} c_n(\boldsymbol{x}_n) \right\} \tag{4a}$$

$$\text{s.t. } \boldsymbol{x}_n \in C_n, \quad \forall n \in N \tag{4b}$$

$$\mathcal{A} \in S. \tag{4c}$$

If convexity and no-uncertainty assumptions are adopted, then the globally optimal solution of problem (4) is generally tractable. In other cases, a Market Mechanism can be evaluated by comparing the Social Welfare that it achieves to the Social Welfare of the theoretically optimal allocation $\mathcal{A}^*$. Note that problem (4) does not have a payment component. Nevertheless, a major reason for introducing payments is to incentivize participants to, directly or indirectly, reveal their private cost functions $c_n(\cdot)$ and facilitate the solution of problem (4).

In cases where strategic behavior, as defined in Section 2.2.2, is taken into account in the system model, the problem takes a game-theoretic form, and *Equilibrium* becomes the relevant solution concept. The predominant notion of equilibrium is the Nash equilibrium, defined as the point $\mathcal{A}^{NE} = \{\boldsymbol{x}_n^{NE}\}_{n\in N}$ from which no participant wishes to make a unilateral deviation, i.e., it is

$$\boldsymbol{x}_n^{NE} \in \operatorname{argmax}_{\boldsymbol{x}_n} \left\{\pi_n(\mathcal{A}) - c_n(\boldsymbol{x}_n)\right\}, \quad \forall n \in N. \tag{5}$$

Thus, problem (5) forms a different objective which can also be identified in the literature. Also, note that multiple equilibria may exist and that, in contrast to problem (4), equilibrium points also depend on the design of the payment functions $\pi_n(\mathcal{A})$. In such systems, the objective of a Market Mechanism can be to identify an equilibrium point that minimizes the welfare loss (also known as the price of anarchy), i.e., (5) is added as a constraint to problem (4).

It is important to highlight that the welfare-maximizing allocation $\mathcal{A}^*$ need not necessarily be an equilibrium. This can become problematic in practice since participants may have reasons to deviate from their dispatch instruction during delivery time. Nevertheless, in the special case where cost functions $c_n(\cdot)$ and feasible regions C_n and S are assumed convex while, additionally, all participants are assumed non-strategic, the optimal solution of (4) is also an equilibrium, i.e. the optimal solution of (4) satisfies (5) without having to model (5) explicitly. This statement draws its theoretical foundations from duality theory and has inspired many studies to apply a dual decomposition method for solving problem (4) distributedly. The solution concept in such cases is called *competitive* equilibrium to distinguish it from Nash equilibrium. A more general formal framework that describes the repeated interaction of strategic participants in an uncertain environment is the so-called *Stochastic* (or *Markov*) game. Very few studies have dealt with market frameworks in such environments [53], partly due to stochastic games being intractable in general.

In contrast to the studies that adopt one of the two main objectives described so far (equilibrium discovery and efficiency in terms of Social Welfare maximization), a third family of studies adopt *Fairness* as the market designer's objective. There are multiple notions of "Fairness", and papers of this category usually define the notion used. Examples include max–min fairness [54], proportional fairness [55], or using the Shapley Value as a formal fairness index [56].

Finally, there are cases where an aggregating entity represents a portfolio of assets in a market to maximize its own profit. Various studies model the interaction between the aggregating entity and the assets within its portfolio as a LEM in which the aggregator acquires (provides) services by (to) its assets (see the Aggregators in Fig. 1). In studies where participants cannot choose a different aggregator, the LEM is monopsonistic (monopolistic), i.e. has only one buyer (seller), and the objective can be the maximization of the aggregator's profit. In such settings, usually, the aggregator is assumed to abide by some form of regulation. For example, in [57], a demand response aggregator is able to choose the LEM prices of different timeslots within a day, but the average price would have to be equal to the average wholesale price to constraint the aggregator's market power. Similarly, in [58] a discriminatory pricing scheme is allowed, but the average participant price must be equal to the price faced by the aggregator.

2.4. Market Mechanisms Definition

A Market Mechanism is the set of rules through which market participants' interaction and exchange of products occur. The central research problem of studies that propose Market Mechanisms, stated in its full generality, is to design the rules such that the interaction of participants under these rules leads to a market outcome that is desirable in terms of the designer's objective (as that was defined in the previous subsection). A Market Mechanism consists of at least three distinct components: the *Communication Model*, the *Allocation Rule*, and the *Payment Rule* (described in 2.4.1, 2.4.2, and 2.4.3 respectively), while a certain mechanism is characterized by its guarantees with respect to certain properties. The main properties of interest are described in 2.4.4.

2.4.1. Communication model

The communication model is a set of rules that fully defines how participants exchange information. A communication model consists of the *communication graph* and the *communication format*. The graph defines which participant exchanges information with which. In general, two types can be clearly distinguished: Centralized markets, where each participant exchanges information exclusively with a coordinating entity (namely the market operator), and decentralized/distributed markets, where each participant exchanges information with its "neighbors" (i.e., a certain subset of N) and a coordinator need not exist. A distributed market is often adopted in the case of P2P market frameworks, which are often combined with blockchain technologies that support the market's financial settlements [59]. However, when it comes to satisfying network constraints, the distributed communication graph is typically supplemented by a coordinating entity that solves the power flows and communicates with all participants (e.g. [60] calculates some pricing signals based on PTDFs and other similar factors as elaborated in [47]). Moreover, the communication graph can be subject to design. For example, in [61], the authors design the graph of a P2P market exchange based on the minimization of the electrical distances so that network congestion is relieved. Finally, it is important to make a distinction between distributed communication (information is exchanged only with neighbors) and distributed energy exchange (energy is exchanged only with neighbors). P2P electricity markets (e.g. [22,62]) typically adopt both the above designs. Nevertheless, we can also have distributed information exchange while energy trading is kept in a pool-market form (see [63] for an example).

The communication format, on the other hand, defines/standardizes the type and form of the exchanged information. A *direct revelation* mechanism is one where the participants are required to communicate their cost function $c_n(\boldsymbol{x}_n)$ and set of local constraints C_n in a closed form (as is done for example, in balancing markets). In such mechanisms, the communication format defines what types of functions and constraints are admissible. An example refers to the case where participants are required to communicate their costs as a set of step-wise functions (one for each timeslot and product) that define a number of price-quantity pairs. The constraints that can be communicated are also subject to predefined types, decided by the market designer. Such constraints include operational limits, ramps and also constraints that link several timeslots like minimum/maximum activation time through the operational horizon.

In most of the literature, participants' models are assumed to be perfectly in line with the market's communication format, i.e., cost functions $c_n(\boldsymbol{x}_n)$ and local constraints (2b) are directly incorporated in the dispatch problem (as is shown in (4)). However, in practice, the types of cost functions and constraints allowed by the communication format are usually restricted to functions that facilitate the dispatch problem's solution (e.g. (4)). In contrast, the actual costs and constraints (2b) may be strongly non-convex. Therefore, the market clearing problem may be solved to optimality in theory, but since the participants' actual constraints and costs are different from those considered, there will be inefficiencies in reality.

Two lines of research can be identified on this issue. The first is about designing the communication format of the Market Mechanism so that it achieves an attractive trade-off between capturing the participants' actual models and not compromising the tractability of an efficient allocation $\mathcal{A}^*$. The second is about how a participant with complex models can optimize its bids/offers to the Market Mechanism, given a restrictive communication format [64].

In contrast to direct revelation mechanisms, indirect mechanisms consider an iterative procedure where participants send/receive a series of *queries* and also communicate their query responses. A query can be a price signal $\lambda_{p,t}$ for product p in timeslot t, based on which each participant n is asked to respond with its preferred supply/demand $x_{n,p,t}$. Examples of such an approach are the decomposition techniques proposed by many studies as a way to solve a social welfare maximization problem in a distributed fashion.

2.4.2. Allocation rule

The allocation rule describes how the final allocation $\mathcal{A}$ is decided. In the special case of a direct revelation mechanism and a communication model that constitutes the problem tractable (e.g. convex), the allocation rule is trivially defined by the objective-optimizing problem itself (e.g. (4), (5), or maximizing fairness etc.). In cases of direct mechanisms, different solvers are applicable depending on the modeling approach (namely the model of the constraints and the cost functions). A thorough classification of models and solvers can be found in [4]. However, in general, the optimal solution may be intractable, in which case the allocation rule is subject to design and evaluation since different allocation rules yield different outcomes. This includes cases of uncertainty, cases of intractable objectives as well as indirect mechanisms.

2.4.3. Payment rule

The payment rule defines the way that payments π_n are decided. In standard nodal markets with a social welfare maximization objective, the payment of participant n is defined by the quantities traded multiplied by the price $\lambda_{n,p,t}$ of the node where n is located, i.e. $\pi_n = \sum_{p\in P}\sum_{t\in T} x_{n,p,t}\lambda_{n,p,t}$. In iterative mechanisms, the payments are usually defined based on the last price broadcasted before the algorithm's convergence, while in direct revelation mechanisms, the nodal price is the Lagrange multiplier of the power balance constraint of each node. Note that interpreting the Lagrange multipliers as prices is relevant only in cases where the objective is maximizing social welfare.

The design of the payment rule is particularly important for systems where the perfect competition assumption is relaxed. In such models, many studies have used techniques from Mechanism Design theory to propose payment rules that align the objective of each market participant (e.g. (2a)) with the market designer's objective (e.g. (4)). For example, towards maximizing social welfare, the Clarke pivot rule was proposed in [3,65] as a payment rule that incentivizes participants to reveal their cost functions to the market operator truthfully. In another example, the authors in [66] design a payment rule based on compensation-and-penalty mechanisms such that truthful declaration also holds for the case where the objective is to optimize the max–min fairness index.

2.4.4. Properties of Market Mechanisms

A Market Mechanism can be evaluated with respect to a number of metrics or property requirements. We describe here the most important of those:

- *Efficiency and constraint satisfaction*: This metric quantifies the mechanism's performance with respect to the objective sought. For example, a mechanism that also considers uncertainty can be evaluated based on its outcome against the optimal-in-hindsight solution and also on the probability that a constraint is violated.
- *Incentive Compatibility*: If a mechanism has this property, it means that the participants' objectives are consistent with the market's objective. In other words, it is to the participants' best interest to help the mechanism maximize efficiency (e.g. by revealing their true costs to the market operator). This property is particularly important for settings with strategic players (Section 2.2.2). In fact, a mechanism can be optimal under the perfect-competition assumption (e.g. Lagrangian methods), but if strategic behavior is present and the mechanism is not incentive compatible, then its efficiency is also compromised. Especially in the LEM context, where the reach of market monitoring and auditing procedures is naturally limited, intelligent agents with computational capabilities, acting on behalf of DERs, can find an inviting place to exploit.
- *Tractability*: This refers to the property of a Market Mechanism to achieve the optimal outcome within the relevant time-frame and scale. Note that a mechanism can be theoretically optimal and incentive compatible, but the optimal outcome may, however, be impossible to reach. For example, in a direct revelation mechanism, the allocation rule may be strongly non-convex, or, in an indirect mechanism calculating the optimal response to a query may be impossible for a participant.
- *Individual Rationality*: A mechanism is individually rational if every participant's payoff ($\pi_n(\mathcal{A}) - c_n(\boldsymbol{x}_n)$) is non-negative. Intuitively, each participant always prefers to participate in the market rather than not participate. An extension of this property is called "Group Rationality", where a mechanism is group rational if no subset of users would be better-off if they jointly withdrew their participation from the market.
- *Budget Balance*: We say that a mechanism is strictly budget-balanced when the market operator does not need to inject money to (or make money from) the system, i.e. $\sum_{n\in N}\pi_n(\mathcal{A}) = c_0(\mathcal{A})$. A weaker form of this property is sometimes sought, where it is required that the market operator does not need to inject money, but can, however, make money from the mechanism, i.e. $\sum_{n\in N}\pi_n(\mathcal{A}) \geq c_0(\mathcal{A})$. This latter property is also called "revenue adequacy".
- *Privacy Preservation*: A mechanism that requires the participants to share their whole set of local models can compromise the participant's privacy, especially in the case of participants offering demand response services by utilizing the flexibility of their residential electricity resources. A mechanism's communication model can account for privacy preservation or be configured with a privacy protecting protocol (e.g. differential privacy). Different levels of privacy protection exist. However, for this paper's scope, we only distinguish between studies that do not account for privacy and studies that propose privacy-aware mechanisms.
- *Explainability*: In real electricity markets, it is vitally important that the dispatch and payments resulting from the mechanism are intuitively understood, so that the market operator can provide relevant explanations to participants or authorities if need be. For example, if the dispatch is obtained by a machine learning algorithm, it might be challenging to rationalize the results and convince participants or authorities about the mechanism's trustworthiness and reliability.

3. Market Mechanisms Methods

The described new challenges of electricity systems have triggered a significant amount of research towards designing Market Mechanisms to accommodate these challenges. The proposed techniques stem from different disciplines. Optimization and Operations Research techniques have been mightily present, while Game Theoretic techniques also have had a high share. Algorithmic Game Theory and Mechanism Design are particularly relevant disciplines, combining concepts from Computer Science, Mathematics and Economics. Finally, the computational and uncertainty-related challenges have motivated the use of heuristic techniques and data-driven techniques, especially methods from AI and Multi-Agent Systems. In the four subsections below, we identify and analyze four distinct families of methods leveraged by the literature towards designing Market Mechanisms for LEMs.

3.1. Lagrangian methods

Lagrangian decomposition methods are the most commonly used mechanisms in LEMs. Their development is inspired by duality theory and the fact that a convex optimization problem features an equivalent dual problem. In particular, by interpreting the optimal dual variables of the power balance constraints as prices, the problem of finding the optimal allocation to problem (4) is equivalent to finding the optimal set of prices. This, in turn, motivates the development of iterative algorithms (resembling of auctions) where the operator communicates price signals $\lambda_{n,p,t}$ to the market participants and they respond by choosing their own allocation $\boldsymbol{x}_n$ for those prices by solving problem (2a), where the payment function is $\pi(\boldsymbol{x}_n) = \sum_{p\in P}\sum_{t\in T}\lambda_{n,p,t}x_{n,p,t}$. The operator receives the responses and updates the prices based on a price update rule. The choice of the price update rule greatly interferes with the algorithm's convergence properties, and thus, has been subject to research. Under certain conditions, such algorithms have been shown to converge to an equilibrium where the prices and the participants' responses no longer change. Furthermore, due to strong duality, this *competitive equilibrium* point also optimizes Social Welfare. Finally, it is worth noting that in such models, Lagrangian mechanisms can be very fast to converge, even for large problems, since the problem of finding the optimal dispatch is effectively decomposed into local problems (one for each participant) that can be solved in parallel.

Based on these observations, it follows that Lagrangian methods are suitable for settings with convex formulations and non-strategic participants, the objective being Social Welfare maximization. Moreover, they are the predominant mechanism towards managing network constraints, by conceptualizing a price signal (multiplier) that implicitly communicates the coupling constraint's status to the participants involved. Naturally, there is a price (dual variable) for each node (corresponding power balance constraint). For this reason this mechanism is also called Locational Marginal Pricing. In the copper-plate case, on the other hand, there is only one coupling constraint (the overall power balance) and hence the market clears with a single price, i.e., the market-clearing price. This simplification can enhance the mechanism's computational time and explainability, but can also sabotage the mechanism's efficiency as discussed in Section 2.2.4. Uncertainty can be accounted for by considering a stochastic programming formulation using a number of scenarios for the realization of uncertain parameters [7]. However, in cases of non-convex cost functions $c_n(\cdot)$, Lagrangian techniques cannot sustain their guarantees towards convergence and efficiency, although some works have shown that they can perform well in practice [6,67,68].

Summarizing the discussion on Lagrangian methods, and putting it into perspective with respect to the desirable mechanism properties described in Section 2.4.4, Lagrangian mechanisms are

- Efficient under the assumptions of convexity and non-strategic behavior
- Not incentive compatible
- Tractable and parallelizable under the convexity assumption
- Individually rational, under the assumption that if a participant opt for $x_{n,p,t} = 0,\ \forall p, t$, it bears zero costs (i.e. no shut-down costs).
- Revenue adequate. In nodal markets, the price of an unbalanced node (which has more demand than supply) can increase due to line congestion. This can lead to higher payments for that node, which is not counterbalanced by lower payments for any other node.
- Privacy-aware, in the sense that the participants are not required to share their whole set of local models with a central entity. Instead, they only respond to price signals, which can be combined with a privacy-preserving protocol that can ensure that the necessary information to construct a participant's cost function is not stored in one place.

Last but not least, it should be noted that Lagrangian methods are not necessarily suitable for alternative objectives, such as fairness or profit maximization as well as equilibrium discovery for non-convex or strategic settings.

3.2. Game-theoretic methods

Game Theory is the formal framework that describes the dynamics of participants' interaction in Games (i.e. settings with given payoff functions), while Mechanism Design deals with the design of the payoff functions themselves, and for this reason, it is sometimes called "Reverse Game Theory". The main goal of Mechanism Design is to identify positive or negative results towards designing Efficient, Incentive Compatible, and Tractable mechanisms for different settings. The most well-known positive result for Social Welfare maximization settings is the so called Vickrey–Clarke–Groves (VCG) mechanism which can achieve all three properties, provided that the welfare maximization problem is tractable. Note that "tractable" is more general than "convex", which is particularly important for LEMs since Mixed Integer Linear Problems often constitute the relevant problem formulation. However, the VCG mechanism comes with two major cons: first, it is notoriously not budget-balanced, and in fact, it can sometimes result in counter-intuitive payments, and second, it is a direct revelation mechanism and therefore suffers from scalability issues and privacy concerns. The scalability issue is due to the fact that the mechanism, by design, needs to solve the dispatch problem N times (one for deciding the dispatch and another $N-1$ to decide the payments). However, the good news is that the payments calculation can also be made ex-post, i.e. offline.

The AGV (Arrow, d'Aspremont and Gerard-Varet) mechanism has been proposed (e.g. in [69]) as an alternative that can restore budget balance, although by sacrificing the strongest form of incentive compatibility. Moreover, the AGV mechanism only aggravates the (already major) explainability problem of the VCG. Towards addressing the scalability and explainability issues, the literature on Mechanism Design has offered many indirect mechanisms usually in the form of iterative auctions. For LEMs, a clock-proxy iterative auction was proposed in [70], while a scoring rule that partly draws also on Lagrangian methods was proposed in [71], although part of the strong guarantees offered by VCG were weakened. In [63], a LEM was modeled, and an iterative auction addressed the scalability and privacy-preservation issues while the VCG efficiency and incentive compatibility properties were maintained. For NP-hard allocation problems, however, the VCG mechanism fails to maintain incentive compatibility, i.e., the VCG mechanism cannot, in general, be configured with an approximately optimal allocation rule and maintain incentive compatibility. Thus, for non-convex dispatch problems, [41] proposes a combinatorial auction that maintains *strategy resistance* (a weaker form of incentive compatibility). Finally, under the assumption of a large population of participants, evolutionary game-theoretic models can provide convergent algorithms, e.g. [72,73]. A subtle observation is that while indirect mechanisms generally exhibit shorter computational times (by parallelizing computations), they necessitate, however, an online calculation of the payments' since those are used as coordination signals.

With respect to alternative objectives, profit maximizing mechanisms are also widely explored in the theory [74], although less widely applied to LEMs. Finally, studies for Fairness-maximizing objectives in electricity markets include core-selecting mechanisms [75], Shapley-Value approximations [56], while an incentive compatible mechanism for max–min fairness is proposed in [66].

In general, with respect to the desirable properties we have set, different Mechanism Design methods fulfill different properties, but generally, most methods account for Efficiency and Incentive Compatibility. Depending on the modeling assumptions (e.g. uncertainty, types of cost functions etc.) different notions of incentive compatibility are relevant. Although we do not go into theoretical details, most Mechanism Design techniques account for some version of this property. Tractability is usually dependent on the particular mechanism and the problem formulation, although some notions (e.g. the Shapley Value) are inherently non-tractable. Overall, the indirect mechanisms mentioned usually improve scalability, privacy-preservation and explainability, at the expense of weaker guarantees on incentive compatibility and efficiency.

3.3. Heuristic methods

Although heuristics generally do not provide guarantees on efficiency and incentive compatibility, they can, however, be effective in cases where formal methods fail to perform due to intractability or scalability problems. Examples include setting with non-convex models or highly uncertain settings.

Sometimes, heuristics are used as a complementary part together with formal or data-driven methods. For example, in [76] two heuristic methods are proposed towards facilitating faster convergence of a P2P Market Mechanism, while in [77,78], the authors propose data-driven methods for Aggregators towards deciding the aggregated profile of a set of DERs where the dispatch of each particular DER is decided via a heuristic (e.g. a priority charging scheme for EVs). In this case, the heuristic provides a fast solution to the LEM dispatch problem, which is necessary to support the computational burden of the data-driven method for deciding the aggregated profile. Such simple heuristics can enhance the mechanism's explainability while the mechanism designer is offered the flexibility to design a communication model and a payment rule that are privacy-preserving and budget balanced respectively. Finally, heuristics can be suitable for dealing with alternative objectives, especially when those objectives are intractable to optimize. For example, in [56], after the formal framework of the (inherently intractable) Shapley value was analyzed, the authors introduced a fairness index and proposed a heuristic that achieved a good performance without compromising user privacy (by not gathering the user information that the formal solution requires). However, this design flexibility allows for customized heuristics based on different LEM models. These customized heuristics are naturally case-specific and not necessarily replicable. Therefore, standardization of relevant LEM models and relevant heuristic solutions is necessary for further development. An effort in this direction (if only for P2P LEMs) is presented in [76].

Beyond customized heuristics, the second subcategory of this family is the *meta*-heuristics. For the profit maximization objective, [57] uses a neural network towards learning to predict the DERs' response to different LEM price vectors, which is then incorporated into a meta-heuristic algorithm that searches the profit-maximizing prices. In a different case, the simulated annealing meta-heuristic was used in [79] to search the exponentially large space of LEM prices that maximize the aggregator's profit. The authors in [80], used simulated annealing after performing a formal game-theoretic analysis for a certain class of payment rules to tune a certain parameter of the payment rule specifically. A genetic algorithm was used in [81] to solve a non-convex social welfare maximization problem for DER facilities (smart homes).

Finally, it should be noted that heuristics generally lack guarantees on the feasibility of the dispatch. In critical systems, this deems them suitable only for providing a good warm-start point for formal methods.

3.4. Data-driven methods

Data-driven methods encompass a large variety of methods, including statistical/machine learning, reinforcement learning and other techniques. For the most part, such methods have been adopted towards optimizing the participation of DER clusters (e.g. buildings, electric vehicle charging stations etc.) in a given market, e.g. [29,42]. However, in this survey, we are interested in cases where such methods are used as a part of the Market Mechanism itself. A general motivation for data-driven Market Mechanisms is that many DERs that need to be integrated adhere to certain transition dynamics, i.e. their flexibility capabilities in a certain timeslot depend on the dispatch they received in previous timeslots. This creates problems for the traditional approaches that typically consider a temporally-decoupled optimization problem or a loosely coupled one (e.g. through ramp constraints).

Data-driven approaches usually use a learning algorithm to learn to optimize dispatch decisions directly. In [82], a deep reinforcement learning algorithm is proposed for making online dispatch decisions for EV charging stations. In [83], price-based control is realized via reinforcement learning, while a Neural Network is used as a function that maps prices to the DERs' response.

An important drawback of the above methods is that they cannot handle constraints explicitly, i.e., constraints are satisfied only in expectation. In [84], a penalty term is designed to teach a Neural Network to respect the local constraints of the DERs. As analyzed in [85], the design of such a penalty term comes with various trade-offs (e.g., efficiency is sacrificed in order to guarantee constraint satisfaction).

A hybrid case between Lagrangian and data-driven approaches includes [32,43], and [86]. In [32,86], the authors apply a standard Lagrangian decomposition to the OPF problem but the DERs in these studies calculate their response not by solving the typical decomposed optimization problem, but by solving a local dynamic program that also accounts for their internal uncertainties. In this approach, the DSO treats the DER responses as if they were deterministic, and all uncertainty management is virtually delegated to the DERs. In contrast, [43] proposes a neural network trained to return the optimal dual variables of the aggregator's economic dispatch problem using simulations. During operation, the system's state is fed into the neural network, which predicts the optimal dual variables. By treating these dual variables as prices, each DER can self-schedule, which guarantees satisfying its constraints. An important advantage of such methods is that the computationally intensive task of training can be executed offline, while at online operation, the computational burden for providing a decision is very small.

We especially mention the model-free paradigm supported by certain methods, namely (multi-agent, deep) reinforcement learning. The model-free approach enhances the mechanism's replicability, since a well-designed model-free mechanism can, in principle, be applied to different cases in a plug-and-play fashion. Moreover, it can accommodate virtually any, if arbitrary, objective while a trained model can provide fast, online decisions under uncertainty and/or partial information. The downside is the absence of guarantees on performance, feasibility, budget-balance, and individual rationality, while remedying the inherent explainability problem of such methods is an open and challenging issue.

Overall, a summary of our observations concerning the four families of Market Mechanisms discussed, is provided in Table 1.

4. Market Mechanisms for Local Electricity Markets: State of the art

In this section we summarize the components of a market model and present representative literature studies for each particular market model choice. The cited papers were selected based on the following methodology: An initial pool of papers was put together by drawing on the authors' personal repositories of LEM literature, by drawing on the studies cited in related literature review papers, and by further searching in Google Scholar, for papers published after 2010, using specific keywords, namely "Local Electricity Markets", "Power Flexibility", "Demand Response", "Demand Side Management", "Demand Aggregator", "Smart Grid", "Power Distribution Network", "Transactive Energy", "Peer-to-Peer Energy Market", "Distributed Energy Resources". The papers were then filtered based on the authors' judgment regarding relevance, quality of publishing venue, and novelty. The ultimate selection criterion was whether a study actually proposes a complete Market Mechanism, in the sense defined in Section 2.4. That is, a study should include all three components that make up a mechanism (communication model, allocation rule, payment rule). For instance, many studies are oriented towards optimizing the behavior of a particular entity that participates in a given Market Mechanism. Examples include optimizing the bids of a storage facility, or a utility company in a given market, as well as optimizing the profile of a prosumer or home energy management system under a given pricing rule [52,148]. Moreover, a vibrant research line is devoted to designing market architectures that coordinate the interaction between different markets. The prevailing thread of such research is the so called "TSO-DSO" coordination topic [149–151]. Such studies do not propose market mechanisms per se (e.g. they do not design payment rules) and thus they are not included in this review. In Table 2 each study is characterized with respect to the modeling assumptions, objective and solution approach that it adopts, based on the definitions of Sections 3, 2.2 and 2.3 respectively.

To visualize the categorization, Fig. 3 presents a four area Venn diagram, where each area represents a particular modeling assumption, i.e., whether accounting for uncertainty, strategic participant behavior, network constraints, and non-convexity of participant models. Each study is placed in the relevant intersection. Moreover, each study is enclosed in a box of different color, depending on the Market Mechanism family that it belongs to. Fig. 3 facilitates the observation of certain patterns:

Table 1
Summary of advantages and limitations for LEM Market Mechanisms.

Mechanism Family	Advantages	Limitations
Lagrangian	Optimal for social welfare maximization, under price-taking participants and convex cost functions. Revenue adequate, individually rational. Conducive to a distributed, privacy-preserving implementation.	Not incentive compatible. Not budget-balanced. Convergence and optimality are not guaranteed for non-convex settings. Not suitable for alternative objectives.
Game-theoretic	Optimal for social welfare maximization, even under strategic behavior. Bounded efficiency loss for some alternative objectives.	Not budget-balanced in general. Payments can be non-intuitive and/or non-explainable. Not suitable for participants with bounded rationality.
Heuristics	Scalable and practical. Can achieve privacy, budget-balance, and convergence by design. Suitable for alternative objectives.	Sub-optimal. No guarantees on dispatch feasibility. Non-standardized, and in need of model-specific design and evaluation.
Data-driven	Potentially model-free. Suitable for alternative objectives. Can be effective for making fast online decisions under uncertainty. Most computation is held offline.	Sub-optimal. Non-explainable payments and dispatch. No guarantees on budget-balance, individual rationality, feasibility.

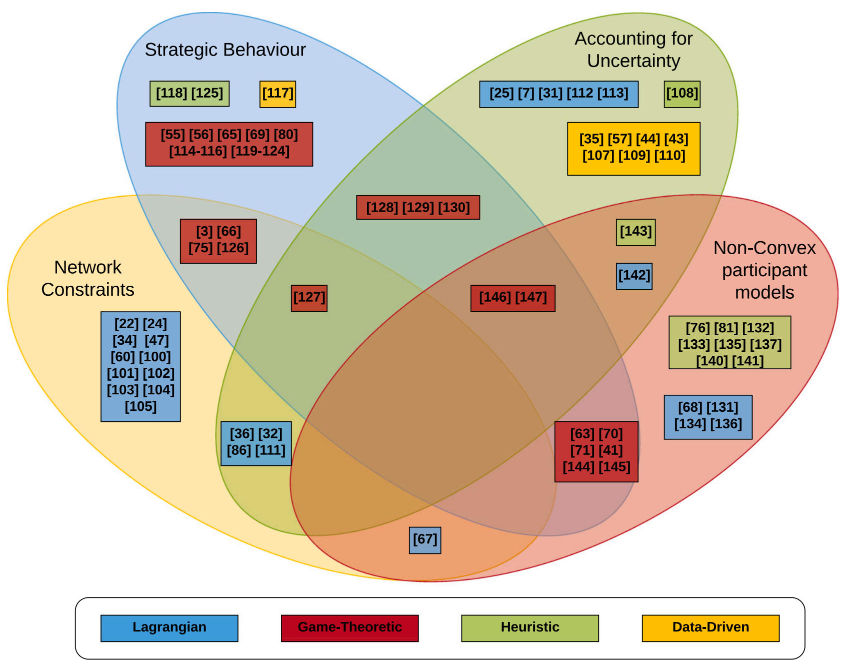

Fig. 3. Venn diagram, positioning the reviewed literature with respect to the modeling assumptions.

- Strategic participant behavior is handled almost exclusively by game-theoretic methods, although with a few exceptions.
- While there are numerous Data-Driven methods in the smart grid literature, they mostly focus on optimizing market participation from the perspective of one participant. Not many studies use Data-Driven techniques towards designing the Market Mechanism per se, and those that do, consider convex user models.
- Studies that account for network constraint satisfaction via Market Mechanisms, do not rely on Heuristics or Data-Driven methods.
- Moving towards the center of the Venn diagram, i.e. incorporating more requirements, there is a dramatic decrease in the number of studies. Moreover, we have identified a gap in the intersection of all four areas. This is not surprising since there are hardly any positive theoretical results for tractable mechanisms that simultaneously address uncertainty, strategic behavior, non-convexity and satisfaction of complicating constraints.

Finally, we present a classification of studies with respect to their adopted objective (Section 2.3) and adopted methodology (Section 3). Table 3 presents this classification, suggesting certain areas that are less researched than others. In particular, not many studies have researched the application of game-theoretic techniques in the context of designing a LEM that maximizes the profit of the LEM operator (e.g. Aggregator), despite the rich theory on revenue-maximizing auction designs [74]. Also, the Table reveals that there is more room for researching the possible applications of Data-Driven market design techniques, particularly in the context of fairness-maximizing objectives.

5. Conclusions and remarks

Motivated by the rich literature in the general context of LEMs, in this paper we presented a systematic framework towards identifying the essential components of a market model for electricity. Based on our analysis, a LEM-related research proposition needs to define its Market Scope, Modeling Assumptions, Market Objective, and Market

Table 2
Classification of literature studies with respect to the modeling assumptions adopted and the technique used.

Studies	Participant Models	Participant Behavior	Uncertainty	System Constraints	Objective	Mechanism
[18,62,87,88]	convex	non-strategic	deterministic	none	social welfare	lagrangian
[73]	convex	non-strategic	deterministic	none	social welfare	game-theoretic
[79]	convex	non-strategic	deterministic	none	profit	heuristic
[89]	convex	non-strategic	deterministic	none	fairness	heuristic
[90]	convex	non-strategic	n/a	none	fairness	heuristic
[33,91–93]	convex	non-strategic	deterministic	resource	social welfare	lagrangian
[77,78]	convex	non-strategic	deterministic	resource	social welfare	heuristic
[94]	convex	non-strategic	deterministic	resource	social welfare	auction
[20,95]	convex	non-strategic	deterministic	resource	profit	lagrangian
[96]	convex	non-strategic	deterministic	resource	profit	auction
[6,97,98] [23,99]	convex	non-strategic	deterministic	DC-OPF	social welfare	lagrangian
[22,47]	convex	non-strategic	deterministic	PTDF	social welfare	lagrangian
[100–102], [24,60,103]	convex	non-strategic	deterministic	AC-OPF	social welfare	lagrangian
[104]	convex	non-strategic	deterministic	AC-OPF	social welfare	auction
[105]	convex	non-strategic	deterministic	AC-OPF	fairness	lagrangian
[34]	convex	non-strategic	deterministic	AC-OPF	profit	lagrangian
[7]	convex	non-strategic	stochastic	none	social welfare	lagrangian
[106]	convex	non-strategic	stochastic	none	social welfare	auction
[43,44,107]	convex	non-strategic	stochastic	none	social welfare	data-driven
[108]	convex	non-strategic	stochastic	none	social welfare	heuristic
[25]	convex	non-strategic	stochastic	none	fairness	lagrangian
[57,109,110]	convex	non-strategic	stochastic	none	profit	data-driven
[31]	convex	non-strategic	stochastic	resource	social welfare	lagrangian
[32,86,111]	convex	non-strategic	stochastic	AC-OPF	social welfare	lagrangian
[112]	convex	non-strategic	online	none	social welfare	lagrangian
[35]	convex	non-strategic	robust	none	social welfare	data-driven
[113]	convex	non-strategic	robust	none	social welfare	lagrangian
[36]	convex	non-strategic	robust	AC-OPF	social welfare	lagrangian
[65,114,115],	convex	strategic	deterministic	none	social welfare	game-theoretic
[55,56,116]	convex	strategic	deterministic	none	fairness	game-theoretic
[117]	convex	strategic	deterministic	none	fairness	data-driven
[118]	convex	strategic	deterministic	none	profit	heuristic
[69,119–121], [80,122–124]	convex	strategic	deterministic	resource	social welfare	game-theoretic
[125]	convex	strategic	deterministic	resource	fairness	heuristic
[126]	convex	strategic	deterministic	DC-OPF	social welfare	game-theoretic
[3,75]	convex	strategic	deterministic	AC-OPF	social welfare	game-theoretic
[66]	convex	strategic	deterministic	AC-OPF	fairness	game-theoretic
[127]	convex	strategic	stochastic	DC-OPF	social welfare	game-theoretic
[128,129]	convex	strategic	stochastic	none	social welfare	game-theoretic
[130]	convex	strategic	stochastic	resource	social welfare	game-theoretic
[131]	non-convex	non-strategic	deterministic	none	social welfare	lagrangian
[76,81,132,133]	non-convex	non-strategic	deterministic	none	social welfare	heuristic
[58]	non-convex	non-strategic	deterministic	none	social welfare	auction
[134]	non-convex	non-strategic	deterministic	none	profit	lagrangian
[135]	non-convex	non-strategic	deterministic	none	profit	heuristic
[68,72,136]	non-convex	non-strategic	deterministic	resource	social welfare	lagrangian
[137]	non-convex	non-strategic	deterministic	resource	social welfare	heuristic
[138,139]	non-convex	non-strategic	deterministic	resource	social welfare	auction
[140,141]	non-convex	non-strategic	deterministic	resource	profit	heuristic
[67]	non-convex	non-strategic	deterministic	AC-OPF	social welfare	lagrangian
[142]	non-convex	non-strategic	stochastic	none	social welfare	lagrangian
[143]	non-convex	non-strategic	stochastic	resource	social welfare	heuristic
[63,70,71]	non-convex	strategic	deterministic	none	social welfare	game-theoretic
[41,144,145]	non-convex	strategic	deterministic	resource	social welfare	game-theoretic
[146]	non-convex	strategic	stochastic	none	profit	game-theoretic
[147]	non-convex	strategic	online	resource	fairness	game-theoretic

Mechanism, in order to identify its contributions with respect to the existing LEM literature. We discussed these attributes thoroughly and presented explanatory examples of various approaches found in the literature. Moreover, a market mechanism proposition needs to define itself with respect to at least three components, i.e. the proposed Communication Model, Allocation rule, and Payment rule, while evaluating the mechanism with respect to the main market mechanism properties (i.e. market efficiency, incentive compatibility, tractability of the market mechanism, individual rationality, budget balance, privacy preservation, and explainability).

Four main families of mechanisms (Lagrangian, Game Theoretic, Data-driven, Heuristic) were identified and presented within the proposed framework. We discussed algorithmic aspects and implications of each family with respect to what modeling assumptions each technique necessitates. Finally, we classified the relevant literature based on the market model that it adopts and the proposed Market Mechanism and visualized the results, deriving insights towards what areas are less researched. From a research perspective, the way forward is to design market mechanisms that simultaneously account for non-convex participant models, strategic behavior, uncertainty, and physical network constraints for each of the identified market objectives (Social Welfare maximization, profit maximization, fairness). Towards evaluating such

Table 3
Classification of literature studies with respect to the objective adopted and the technique used.

	Lagrangian	Game-Theoretic	Heuristic	Data-Driven
Social Welfare	[18,33,62,87,88], [23,93,100–102], [7,24,31,99,111], [36,68,112,113,131], [47,67,72,91,142] [32,86,92,103,136]	[65,114,115], [123,124,126], [127–129], [3,80,130] [22,75,122] [73]	[77,78,108], [81,132,133], [76,137,143]	[43,44], [35,107]
Profit Maximization	[20,95] [34,134]	[146]	[79,118,135], [140,141]	[57,109], [110]
Fairness	[25,105]	[55,56,66,116]	[89,90,125]	[117]

propositions, there is an emerging need for standardized and realistic testbeds for Market Mechanisms, since various mechanisms in the literature have been custom-designed for specific modeling choices and are therefore incomparable to each other. The final challenge is to apply and test several elaborate Market Mechanisms into real case studies.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

References

[1] European Commission. Communication from the commission to the European Parliament, the council, the European economic and social committee and the committee of regions; 2011.
[2] Papavasiliou A. Analysis of distribution locational marginal prices. IEEE Trans Smart Grid 2018;9(5):4872–82.
[3] Seklos K, Tsaousoglou G, Steriotis K, Efthymiopoulos N, Makris P, Varvarigos E. Designing a distribution level flexibility market using mechanism design and optimal power flow. In: 2020 International conference on smart energy systems and technologies. 2020, p. 1–6.
[4] Jin X, Wu Q, Jia H. Local flexibility markets: Literature review on concepts, models and clearing methods. Appl Energy 2020;261:114387.
[5] Behboodi S, Chassin DP, Djilali N, Crawford C. Transactive control of fast-acting demand response based on thermostatic loads in real-time retail electricity markets. Appl Energy 2018;210:1310–20.
[6] Moret F, Pinson P. Energy collectives: A community and fairness based approach to future electricity markets. IEEE Trans Power Syst 2019;34(5):3994–4004. http://dx.doi.org/10.1109/TPWRS.2018.2808961.
[7] Crespo-Vazquez JL, Skaif TA, González-Rueda AM, Gibescu M. A community-based energy market design using decentralized decision-making under uncertainty. IEEE Trans Smart Grid 2020;1. http://dx.doi.org/10.1109/TSG.2020.3036915.
[8] Tsaousoglou G, Makris P, Varvarigos E. Electricity market policies for penalizing volatility and scheduling strategies: The value of aggregation, flexibility, and correlation. Sustain Energy Grids Netw 2017;12:57–68.
[9] Klein SJ, Coffey S. Building a sustainable energy future, one community at a time. Renew Sustain Energy Rev 2016;60:867–80.
[10] Koirala BP, Koliou E, Friege J, Hakvoort RA, Herder PM. Energetic communities for community energy: A review of key issues and trends shaping integrated community energy systems. Renew Sustain Energy Rev 2016;56:722–44.
[11] Hu J, Morais H, Sousa T, Lind M. Electric vehicle fleet management in smart grids: A review of services, optimization and control aspects. Renew Sustain Energy Rev 2016;56:1207–26.
[12] Antonopoulos I, Robu V, Couraud B, Kirli D, Norbu S, Kiprakis A, Flynn D, Elizondo-Gonzalez S, Wattam S. Artificial intelligence and machine learning approaches to energy demand-side response: A systematic review. Renew Sustain Energy Rev 2020;130:109899.
[13] Tushar W, Yuen C, Saha TK, Morstyn T, Chapman AC, Alam MJE, Hanif S, Poor HV. Peer-to-peer energy systems for connected communities: A review of recent advances and emerging challenges. Appl Energy 2021;282:116131.
[14] Eid C, Codani P, Perez Y, Reneses J, Hakvoort R. Managing electric flexibility from distributed energy resources: A review of incentives for market design. Renew Sustain Energy Rev 2016;64:237–47.
[15] Guerrero J, Gebbran D, Mhanna S, Chapman AC, Verbič G. Towards a transactive energy system for integration of distributed energy resources: Home energy management, distributed optimal power flow, and peer-to-peer energy trading. Renew Sustain Energy Rev 2020;132:110000.
[16] Sousa T, Soares T, Pinson P, Moret F, Baroche T, Sorin E. Peer-to-peer and community-based markets: A comprehensive review. Renew Sustain Energy Rev 2019;104:367–78.
[17] Parag Y, Sovacool BK. Electricity market design for the prosumer era. Nat Energy 2016;1(4):1–6.
[18] Li N, Chen L, Low SH. Optimal demand response based on utility maximization in power networks. In: 2011 IEEE power and energy society general meeting. IEEE; 2011, p. 1–8.
[19] Mohsenian-Rad A, Wong VWS, Jatskevich J, Schober R, Leon-Garcia A. Autonomous demand-side management based on game-theoretic energy consumption scheduling for the future smart grid. IEEE Trans Smart Grid 2010;1(3):320–31. http://dx.doi.org/10.1109/TSG.2010.2089069.
[20] Gkatzikis L, Koutsopoulos I, Salonidis T. The role of aggregators in smart grid demand response markets. IEEE J Sel Areas Commun 2013;31(7):1247–57.
[21] Han L, Kazempour J, Pinson P. Monetizing customer load data for an energy retailer: A cooperative game approach. 2020, arXiv preprint arXiv:2012.05519.
[22] Khorasany M, Mishra Y, Ledwich G. A decentralized bilateral energy trading system for peer-to-peer electricity markets. IEEE Trans Ind Electron 2019;67(6):4646–57.
[23] Kim H, Lee J, Bahrami S, Wong VWS. Direct energy trading of microgrids in distribution energy market. IEEE Trans Power Syst 2020;35(1):639–51. http://dx.doi.org/10.1109/TPWRS.2019.2926305.
[24] Paudel A, Khorasany M, Gooi HB. Decentralized local energy trading in microgrids with voltage management. IEEE Trans Ind Inf 2021;17(2):1111–21. http://dx.doi.org/10.1109/TII.2020.2980160.
[25] Moret F, Pinson P, Papakonstantinou A. Heterogeneous risk preferences in community-based electricity markets. European J Oper Res 2020.
[26] Steriotis K, Smpoukis K, Efthymiopoulos N, Tsaousoglou G, Makris P, Varvarigos EM. Strategic and network-aware bidding policy for electric utilities through the optimal orchestration of a virtual and heterogeneous flexibility assets' portfolio. Electr Power Syst Res 2020;184:106302.
[27] Ye Y, Qiu D, Li J, Strbac G. Multi-period and multi-spatial equilibrium analysis in imperfect electricity markets: A novel multi-agent deep reinforcement learning approach. IEEE Access 2019;7:130515–29.
[28] Vázquez-Canteli JR, Nagy Z. Reinforcement learning for demand response: A review of algorithms and modeling techniques. Appl Energy 2019;235:1072–89.
[29] Ruelens F, Claessens BJ, Vandael S, De Schutter B, Babuška R, Belmans R. Residential demand response of thermostatically controlled loads using batch reinforcement learning. IEEE Trans Smart Grid 2017;8(5):2149–59. http://dx.doi.org/10.1109/TSG.2016.2517211.
[30] Bertsekas DP, et al. Dynamic programming and optimal control: vol. 1. Athena scientific Belmont; 2000.
[31] Tucker N, Alizadeh M. An online admission control mechanism for electric vehicles at public parking infrastructures. IEEE Trans Smart Grid 2019;11(1):161–70.
[32] Pan Z, Yu T, Li J, Qu K, Chen L, Yang B, Guo W. Stochastic transactive control for electric vehicle aggregators coordination: A decentralized approximate dynamic programming approach. IEEE Trans Smart Grid 2020;11(5):4261–77.
[33] Rivera J, Goebel C, Jacobsen H-A. Distributed convex optimization for electric vehicle aggregators. IEEE Trans Smart Grid 2016;8(4):1852–63.
[34] Yoon A-Y, Kim Y-J, Moon S-I. Optimal retail pricing for demand response of HVAC systems in commercial buildings considering distribution network voltages. IEEE Trans Smart Grid 2018;10(5):5492–505.
[35] Kim S-J, Giannakis GB. Scalable and robust demand response with mixed-integer constraints. IEEE Trans Smart Grid 2013;4(4):2089–99.
[36] Bahrami S, Amini MH, Shafie-Khah M, Catalão JPS. A decentralized renewable generation management and demand response in power distribution networks. IEEE Trans Sustain Energy 2018;9(4):1783–97. http://dx.doi.org/10.1109/TSTE.2018.2815502.
[37] Majidi M, Zare K. Integration of smart energy hubs in distribution networks under uncertainties and demand response concept. IEEE Trans Power Syst 2018;34(1):566–74.
[38] Conejo AJ, Carrión M, Morales JM, et al. Decision making under uncertainty in electricity markets, vol. 1. Springer; 2010.
[39] Giraldo JS, Salazar M, Vergara PP, Tsaousoglou G, Slootweg J, Paterakis NG. Optimal operation of community energy storage using stochastic gradient boosting trees. In: 2021 IEEE madrid powertech. 2021, p. 1–6.
[40] Singh MK, Gupta S, Kekatos V, Cavraro G, Bernstein A. Learning to optimize power distribution grids using sensitivity-informed deep neural networks. In: 2020 IEEE international conference on communications, control, and computing technologies for smart grids. IEEE; 2020, p. 1–6.
[41] Tsaousoglou G, Pinson P, Paterakis NG. Transactive energy for flexible prosumers using algorithmic game theory. IEEE Trans Sustain Energy 2021;1. http://dx.doi.org/10.1109/TSTE.2021.3055764.
[42] Azuatalam D, Lee W-L, de Nijs F, Liebman A. Reinforcement learning for whole-building HVAC control and demand response. Energy AI 2020;2:100020.
[43] Tsaousoglou G, Mitropoulou K, Steriotis K, Paterakis NG, Pinson P, Varvarigos E. Managing distributed flexibility under uncertainty by combining deep learning with duality. IEEE Trans Sustain Energy 2021.

[44] Kim B, Zhang Y, van der Schaar M, Lee J. Dynamic pricing and energy consumption scheduling with reinforcement learning. IEEE Trans Smart Grid 2016;7(5):2187–98. http://dx.doi.org/10.1109/TSG.2015.2495145.
[45] Lu R, Hong SH, Zhang X. A dynamic pricing demand response algorithm for smart grid: reinforcement learning approach. Appl Energy 2018;220:220–30.
[46] Liu M, Gross G. Role of distribution factors in congestion revenue rights applications. IEEE Trans Power Syst 2004;19(2):802–10.
[47] Guerrero J, Chapman AC, Verbič G. Decentralized P2P energy trading under network constraints in a low-voltage network. IEEE Trans Smart Grid 2018;10(5):5163–73.
[48] Molzahn DK, Dörfler F, Sandberg H, Low SH, Chakrabarti S, Baldick R, Lavaei J. A survey of distributed optimization and control algorithms for electric power systems. IEEE Trans Smart Grid 2017;8(6):2941–62.
[49] Bobo L, Venzke A, Chatzivasileiadis S. Second-order cone relaxations of the optimal power flow for active distribution grids: Comparison of methods. Int J Electr Power Energy Syst 2021;127:106625.
[50] Giraldo JS, Vergara PP, López JC, Nguyen PH, Paterakis NG. A linear AC-OPF formulation for unbalanced distribution networks. IEEE Trans Ind Appl 2021;57(5):4462–72. http://dx.doi.org/10.1109/TIA.2021.3085799.
[51] Coffrin C, Hijazi H, Van Hentenryck P. Network flow and copper plate relaxations for AC transmission systems. In: 2016 power systems computation conference. IEEE; 2016, p. 1–8.
[52] Iria J, Scott P, Attarha A. Network-constrained bidding optimization strategy for aggregators of prosumers. Energy 2020;207:118266.
[53] Bahrami S, Wong VW, Huang J. An online learning algorithm for demand response in smart grid. IEEE Trans Smart Grid 2017;9(5):4712–25.
[54] Tsaousoglou G, Pinson P, Paterakis NG. Max-min fairness for demand side management under high RES penetration: Dealing with undefined consumer valuation functions. In: 2020 international conference on smart energy systems and technologies. 2020, p. 1–6.
[55] Tsaousoglou G, Efthymiopoulos N, Makris P, Varvarigos E. Personalized real time pricing for efficient and fair demand response in energy cooperatives and highly competitive flexibility markets. J Mod Power Syst Clean Energy 2019;7:151–62.
[56] Baharlouei Z, Hashemi M, Narimani H, Mohsenian-Rad H. Achieving optimality and fairness in autonomous demand response: Benchmarks and billing mechanisms. IEEE Trans Smart Grid 2013;4(2):968–75. http://dx.doi.org/10.1109/TSG.2012.2228241.
[57] Dehghanpour K, Nehrir MH, Sheppard JW, Kelly NC. Agent-based modeling of retail electrical energy markets with demand response. IEEE Trans Smart Grid 2016;9(4):3465–75.
[58] Yu M, Hong SH. A real-time demand-response algorithm for smart grids: A stackelberg game approach. IEEE Trans Smart Grid 2016;7(2):879–88. http://dx.doi.org/10.1109/TSG.2015.2413813.
[59] Andoni M, Robu V, Flynn D, Abram S, Geach D, Jenkins D, McCallum P, Peacock A. Blockchain technology in the energy sector: A systematic review of challenges and opportunities. Renew Sustain Energy Rev 2019;100:143–74.
[60] Kim J, Dvorkin Y. A P2P-dominant distribution system architecture. IEEE Trans Power Syst 2019;35(4):2716–25.
[61] Guerrero J, Sok B, Chapman AC, Verbič G. Electrical-distance driven peer-to-peer energy trading in a low-voltage network. Appl Energy 2021;287:116598.
[62] Baroche T, Moret F, Pinson P. Prosumer markets: A unified formulation. In: 2019 IEEE Milan powertech. IEEE; 2019, p. 1–6.
[63] Tsaousoglou G, Steriotis K, Efthymiopoulos N, Makris P, Varvarigos E. Truthful, practical and privacy-aware demand response in the smart grid via a distributed and optimal mechanism. IEEE Trans Smart Grid 2020;11(4):3119–30. http://dx.doi.org/10.1109/TSG.2020.2965221.
[64] Chen X, Dall'Anese E, Zhao C, Li N. Aggregate power flexibility in unbalanced distribution systems. IEEE Trans Smart Grid 2019;11(1):258–69.
[65] Samadi P, Mohsenian-Rad H, Schober R, Wong VWS. Advanced demand side management for the future smart grid using mechanism design. IEEE Trans Smart Grid 2012;3(3):1170–80. http://dx.doi.org/10.1109/TSG.2012.2203341.
[66] Tsaousoglou G, Giraldo JS, Pinson P, Paterakis NG. Mechanism design for fair and efficient DSO flexibility markets. IEEE Trans Smart Grid 2020;1. http://dx.doi.org/10.1109/TSG.2020.3048738.
[67] Orozco C, Lilla S, Borghetti A, Napolitano F, Tossani F. An ADMM approach for day-ahead scheduling of a local energy community. In: 2019 IEEE Milan powertech. 2019, p. 1–6.
[68] Dukovska I, Paterakis NG, Slootweg HJG. Coordination for prosumers' electricity trading agents via distributed optimization. In: 2019 International conference on smart energy systems and technologies. 2019, p. 1–6.
[69] Ma J, Deng J, Song L, Han Z. Incentive mechanism for demand side management in smart grid using auction. IEEE Trans Smart Grid 2014;5(3):1379–88. http://dx.doi.org/10.1109/TSG.2014.2302915.
[70] Chapman AC, Verbič G. An iterative on-line auction mechanism for aggregated demand-side participation. IEEE Trans Smart Grid 2015;8(1):158–68.
[71] Mhanna S, Chapman AC, Verbič G. A faithful and tractable distributed mechanism for residential electricity pricing. IEEE Trans Power Syst 2017;33(4):4238–52.
[72] Srikantha P, Kundur D. Resilient distributed real-time demand response via population games. IEEE Trans Smart Grid 2017;8(6):2532–43. http://dx.doi.org/10.1109/TSG.2016.2526651.
[73] Paudel A, Chaudhari K, Long C, Gooi HB. Peer-to-peer energy trading in a prosumer-based community microgrid: A game-theoretic model. IEEE Trans Ind Electron 2018;66(8):6087–97.
[74] Myerson RB. Optimal auction design. Math Oper Res 1981;6(1):58–73.
[75] Karaca O, Kamgarpour M. Core-selecting mechanisms in electricity markets. IEEE Trans Smart Grid 2020;11(3):2604–14. http://dx.doi.org/10.1109/TSG.2019.2958710.
[76] Zhou Y, Wu J, Long C. Evaluation of peer-to-peer energy sharing mechanisms based on a multiagent simulation framework. Appl Energy 2018;222:993–1022.
[77] Vandael S, Claessens B, Hommelberg M, Holvoet T, Deconinck G. A scalable three-step approach for demand side management of plug-in hybrid vehicles. IEEE Trans Smart Grid 2012;4(2):720–8.
[78] De Craemer K, Vandael S, Claessens B, Deconinck G. An event-driven dual coordination mechanism for demand side management of PHEVs. IEEE Trans Smart Grid 2013;5(2):751–60.
[79] Qian LP, Zhang YJA, Huang J, Wu Y. Demand response management via real-time electricity price control in smart grids. IEEE J Sel Areas Commun 2013;31(7):1268–80.
[80] Tsaousoglou G, Steriotis K, Efthymiopoulos N, Smpoukis K, Varvarigos E. Near-optimal demand side management for retail electricity markets with strategic users and coupling constraints. Sustain Energy Grids Netw 2019;19:100236.
[81] Zhao Z, Lee WC, Shin Y, Song K-B. An optimal power scheduling method for demand response in home energy management system. IEEE Trans Smart Grid 2013;4(3):1391–400.
[82] Shin M, Choi D-H, Kim J. Cooperative management for PV/ESS-enabled electric vehicle charging stations: A multiagent deep reinforcement learning approach. IEEE Trans Ind Inf 2019;16(5):3493–503.
[83] Du Y, Li F. Intelligent multi-microgrid energy management based on deep neural network and model-free reinforcement learning. IEEE Trans Smart Grid 2019;11(2):1066–76.
[84] Wan Z, Li H, He H, Prokhorov D. Model-free real-time EV charging scheduling based on deep reinforcement learning. IEEE Trans Smart Grid 2018;10(5):5246–57.
[85] Li H, Wan Z, He H. Constrained EV charging scheduling based on safe deep reinforcement learning. IEEE Trans Smart Grid 2019;11(3):2427–39.
[86] Chertkov M, Deka D, Dvorkin Y. Optimal ensemble control of loads in distribution grids with network constraints. In: 2018 Power systems computation conference. IEEE; 2018, p. 1–7.
[87] Samadi P, Mohsenian-Rad A-H, Schober R, Wong VW, Jatskevich J. Optimal real-time pricing algorithm based on utility maximization for smart grid. In: 2010 First IEEE international conference on smart grid communications. IEEE; 2010, p. 415–20.
[88] Sorin E, Bobo L, Pinson P. Consensus-based approach to peer-to-peer electricity markets with product differentiation. IEEE Trans Power Syst 2018;34(2):994–1004.
[89] Yaghmaee MH, Kouhi MS, Garcia AL. Personalized pricing: A new approach for dynamic pricing in the smart grid. In: 2016 IEEE smart energy grid engineering. IEEE; 2016, p. 46–51.
[90] Assaf T, Osman AH, Hassan M. Fair autonomous energy consumption scheduling based on game-theoretic approach for the future smart grid. In: 2016 UKSim-AMSS 18th international conference on computer modelling and simulation. IEEE; 2016, p. 235–9.
[91] Hu J, You S, Lind M, Østergaard J. Coordinated charging of electric vehicles for congestion prevention in the distribution grid. IEEE Trans Smart Grid 2013;5(2):703–11.
[92] Garella M, Sousa T, Pinson P. Provision of flexibility services through energy communities. AIM; 2019.
[93] Hu J, Saleem A, You S, Nordström L, Lind M, Østergaard J. A multi-agent system for distribution grid congestion management with electric vehicles. Eng Appl Artif Intell 2015;38:45–58.
[94] Lian J, Ren H, Sun Y, Hammerstrom DJ. Performance evaluation for transactive energy systems using double-auction market. IEEE Trans Power Syst 2018;34(5):4128–37.
[95] Yazdani-Damavandi M, Neyestani N, Shafie-khah M, Contreras J, Catalao JP. Strategic behavior of multi-energy players in electricity markets as aggregators of demand side resources using a bi-level approach. IEEE Trans Power Syst 2017;33(1):397–411.
[96] Yu M, Hong SH. Incentive-based demand response considering hierarchical electricity market: A stackelberg game approach. Appl Energy 2017;203:267–79.
[97] Verzijlbergh RA, De Vries LJ, Lukszo Z. Renewable energy sources and responsive demand. Do we need congestion management in the distribution grid? IEEE Trans Power Syst 2014;29(5):2119–28. http://dx.doi.org/10.1109/TPWRS.2014.2300941.
[98] Cornélusse B, Savelli I, Paoletti S, Giannitrapani A, Vicino A. A community microgrid architecture with an internal local market. Appl Energy 2019;242:547–60.

[99] Le Cadre H, Jacquot P, Wan C, Alasseur C. Peer-to-peer electricity market analysis: From variational to generalized Nash equilibrium. European J Oper Res 2020;282(2):753–71. http://dx.doi.org/10.1016/j.ejor.2019.09.035.
[100] Li N. A market mechanism for electric distribution networks. In: 2015 54th IEEE conference on decision and control. 2015, p. 2276–2282.
[101] Weckx S, D'Hulst R, Claessens B, Driesensam J. Multiagent charging of electric vehicles respecting distribution transformer loading and voltage limits. IEEE Trans Smart Grid 2014;5(6):2857–67. http://dx.doi.org/10.1109/TSG.2014.2345886.
[102] Zhang K, Troitzsch S, Hanif S, Hamacher T. Coordinated market design for peer-to-peer energy trade and ancillary services in distribution grids. IEEE Trans Smart Grid 2020;11(4):2929–41. http://dx.doi.org/10.1109/TSG.2020.2966216.
[103] Hu J, Yang G, Ziras C, Kok K. Aggregator operation in the balancing market through network-constrained transactive energy. IEEE Trans Power Syst 2019;34(5):4071–80. http://dx.doi.org/10.1109/TPWRS.2018.2874255.
[104] Faqiry MN, Das S. Distributed bilevel energy allocation mechanism with grid constraints and hidden user information. IEEE Trans Smart Grid 2019;10(2):1869–79. http://dx.doi.org/10.1109/TSG.2017.2779826.
[105] Zarabie AK, Das S, Faqiry MN. Fairness-regularized DLMP-based bilevel transactive energy mechanism in distribution systems. IEEE Trans Smart Grid 2019;10(6):6029–40.
[106] Morstyn T, Teytelboym A, Hepburn C, McCulloch MD. Integrating P2P energy trading with probabilistic distribution locational marginal pricing. IEEE Trans Smart Grid 2020;11(4):3095–106. http://dx.doi.org/10.1109/TSG.2019.2963238.
[107] Lu R, Hong SH. Incentive-based demand response for smart grid with reinforcement learning and deep neural network. Appl Energy 2019;236:937–49.
[108] Samadi P, Mohsenian-Rad H, Wong VWS, Schober R. Real-time pricing for demand response based on stochastic approximation. IEEE Trans Smart Grid 2014;5(2):789–98. http://dx.doi.org/10.1109/TSG.2013.2293131.
[109] Xu H, Sun H, Nikovski D, Kitamura S, Mori K, Hashimoto H. Deep reinforcement learning for joint bidding and pricing of load serving entity. IEEE Trans Smart Grid 2019;10(6):6366–75.
[110] Jia L, Zhao Q, Tong L. Retail pricing for stochastic demand with unknown parameters: An online machine learning approach. In: 2013 51st Annual allerton conference on communication, control, and computing. IEEE; 2013, p. 1353–8.
[111] Morstyn T, Teytelboym A, McCulloch MD. Bilateral contract networks for peer-to-peer energy trading. IEEE Trans Smart Grid 2018;10(2):2026–35.
[112] Enyioha C, Magnússon S, Heal K, Li N, Fischione C, Tarokh V. On variability of renewable energy and online power allocation. IEEE Trans Power Syst 2017;33(1):451–62.
[113] Diekerhof M, Peterssen F, Monti A. Hierarchical distributed robust optimization for demand response services. IEEE Trans Smart Grid 2017;9(6):6018–29.
[114] Jacquot P, Beaude O, Gaubert S, Oudjane N. Demand response in the smart grid: The impact of consumers temporal preferences. In: 2017 IEEE international conference on smart grid communications. 2017, p. 540–5.
[115] Mohsenian-Rad A, Wong VWS, Jatskevich J, Schober R, Leon-Garcia A. Autonomous demand-side management based on game-theoretic energy consumption scheduling for the future smart grid. IEEE Trans Smart Grid 2010;1(3):320–31. http://dx.doi.org/10.1109/TSG.2010.2089069.
[116] Baharlouei Z, Hashemi M. Efficiency-fairness trade-off in privacy-preserving autonomous demand side management. IEEE Trans Smart Grid 2014;5(2):799–808. http://dx.doi.org/10.1109/TSG.2013.2296714.
[117] O'Brien G, El Gamal A, Rajagopal R. Shapley value estimation for compensation of participants in demand response programs. IEEE Trans Smart Grid 2015;6(6):2837–44.
[118] Steriotis K, Tsaousoglou G, Efthymiopoulos N, Makris P, Varvarigos EM. A novel behavioral real time pricing scheme for the active energy consumers' participation in emerging flexibility markets. Sustain Energy Grids Netw 2018;16:14–27.
[119] Faqiry MN, Das S. Double-sided energy auction in microgrid: Equilibrium under price anticipation. IEEE Access 2016;4:3794–805. http://dx.doi.org/10.1109/ACCESS.2016.2591912.
[120] Mediwaththe CP, Shaw M, Halgamuge S, Smith DB, Scott P. An incentive-compatible energy trading framework for neighborhood area networks with shared energy storage. IEEE Trans Sustain Energy 2020;11(1):467–76. http://dx.doi.org/10.1109/TSTE.2019.2895387.
[121] Mitridati L, Kazempour J, Pinson P. Design and game-theoretic analysis of community-based market mechanisms in heat and electricity systems. Omega 2019;102177.
[122] Nekouei E, Alpcan T, Chattopadhyay D. Game-theoretic frameworks for demand response in electricity markets. IEEE Trans Smart Grid 2014;6(2):748–58.
[123] Li D, Jayaweera SK. Distributed smart-home decision-making in a hierarchical interactive smart grid architecture. IEEE Trans Parallel Distrib Syst 2015;26(1):75–84. http://dx.doi.org/10.1109/TPDS.2014.2308204.
[124] Xu Y, Li N, Low SH. Demand response with capacity constrained supply function bidding. IEEE Trans Power Syst 2016;31(2):1377–94. http://dx.doi.org/10.1109/TPWRS.2015.2421932.
[125] Steriotis K, Tsaousoglou G, Efthymiopoulos N, Makris P, Varvarigos EM. Real-time pricing in environments with shared energy storage systems. Energy Efficiency 2019;12(5):1085–104.
[126] Zou P, Chen Q, Xia Q, He C, Kang C. Incentive compatible pool-based electricity market design and implementation: A Bayesian mechanism design approach. Appl Energy 2015;158:508–18.
[127] Exizidis L, Kazempour J, Papakonstantinou A, Pinson P, De Grève Z, Vallée F. Incentive-compatibility in a two-stage stochastic electricity market with high wind power penetration. IEEE Trans Power Syst 2019;34(4):2846–58. http://dx.doi.org/10.1109/TPWRS.2019.2901249.
[128] Li Y, Li N. Mechanism design for reliability in demand response with uncertainty. In: 2017 American control conference. IEEE; 2017, p. 3400–5.
[129] Ma H, Robu V, Li N, Parkes DC. Incentivizing reliability in demand-side response. In: Proceedings of the 25th international joint conference on artificial intelligence. 2016.
[130] Muthirayan D, Kalathil D, Poolla K, Varaiya P. Mechanism design for demand response programs. IEEE Trans Smart Grid 2019;11(1):61–73.
[131] Mhanna S, Chapman AC, Verbič G. A fast distributed algorithm for large-scale demand response aggregation. IEEE Trans Smart Grid 2016;7(4):2094–107. http://dx.doi.org/10.1109/TSG.2016.2536740.
[132] liu z, Wu Q, Shahidehpour M, Li C, Huang S, Wei W. Transactive real-time electric vehicle charging management for commercial buildings with PV on-site generation. IEEE Trans Smart Grid 2019;10(5):4939–50. http://dx.doi.org/10.1109/TSG.2018.2871171.
[133] Yaagoubi N, Mouftah HT. User-aware game theoretic approach for demand management. IEEE Trans Smart Grid 2015;6(2):716–25. http://dx.doi.org/10.1109/TSG.2014.2363098.
[134] Radoszynski AM, Dvorkin V, Pinson P. Accommodating bounded rationality in pricing demand response. In: 2019 IEEE Milan powertech. IEEE; 2019, p. 1–6.
[135] Carrasqueira P, Alves MJa, Antunes CH. Bi-level particle swarm optimization and evolutionary algorithm approaches for residential demand response with different user profiles. Inform Sci 2017;418:405–20.
[136] Tsaousoglou G, Steriotis K, Varvarigos E. A stochastic approximation method for price-based assignment of Electric Vehicles to Charging Stations. In: 2019 International conference on smart energy systems and technologies. 2019, p. 1–6.
[137] Paudyal P, Munankarmi P, Ni Z, Hansen TM. A hierarchical control framework with a novel bidding scheme for residential community energy optimization. IEEE Trans Smart Grid 2020;11(1):710–9. http://dx.doi.org/10.1109/TSG.2019.2927928.
[138] Torbaghan SS, Blaauwbroek N, Kuiken D, Gibescu M, Hajighasemi M, Nguyen P, Smit GJ, Roggenkamp M, Hurink J. A market-based framework for demand side flexibility scheduling and dispatching. Sustain Energy Grids Netw 2018;14:47–61.
[139] Nizami MSH, Hossain MJ, Fernandez E. Multiagent-based transactive energy management systems for residential buildings with distributed energy resources. IEEE Trans Ind Inf 2020;16(3):1836–47. http://dx.doi.org/10.1109/TII.2019.2932109.
[140] Nizami MSH, Hossain MJ, Mahmud K. A nested transactive energy market model to trade demand-side flexibility of residential consumers. IEEE Trans Smart Grid 2021;12(1):479–90. http://dx.doi.org/10.1109/TSG.2020.3011192.
[141] Meng F, Zeng X-J, Zhang Y, Dent CJ, Gong D. An integrated optimization+learning approach to optimal dynamic pricing for the retailer with multi-type customers in smart grids. Inform Sci 2018;448:215–32.
[142] Kok C, Kazempour J, Pinson P. A DSO-level contract market for conditional demand response. In: 2019 IEEE Milan powertech. 2019, p. 1–6.
[143] Yao E, Samadi P, Wong VWS, Schober R. Residential demand side management under high penetration of rooftop photovoltaic units. IEEE Trans Smart Grid 2016;7(3):1597–608. http://dx.doi.org/10.1109/TSG.2015.2472523.
[144] Kim H, Lee J, Bahrami S, Wong VWS. Direct energy trading of microgrids in distribution energy market. IEEE Trans Power Syst 2020;35(1):639–51. http://dx.doi.org/10.1109/TPWRS.2019.2926305.
[145] Rigas E, Gerding E, Stein S, Ramchurn S, Bassiliades N. Mechanism design for efficient online and offline allocation of electric vehicles to charging stations. 2020, arXiv preprint arXiv:2007.09715.
[146] Bitar E, Xu Y. Deadline differentiated pricing of deferrable electric loads. IEEE Trans Smart Grid 2016;8(1):13–25.
[147] Mathioudaki A, Tsaousoglou G, Varvarigos E, Fotakis D. Efficient online scheduling of electric vehicle charging using a service-price menu. In: 2021 international conference on smart energy systems and technologies.
[148] Correa-Florez CA, Michiorri A, Kariniotakis G. Optimal participation of residential aggregators in energy and local flexibility markets. IEEE Trans Smart Grid 2019;11(2):1644–56.
[149] Gerard H, Puente EIR, Six D. Coordination between transmission and distribution system operators in the electricity sector: A conceptual framework. Util Policy 2018;50:40–8.
[150] Savvopoulos N, Konstantinou T, Hatziargyriou N. TSO-DSO Coordination in decentralized ancillary services markets. In: 2019 International conference on smart energy systems and technologies. IEEE; 2019, p. 1–6.
[151] Givisiez AG, Petrou K, Ochoa LF. A review on TSO-DSO coordination models and solution techniques. Electr Power Syst Res 2020;189:106659.