Distributed Smart-home Decision-making in a Hierarchical Interactive Smart Grid Architecture

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Abstract—In this paper, we develop a comprehensive real-time interactive framework for the Utility and customers in a smart grid while ensuring grid-stability and Quality-of-Service (QoS). First, we propose a hierarchical architecture for the Utility-customer interaction consisting of sub-components of *customer load prediction*, *renewable generation integration*, *power-load balancing* and *demand response (DR)*. Within this hierarchical architecture, we focus on the problem of real-time scheduling in an abstract grid model consisting of one controller and multiple customer units. A scalable solution to the real-time scheduling problem is proposed by combining solutions to two sub-problems: (1) centralized sequential decision making at the controller to maximize an accumulated reward for the whole micro-grid and (2) distributed auctioning among all customers based on the optimal load profile obtained by solving the first problem to coordinate their interactions. We formulate the centralized sequential decision making at the controller as a hidden mode Markov decision process (HM-MDP). Next, a Vikrey auctioning game is designed to coordinate the actions of the individual smart-homes to actually achieve the optimal solution derived by the controller under realistic gird interaction assumptions. We show that though truthful bidding is a weakly dominant strategy for all smart-homes in the auctioning game, collusive equilibria do exist and can jeopardize the effectiveness and efficiency of the trading opportunity allocation. Analysis on the structure of the Bayesian Nash equilibrium solution set shows that the Vickrey auctioning game can be made more robust against collusion by customers (anticipating distributed smart-homes) by introducing a positive reserve price. The corresponding auctioning game is then shown to converge to the unique incentive compatible truthful bidding Bayesian Nash equilibrium, without jeopardizing the auctioneer's (microgrid controller's) profit. The paper also explicitly discusses how this two-step solution approach can be scaled to be suitable for more complicated smart grid architectures beyond the assumed abstract model.

Index Terms—Bayesian Nash equilibria, hidden mode Markov decision process (HM-MDP), hierarchical architecture, microgrid, resource pooling, smart-home, truthful bidding strategy, Utility-customer interaction, Vickrey auction.

1 Introduction

Proliferation of distributed energy resources (DER), in particular renewable distributed generation, provides great promise in significantly improving the efficiency of electricity distribution. However, as DER's proliferate to a significant fraction of the overall electric energy on the distribution network, without proper procedures integration may lead to highly imbalanced transient behaviors which may overwhelm current infrastructure not to mention outages and brown-outs. *In a future smart grid, a customer with renewable generation capability (such as PV panels and wind turbines) may use predictive strategies to optimize its energy demand requests over time and determine when to use, sell or store its own renewable generation, flexibly interacting with the electric-grid and other customers, as opposed to being a passive energy consumer as today.* The information shared among distributed nodes (customers) endowed with generation, storage and consumption attributes can result in a distributed decision and control framework that will lead to both overall energy and cost efficiencies. Realizing the full potential promised by smart grid concept, however, requires systematic design principles, a comprehensive protocol framework for interaction among distributed entities that make up the grid and robust and computationally efficient control and optimization algorithms.

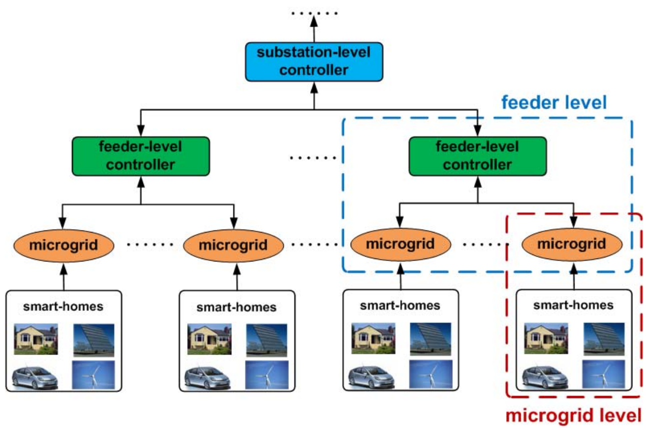

Fig. 1. Hierarchical smart grid architecture that is scalable while allowing for sufficient resource pooling.

Although a comprehensive formulation and an analysis is not yet available, still there have been some attempts

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to understand, model and analyze these effects [1], [2]. For example, a multi-stage frequency control framework is presented in [3]–[5]. However, it does not address the issue of consumption planning on the customer side. The uncertainty in supply due to integrated renewable DER's and the challenges they impose on the existing distribution infrastructure and the system operator have been discussed in [6]. The distribution-level smart grid features such as interconnection of distributed generation and active distribution management, automated meter reading (AMR) systems in network management and power quality monitoring were discussed in [7]. In [8], the implementation of vehicle-to-grid (V2G) power issues, strategies and business models for doing so, for purposes of both stabilizing the grid and supporting large-scale renewable energy were discussed.

Usually, peak load shaving and load profile flattening are achieved by incorporating demand response (DR) schemes that are based on the predicted renewable generation. Various demand response (DR) schemes have been reported in literature [9]–[16] based on different pricing schemes such as time-of-use (TOU), peak-time pricing and real-time pricing [17]. However, DR schemes only provide a nominal operating point for the nodes in the grid (i.e. the flat load profiles for customers) without allowing for the real-time fluctuations and intermittence in the grid due to the inevitable mismatches between the actual and predicted renewable generations.

Various control-theoretic and system-level problem formulations of smart grid architectures have been discussed in [18] and [19]. In [18], for example, the authors showed that significant improvements can be made to the operations of a smart grid by providing information about the likely behavior of renewable energy through both online short-term forecasting and longer-term assessments. In [19], a distributed control method was proposed for converter-interfaced renewable generation units with active filtering capability.

However, all these existing architectures mainly focus on the system-wise operation from the perspectives of the power generation side and the Utility companies. None of them has considered a comprehensive cycle of interactions between the Utility and the distributed entities (customers) taking into account aspects of customer-side decision making, Utility-side demand response scheduling, renewable DER integration and power-load balances for grid-stability and the effects of information and communication technology (ICT) infrastructure on all these.

The major contributions of this paper include:

1) Proposing a comprehensive architecture that addresses not only the generation control and the consumption planning *separately*, as have been done in almost all previous work, but also the interaction and integration of the two within a unified framework.
2) Proposing a hierarchical architecture, as shown in Fig. 1, that is the first framework, to the best of our knowledge, that not only assures the scalability of the grid model, but also allows for sufficient resource pooling among customer units. This enables us to focus on an abstract power grid model consisting of one controller and multiple customer units without loss of generality.
3) Extending the concept of "smart-home". In most current smart grid literature, the term "smart-home" is used to refer to households with "smart devices" such as Advanced Metering Infrastructure (AMI) [20], [21], which enables remote meter reading and electricity bill estimation based on real-time pricing information. In this paper, the concept of "smart-home" is extended in two aspects: First, smart-home is capable of not only intelligently managing its own energy consumption, but also actively interacting with the grid in real-time. Second, the concept of "smart-home" can scale up to a broader customer unit consisting of a cluster of households. For example, a microgrid can also be a broad smart customer unit in the feeder-level.
4) Proposing a hidden mode Markov decision process (HM-MDP) based model for the smart grid real-time planning. The HM-MDP model allows for the two-step decision framework containing both centralized sequential decision making at the controller and the auctioning game design among distributed customers.
5) Proposing a novel auctioning game for distributed customers to compete for limited energy trading opportunities. The proposed auctioning game with a reserved price has several advantages: (1) being robust to adding/removing customers, (2) being robust against collusion by customers with untruthful bidding strategies, and (3) converging to the unique Bayesian-Nash equilibrium.

It is worth pointing out that application of different auction schemes for smart grid problems have been reported in [22]–[24]. For example, auction mechanisms that can be used by the aggregators for procuring stochastic renewable generations are proposed in [22]. In [23] and [24], double auction is adopted for distributed energy resources (DERs) management and Plug-in hybrid electric vehicles (PHEVs), respectively. However, most of these are focused on the solution derivation of auctions and fail to address the connection between the centralized and distributed decision schemes, which is important for the hierarchical architecture of the modern smart grid.

The rest of this paper is organized as follows: In section 2, we present our hierarchical interactive smart grid architecture with the proposed two-step decision-making framework. In section 3, with a hidden mode Markov decision process (HM-MDP) framework developed for the centralized controller sequential decision making (addressed in detail in the supplementary part of this paper), we present a Vickrey auctioning game for the distributed customer decision making problem and the truthful bidding strategy is discussed in detail. In section 4, a detailed analysis on the solution set of the Bayesian Nash equilibria is presented. By introducing a reserve price, the Vickrey auction is shown to be more robust against collusive customers and converges to the unique truthful bidding Bayesian Nash equilibrium. Simulation results with performance analysis are also presented in section 4. The conclusions from this study are given in section 5.

2 A Hierarchical Interactive Architecture for Smart Grid

2.1 A Hierarchical Smart Grid Architecture

We propose a hierarchical architecture for the smart grid that is scalable while allowing for sufficient resource pooling, as shown in Fig. 1. The scalability of the grid requires being able to easily integrate additional customers into the grid without affecting the established operational conditions of the grid. Ideally this might be achievable if each individual household is managed separately, but, of course, this would preclude any resource pooling, which is one of the most important strategies to energy efficiency in the grid. A tradeoff to this can be achieved by using the notion of microgrids with DER's. Each microgrid is a collection of households with certain self-containing capabilities, which are geographically adjacent and coordinated by a microgrid controller, as shown in the red box in Fig. 1. However, we can also think of each approximately self-contained microgrid as a broader customer unit coordinated by a feeder-level controller as shown in the blue box in Fig. 1. Similarly, we can scale up to the substation level and above and develop an entire hierarchical smart grid architecture, as shown in Fig. 1.

As we scale up to construct the entire grid, at each level, all branches with the same structure of one controller and multiple customer units are all approximately self-contained and are coordinated by the controller at a higher level. For example, at the microgrid level in Fig. 1, all microgrid branches identical to the red box are approximately self-contained. When the power-load mismatch is too big to be mitigated within a single microgrid, electric power flow will be routed among different microgrids under the coordination of a feeder-level controller. Similarly, at the feeder-level in Fig. 1, all branches identical to the blue box are approximately self-contained. Power flow among feeder-level branches are to be coordinated by the substation-level controller. Hence, with this hierarchical architecture interpretation, any decision-making framework designed for a controller and the individual units below it is applicable to each of the levels in this hierarchical smart grid. Thus, in the following, we may focus on an abstract model made of a single (micro-grid) controller and a collection of multiple (smart-home) customers managed by it.

It is also important to notice that this hierarchical architecture can be robust against cascading failures in a power grid due to its design based on self-containment at various granular levels. When the deviation is too large to be mitigated, the Utility can temporarily isolate the individual branch, in which the initial failure started, from the grid to prevent cascading failures. Therefore, this hierarchical structure significantly enhances the power grid reliability by routing power flow within and across different customer units to mitigate uncertainties.

2.2 A Utility-Customer Interaction Model between the Generation and Consumption Sides

Utility-customer (generation-consumption) interaction is an important topic in smart grid design. The interaction between the generation and consumption sides allows more efficient power-load scheduling compared to conventional power grid planning, which is purely matching generation to demand. However, the Utility-customer interaction varies depending on different time scales of the interaction periods, as well as different customer units at different levels of the hierarchical architecture. For example, in a microgrid, the smart-homes are the customer units at the microgrid level while the microgrid controller is a customer unit at the feeder-level (one level above). To address different interactions between the generation and consumption sides, in this section, we propose a two-stage model for the Utility-customer interaction, consisting of the initial scheduling (long-term planning) and the real-time scheduling (short-term planning).

2.2.1 Initial Scheduling: Prediction based Long-term Planning

In the initial interaction (long-term planning) stage, demand response (DR) schemes are implemented and it is desired that the customer loads always stay relatively flat. Note that, a flat load profile with low peak-to-average ratio means a need for relatively low generation capacity reserve, leading to more efficient operations of conventional generation facilities and a less number of idle generators for most of the time. In [13], [14], [25], we presented optimization-based and game theoretic DR schemes for the Utility to achieve this goal. In these DR schemes, customers pay less (or receive incentive payments) if they strictly fulfill their energy commitments. Similarly, they will have to pay extra as a penalty if they fail to honor the agreement reached during the long-term planning. Interaction at this level usually happens at the beginning of each scheduling period [12], [13], [15], [16] and is called the initial interaction or long-term planning in our interaction framework.

2.2.2 Real-time Scheduling: Short-term Planning

The DR schemes in the initial scheduling provide a nominal operating point for the nodes in the grid (the flat customer load profiles). However, since all DR schemes are based on the prediction of the renewable generations within the scheduling period (for example, a 12-hour or 24-hour period), they may not properly handle the real-time fluctuations and intermittence in power grid due to the inevitable mismatches between the actual and predicted renewable generations. This can be overcome, and the overall efficiency and stability can be improved, by allowing for (near real-time) interactions at a finer time scale (short-term) between the Utility and customers (generation and consumption sides).

From the perspective of the Utility (conventional generation side), both frequency control and voltage control schemes are needed for keeping active and reactive power-load balances [3], [4], [26]–[28]. From the perspective of customers (consumption side), who are most likely self-oriented, the objective is to make optimal decisions to maximize the accumulated profits (or minimize the payments) by taking advantage of their local DER's. Given the relatively flat load profiles computed by DR schemes, a customer can decide to sell part of its excess renewable energy to the grid and storing the rest for future use, according to the real-time pricing information.

It is worth pointing out that though the real-time decision schemes are important supplements to the DR schemes, they are different not only in scales of scheduling period but also in their functionalities. The DR scheme design (long-term planning) provides a nominal operating point (flat load profiles) for the nodes. In real-time scheduling, on the other hand, if local generations are less than the nominal load demands computed in the long-term planning, customers do not have much flexibility other than to buy electricity they need from the Utility. However, if local renewable generations are more than the nominal load demands, customers can flexibly decide how much of their own excess energy to be sold. Therefore, no matter in what scenario (buying or selling), the real-time scheduling is always based on the flat load profiles computed by the DR schemes.

2.3 A Two-step Decision Framework for Real-time Scheduling

Various DR schemes for the long-term planning problem have already been reported in literature [9]–[16]. In this paper, however, our focus is on the real-time scheduling problem in the above assumed abstract grid model (consisting of one controller and multiple customer units). Within this abstract model, there are two main decision problems (for real-time scheduling) to be addressed: (1) centralized controller decisions and (2) distributed customer decisions.

Take a microgrid as an example. On one hand, as a customer unit at the feeder-level, the microgrid controller needs to make sequential decisions to maximize the accumulated reward of the entire microgrid. At each time step the microgrid controller decides how much electric energy need to buy or sold by the microgrid, taking into account of all local DER's within the microgrid (first problem). On the other hand, smart-homes (customers) with excess energy also need to make distributed decisions when the microgrid controller needs to sell part of the excess energy. The distributed decisions indicate how much excess energy each smart-home contributes to the total amount of electric energy to be sold by the whole microgrid (second problem). To address both the centralized and distributed decision making problems, we propose a two-step decision framework for real-time scheduling, as shown in Fig. 2. The centralized microgrid controller decision making problem is shown in the upper level in Fig. 2 and the distributed smart-home decision making problem is shown in the lower level in Fig. 2. In light of the discussion on how the abstract model can represent scaled up units in the hierarchical model, the optimal decision making strategies developed for this abstract model can also be applied to different levels in the hierarchical smart grid with relevant modifications.

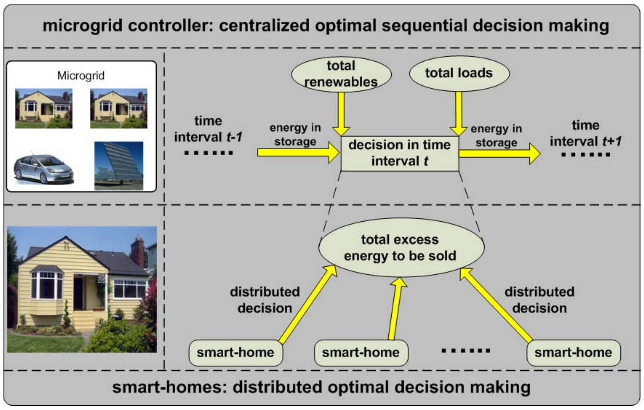

Fig. 2. A two-step decision framework for a microgrid addressing (1) centralized microgrid controller decisions and (2) distributed smart-home decisions.

2.4 Centralized Decision Making: a Hidden Mode Markov Decision Process (HM-MDP) Model

In the main part of this paper, we present a brief discussion on the centralized decision scheme design. Detailed problem formulation and model development for the centralized decision making have been included in the supplementary part of this paper. From the perspective of the controller, the Markov properties of load demands and renewable generations [29]–[31] allow us to characterize the transitions of these quantities defined above by a (possibly non-stationary) Markov decision process (MDP). Though all the energy related quantities are continuous valued, we can quantize the state space into discrete levels. On one hand, a certain level of granularity, say, a "basic energy unit", is essential in practice for energy operations to be effective enough for microgrid level scheduling. On the other hand, not too much error would be introduced as long as the quantization level is sufficiently small. By doing this, we obtain a discrete state space. Similarly, we can define the action of the MDP, with a discrete action space, as the number of basic energy units to be sold by the controller. By solving the formulated MDP, the controller makes optimal decisions in each time interval and maximizes the accumulated reward defined over the scheduling period.

One major difficulty on the solution derivation is the non-stationarity of the MDP. However, observations on environmental transitions reveal a possible environment characterization with the concept of "environment mode". Different from the internal state, which is based only on local information and fully observable, the environment mode is actually hidden from the microgrid controller (as it is not local information). Thus, the environment mode can only be estimated based on observations of other information, such as renewable generations and energy consumptions.

With the fully observable internal state and the hidden environment mode defined, we may adopt a hidden mode Markov decision process (HM-MDP) model to solve the centralized controller sequential decision making problem [32], [33].

With the centralized solution algorithm design for the controller addressed in an earlier paper [34], in this paper we focus on the distributed decision scheme for customers. It must be pointed out that the solution proposal for the distributed decision problem (which is the focus of this paper) is independent of the solution approach to the centralized decision problem. No matter what type of centralized solution algorithm is adopted for the controller, given the optimal energy profile computed by implementing that algorithm, the proposed distributed decision scheme can be always adopted in each time interval. The only link between these two schemes is that the solution from the first stage (centralized problem) is the starting point for the second-stage (distributed problem). The second-stage attempts to find an equitable (fair) implementation of the solution computed by the first stage under realistic interactions among the customer units. As will be discussed in section 3, from the perspective of problem formulation, the centralized decision and distributed decisions together make the real-time decision making scheme complete and applicable at different levels in the proposed hierarchical smart grid architecture. While from the perspective of problem solving, the solutions to the centralized and distributed decision making problems can be designed separately.

3 Distributed Optimal Decision Making: An Auctioning Game Design

Based on the optimal sequential decisions of the microgrid controller obtained by solving the HM-MDP model as discussed in the previous section, in this section we focus on the decision scheme design for distributed customers (smart-homes). When the microgrid controller decides to sell part of the total excess energy of the entire microgrid, this distributed decision scheme is especially important to decide how many excess energy units each smart-home contributes to the total amount of energy to be sold, considering the fact that smart-homes are all self-oriented. Several important issues need to be addressed about the distributed decision scheme design:

1) First, the optimal distributed scheme needs to be robust to adding/removing customers. This is because the number of smart-homes within a microgrid could be large and the status of smart-homes (buying-mode or selling-mode) also vary over time.
2) Second, the optimal distributed scheme needs to allow all participating selling-mode smart-homes to specify how eager they are to sell their excess energy units. Because usually not all excess energy units can be sold, a fair and efficient distributed decision scheme needs to make sure that the excess energy units to be sold are those units that the selling-mode smart-homes are highly eager to sell. Hence, to quantitatively describe the eagerness of selling-mode smart-homes, we need to define a metric of eagerness. It is worth pointing out that not only could the eagerness-metrics be different among different selling-mode smart-homes, even for the same selling-mode smart-home, the eagerness-metric might vary as the number of remaining excess energy units changes. Therefore, according to different eagerness-metrics of distributed customers, the microgrid controller needs to guarantee that the energy units sold always correspond to high eagerness metrics.
3) Third, the optimal distributed scheme needs to be robust against collusive smart-homes. This is because that individual selling-mode smart-homes are all self-oriented and interested in maximizing their own benefits. Thus, selling-mode smart-homes might not necessarily telling their true eagerness metrics and they might tell the untrue values if doing so results in higher benefits.

Denote by E_l^t the total amount of excess energy (assuming E_l^t is an integer multiple of the basic energy units) that the microgrid will sell to the outside grid. Recall that E_l^t is obtained from the optimal solution of the centralized decision problem, in which the microgrid controller decides how much electric energy need to buy or sold by the microgrid in order to maximize the accumulated reward of the entire microgrid. Since this E_l^t number of energy units comes from possibly different selling-mode smart-homes, we can define the number of *trading opportunities* to be E_l^t, where each trading opportunity corresponds to the trading of a single basic energy unit. The eagerness metric of a selling-mode smart-home associated to each trading opportunity is defined as the valuation (measured in money unit) of the trading opportunity that the smart-home has. The valuation that the smart-home has associated to an individual trading opportunity is defined as how much the smart-home expects to get from selling its excess energy unit. The valuations of the E_l^t trading opportunities are private information of smart-homes and are usually determined by factors such as energy storage, power consumptions and so on. For example, when a smart-home needs to sell its excess energy units more urgently, it will associate higher values to these trading opportunities. Hence, the eagerness-metrics it associates to these trading opportunities are also higher. With the eagerness-metric defined above, the original distributed decision making problem is equivalent to an optimal allocation problem, in which E_l^t number of trading opportunities are to be allocated among selling-mode smart-homes.

3.1 Vickrey Auction based Distributed Allocation Scheme

Considering all the desired properties required by the distributed decision making scheme, we propose a Vickrey auction based allocation scheme for distributed smart-homes in the microgrid, as shown in Fig. 2. Assume that out of the total K number of smart-homes, there are $\hat{K}_t$ number of selling-mode smart-homes in time interval t participating in the Vickrey auction competing for E_l^t number of trading opportunities. Note that in a one-shot auction in each time interval, selling excess energy always increases the smart-home's immediate reward. Thus, every smart-home wants to sell as much excess energy as possible for its own benefit. However, from the microgrid controller's perspective, to maximize the total accumulated reward in a long run, E_l^t number of energy units must be sold to the grid at time t (this is what the first step solution determines). Since E_l^t is no greater than the total excess energy $E_x(t)$ among all smart-homes in the microgrid, only part of the excess energy units can be sold. Selling-mode smart-homes compete for the E_l^t number of trading opportunities by telling that how much money (the bids) they are willing to pay for each of the trading opportunities. Selling-mode smart-homes determine the bids based on their own valuation associated to each trading opportunity. These bids are not necessarily equal to their valuations. Thus, selling-mode smart-homes need to take into account the payments they need to make for the trading opportunities and the profits they may have by selling their excess energy units. Here the profits of a smart-home equal to the difference between the total valuations associated to all trading opportunities it obtains and the total payments it makes.

In the Vickrey auction, the k-th ($k = 1, 2, \dots, \hat{K}_t$) selling-mode smart-home submits E_l^t number of bids $b_{t,k}^n$'s ($n = 1, 2, \dots, E_l^t$) to indicate how much it is willing to pay for each additional trading opportunity in time interval t. Thus, bid $b_{t,k}^n$ is the amount of money the selling-mode smart-home k is willing to pay for its n-th trading opportunity. Let $\mathbf{b}_{t,k} = (b_{t,k}^1, b_{t,k}^2, \dots, b_{t,k}^{E_l^t})$ denote the E_l^t dimensional *bid vector* with nonnegative elements of selling-mode smart-home k at time interval t. We assume that the components in the bid vector is always non-increasing in index and denote by $\mathbf{B}$ the bid vector space. $\mathbf{B}$ is a subspace of the E_l^t dimensional real vector space $\mathbb{R}_+^{E_l^t}$, which contains all E_l^t dimensional real vectors with nonnegative components. Mathematically, we have

$$\mathbf{B} := \{\mathbf{b}_{t,k} \in \mathbb{R}_+^{E_l^t} | b_{t,k}^1 \geq b_{t,k}^2 \geq \dots \geq b_{t,k}^{E_l^t}, \forall k = 1, 2, \dots, \hat{K}_t\} \tag{1}$$

Note that, in practice restricting bid vectors to have non-increasing components makes sense. This is because the selling-mode smart-home's valuations attached to individual trading opportunities is non-increasing as the smart-home gets more and more trading opportunities. For example, if a selling-mode smart-home has no trading opportunity, it needs to sell its excess energy the most urgently and its valuation for its first trading opportunity is the highest. As it sells out more and more excess energy, its storage facility gets released gradually and the marginal valuation (marginal eagerness-metric) is thus non-increasing. If a selling-mode smart-home k is only interested in selling $e_{t,k}$ ($e_{t,k} \leq E_l^t$) number of excess energy units in the auction at time t, then the last $E_l^t - e_{t,k}$ elements of its bid vector are all zeros.

A total of $\hat{K}_t \times E_l^t$ bids b_k^n's ($k = 1, 2, \dots, \hat{K}_t; n = 1, 2, \dots, E_l^t$) are placed for the action at time t, and the E_l^t number of trading opportunities are assigned to the E_l^t highest of these bids, which are deemed *winning bids*. Ties are broken by choosing with equal probability among all tying bids. The number of trading opportunities assigned to a selling-mode smart-home is equal to the number of winning bids submitted by that selling-mode smart-home. Thus if selling-mode smart-home k has $n_k \leq E_l^t$ of the highest bids, then it gets n_k units of trading opportunities in time interval t.

Denote by $\mathbf{c}^{-k}$ the E_l^t dimensional *competing bid* vector, which consists of the E_l^t highest others' bids, facing selling-mode smart-home k, so that c_1^{-k} is the highest of the other bids, c_2^{-k} is the second highest of the other bids, and so on. To win exactly n trading opportunities, selling-mode smart-home k's n-th highest bid must defeat the n-th lowest competing bid. If selling-mode smart-home k wins $n_{t,k}$ trading opportunities, then the the payment g_k it makes is the sum of n_k highest losing bids of the other customers [35], which is given by

$$g_k = \sum_{n=1}^{n_k} g_k^n = \sum_{n=1}^{n_k} c_{E_l^t - n_k + n}^{-k}, \tag{2}$$

where g_k^n is the payment for the n-th trading opportunity.

3.2 Truthful Bidding Strategy for Vickrey Auction

In the auction in each time interval, all selling-mode smart-homes have their own valuations, which determine the bidding strategies, corresponding to all E_l^t number of trading opportunities. In the microgrid, selling-mode smart-homes do not know other's valuations precisely (*incomplete information*) since valuations of different customers are determined by their own energy storage status (*private valuation*). Denoted by $\mathbf{v}_{t,k} = [v_{t,k}^1, v_{t,k}^2, \dots, v_{t,k}^{E_l^t}]$ the private *valuation vector* of selling-mode smart-home k at time interval t, where $v_{t,k}^n$ represents the marginal value of obtaining the n-th trading opportunity. These marginal values are assumed to be non-increasing for similar reasons that we assumed non-increasing marginal bids so that

$$v_{t,k}^1 \geq v_{t,k}^2 \geq \dots \geq v_{t,k}^{E_l^t},\ k = 1, 2, \dots, \hat{K}_t. \tag{3}$$

The total value to the selling-mode smart-home k of obtaining exactly $n_{t,k} \leq E_l^t$ trading opportunities is then the sum of the first $n_{t,k}$ marginal values: $\sum_{j=1}^{n_{t,k}} v_{t,k}^j$. Note that symmetry on valuations is usually assumed in Vickrey auction literature [35], [36], in which $\mathbf{v}_{t,k}$'s are independently and identically distributed (i.i.d) on the valuation set

$$\mathbf{V}_{t,k} = \{\mathbf{v}_{t,k} \in [0, \omega_t]^{E_l^t} : \forall n, v_{t,k}^n \geq v_{t,k}^{n+1}\}, \tag{4}$$

where ω_t is the maximum valuation for all selling-mode smart-homes. However, the i.i.d symmetric condition is too strong for our problem since the valuations of different selling-mode smart-homes could be different depending on individual energy consumption and storage information. Thus we drop the condition of identical distribution and assume more general asymmetric selling-mode smart-homes—smart-home k's valuation vector $\mathbf{v}_{t,k}$ is independently drawn from some distribution that has positive density everywhere on the set $\mathbf{V}_{t,k}$.

The Vickrey auction in each time interval actually forms a game with incomplete information, in which every selling-mode smart-home wants to maximize its own payoff. Here a smart-home's payoff equals the sum of valuations obtained from winning trading opportunities minus the total payment. To better analyze the formulated Vickrey auctioning game, we first introduce several important concepts from game theory and then propose an important proposition.

1) Bayesian Nash equilibrium: A Bayesian Nash equilibrium for a game with incomplete information is a strategy profile for each player that maximizes the expected payoff for each player given the strategies played by other players [35], [37], [38].
2) Strictly dominant strategy: A *strictly dominant strategy* is an action strategy that gives higher reward than any other strategy [37].
3) Weakly dominant strategy: A *weakly dominant strategy* is an action strategy that gives reward no lower than any other strategy [37].

With these concepts introduced above, we present an incentive compatibility proposition for Vickrey auction, along with its proof [35].

Proposition 1: The Vickrey auction is *incentive compatible*, meaning truthful bidding (bidding the real valuation) maximizes each selling-mode smart-home's payoff and is a weakly dominant strategy for every selling-mode smart-home.

Proof: Consider selling-mode smart-home k and the competing bids $\mathbf{c}^{-k}$ facing it. Suppose that when smart-home k submits a bid vector $\mathbf{b}_{k,t} = \mathbf{v}_{k,t}$, it is assigned n_k trading opportunities. According to the Vickrey pricing rule, its payment is given by $\sum_{n=1}^{n_k} c^{-k}_{E^t_l - n_k + n}$ [35]. It is the case that for all $n \leq n_k$, $v^n_k \geq c^{-k}_{E^t_l - n_k + n}$ (where, $c^{-k}_{E^t_l - n_k + n} = g^n_k$), whereas for all $n > n_k$, $v^n_k < c^{-k}_{E^t_l - n_k + n}$ (where, $c^{-k}_{E^t_l - n_k + n} = g^n_k$). Now suppose selling-mode smart-home k were to submit a bid vector $\mathbf{b}_{k,t} \neq \mathbf{v}_{k,t}$ such that it is assigned the same number of trading opportunities as when it submitted its true value vector $\mathbf{v}_{k,t}$, then the payment it pays for these trading opportunities would be unaffected, as would its overall payoff. If selling-mode smart-home k were to submit a $\mathbf{b}_{k,t} \neq \mathbf{v}_{k,t}$ so that it is assigned a greater number of trading opportunities, say $n^{'}_k > n_k$, then the payments it would pay for the first n_k trading opportunities would be unchanged, and so would the payoff derived from these. For any trading opportunity $n > n_k$, the payment g^n_k exceeds (or at best equals) the n-th marginal value $v^n_{t,k}$, so the payoff from these $n^{'}_k - n_k$ trading opportunities would be negative (or at best zero). As a result, the overall surplus would be lower (or at best, the same) than that if it were to bid truthfully. Finally, if selling-mode smart-home k were to submit a $\mathbf{b}_{k,t} \neq \mathbf{v}_{t,k}$ such that it is assigned a smaller number of trading opportunities, say $n^{'}_k < n_k$, then the payments it would pay for the first $n^{'}_k$ ones would be unchanged and therefore so would the payoff derived from these. But the payoff from any trading opportunity $n < n_k$ was positive and is now forgone. Thus by winning fewer trading opportunities selling-mode smart-home k's overall payoff would be lower than if it were to bid truthfully. Based on the argument above, truthful bidding is a weakly dominant strategy for every selling-mode smart-home. □

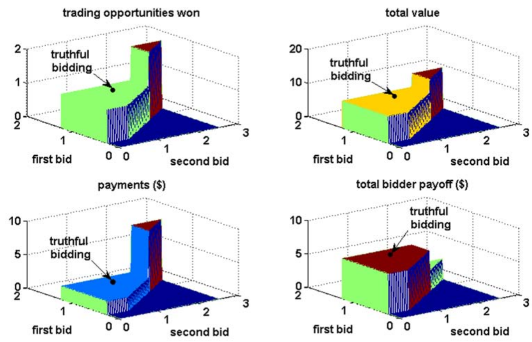

Fig. 3. Incentive compatibility of the Vickrey auction. The normalized truthful bidding strategy point $(1, 1)$ maximizes the payoff of the individual smart-home. However, it is only weakly dominant because bidding strategies represented by other points in the same plane, within which the truthful bidding point stays, achieve the same maximum payoff.

As shown above, the truthful bidding strategy forms a Bayesian Nash equilibrium. Figure 3 shows an example of an individual smart-home in a Vickrey auction bidding for two trading opportunities. The competing bids from other selling-mode smart-homes are assumed to be fixed. As we can see, with the bids normalized by the real valuations of the first and second trading opportunities, the truthful bidding strategy $\mathbf{b} = (1, 1)$ leads to the maximum payoff (bottom right plot). Deviation from the truthful bidding point $(1, 1)$ might increases the number of trading opportunities obtained by the smart-home (top left plot), however, the individual payoff (bottom right plot) becomes lower. Moreover, we can see that the truthful bidding strategy is only a weakly dominant strategy, because other bidding strategies represented by the points in the same plane, within which the truthful bidding point stays, achieve the same maximum payoff.

4 Bayesian Nash Equilibria Solution Set Structure Analysis

Though every selling-mode smart-home's payoff is maximized by the truthful bidding strategy, there is no guarantee that such Vickrey auctioning games always converge to the truthful bidding equilibrium. This is because truthful bidding is only a weakly dominant strategy and truthful bidding equilibrium is not the unique Bayesian Nash equilibrium in a Vickrey auction. Therefore detailed analysis on the entire equilibrium solution set of Vickrey auction is required.

4.1 The Two Types of Bayesian Nash Equilibria

Following [39], we divide the Bayesian Nash equilibria in the Vickrey auction solution set into two categories. Equilibria in the first category can be described as follows: There exists at least one selling-mode smart-home k who has at least one bid $b^n_{t,k} \in (0, \omega_t)$ with positive probability. There is a threshold $b^*_t \in (0, \omega_t)$ for all selling-mode smart-homes such that all participants bid truthfully for which they have a valuation exceeding b^*_t. Furthermore, there is a unique distinct selling-mode smart-home $\hat{k}$ who bids b^*_t on any trading opportunity for which his valuation is below the threshold. The remaining selling-mode smart-homes bid zero on any trading opportunity for which their valuation is below the threshold. Put in a more mathematical format:

$$b^n_{t,\hat{k}} = \begin{cases} v^n_{t,\hat{k}} & \text{if } v^n_{t,\hat{k}} \in [b^*_t, \omega_t] \\ b^*_t & \text{if } v^n_{t,\hat{k}} \in [0, b^*_t), \end{cases} \tag{5}$$

for all $n = 1, 2, \dots, E^t_l$ and

$$b^n_{t,k} = \begin{cases} v^n_{t,k} & \text{if } v^n_{t,k} \in (b^*_t, \omega_t] \\ 0 & \text{if } v^n_{t,k} \in [0, b^*_t], \end{cases} \tag{6}$$

for all $k \neq \hat{k}$ and all $n = 1, 2, \dots, E^t_l$, where ω_t is the highest valuation over all customers and

$$b^*_t := \inf\{b \in (0, \omega_t) | \exists k, n \text{ s. t. } \forall \epsilon > 0, \text{Prob}\{b^n_{t,k} \in [b, b+\epsilon]\} > 0\}. \tag{7}$$

It can be proved that any bid strategy profile that can be described as above forms an Bayesian Nash equilibrium [39]. Conversely for any equilibrium in which certain $b^n_k \in (0, \omega_t)$ with positive probability for some selling-mode smart-home k and trading opportunity n, there is a profile of bid functions in the first category that describes the behavior of each selling-mode smart-home for almost all valuations, allowing variants (deviating behavior) on sets of measure zero of valuations. Specifically, as in reality selling-mode smart-homes usually have continuous distribution over the valuation set, there usually exists at least one selling-mode smart-home whose valuation distribution over $(0, \omega_t)$ assigns positive probability to arbitrarily small positive values. In this case, we have $b^*_t = 0$ and the first category equilibria reduce to the truthful bidding equilibrium.

For all equilibria that are not of the first type, there is zero probability of positive bids below the highest valuation ω_t. Each selling-mode smart-home k ($k = 1, 2, \dots, \hat{K}_t$) bids at or above the highest valuation ω_t on $\hat{n}_{t,k}$ number of trading opportunities and bids zero on the remaining ones in such a manner that the total number of positive bids across all selling-mode smart-homes equals the number of trading opportunities to be sold, i.e. $\sum_{k=1}^{\hat{K}_t} \hat{n}_{t,k} = E^t_l$. The second type of Bayesian Nash equilibria reveals the possibility that the Vickrey auction might end up with a collusive equilibrium that selling-mode smart-homes bid untruthfully and all trading opportunities are sold with zero payment.

4.2 Vickrey Auction Equilibrium Analysis

Vickrey auction with truthful bidding equilibrium has many good properties. For example, it is an *efficient mechanism* as it maximizes the social welfare (maximizing the sum of participants' values [35], [37], [38]). It is also incentive compatible as bidding the real values is a weakly dominant strategy for all customers [35], [37], [38]. However, as mentioned above, Vickrey auction is vulnerable to collusion by selling-mode smart-homes. In the first type of Bayesian Nash equilibria, if the number of bids above the threshold is less than the number of trading opportunities for sale, then some selling-mode smart-homes will get some trading opportunities for free. In the second category of Bayesian Nash equilibria, all winning smart-homes pay zero payment for the trading opportunities they win. Generally speaking, equilibria of both categories are collusive in the sense that there are positive probabilities that customers get some trading opportunities with zero payment.

The collusive equilibria jeopardize the distributed control framework in two ways: (1) The collusive equilibria fails to achieve the most important goal of the distributed decision scheme, which is to guarantee that the trading opportunities are allocated to selling-mode smart-homes who value them the highest (with highest eagerness-metric). (2) The collusive equilibria does not guarantee the profit of the auctioneer (the microgrid controller). Though in our problem, the profit of the auctioneer (the microgrid controller) is not one of the objectives to be maximized, zero payments are not desired either considering reasonable operation cost of the microgrid controller.

4.3 Vickrey Auction with a Reserve Price

To address the two issues raised from collusive Bayesian Nash equilibria, we further extend the Vickrey auctioning game design by introducing a reserve price. It can be proved that the Vickrey auction can be made more robust against collusive selling-mode smart-homes by introducing a positive reserve price by the microgrid controller [39], [40]. Suppose the microgrid controller sets a positive reserve price r_t for the auction in time interval t such that each selling-mode smart-home has to pay at least the reserve price for any trading opportunity obtained. Without loss of generality, bids below the reserve price, or not bidding, are identified with bidding zero. Refer to $n^{'}_t$ the number of bids at or above r_t. Then at the end of the auction, there are $\mu_t = \min\{n^{'}_t, E^t_l\}$ units are sold to the selling-mode smart-homes with the μ_t highest bids. A selling-mode smart-home who wins n_k units pays $\sum_{j=1}^{n_k} \max\{c^{-k}_{E^t_l - n_k + j}, r_t\}$. It can be shown that with a positive reserve price r_t, the Vickrey auction with more than two participants converges to a unique Bayesian Nash equilibrium, in which selling-mode smart-homes refrain from bidding on any trading opportunity for which their valuation is less than r_t and otherwise bid their valuation for each trading opportunity [39]. Introducing a reserve price not only guarantees the uniqueness of equilibrium solution of Vickrey auction, therefore making the Vickrey auction more robust to collusion by selling-mode smart-homes, but also guarantees a certain amount of benefit of the microgrid controller.

In sum, the Vickrey auction with a reserve price gives a better allocation scheme in the following aspects: (1) The Vickrey auction with a reserve price is robust to collusion by selling-mode smart-homes. (2) The Vickrey auction with a reserve price is incentive compatible, meaning assigning trading opportunities to smart-homes with highest eagerness-metrics. (3) The Vickrey auctioning game with a reserve price converges to the unique Bayesian Nash equilibrium. (4) The Vickrey auction with a reserve price guarantees a certain amount of benefit of the microgrid controller. The only possible issue with the Vickrey auction with a reserve price is that, when the reserve price is too high, it is possible that the number of bids above the reserve price is less than E_l^t, therefore the trading opportunities assigned to selling-mode smart-homes is not enough. However, in our problem formulation, the auctioneer's profit is not one of the objectives of the distributed decision framework, thus there is no reason for the microgrid controller to set a high reserve price. In the worst case that this situation happens, repeated Vickrey auctions can be adopted and the reserve price can be adjusted until all E_l^t trading opportunities are assigned.

4.4 Simulation Results

We implement the Vickrey auction (without collusion) for a microgrid model with 10 smart-homes bidding for 20 trading opportunities. The truthful valuations on the trading opportunities are within $[0, 1](\$)$. For comparison purpose, we also analyze the performance of two other auction schemes: discriminatory auction and uniform-price auction [35]. In discriminatory auction, smart-homes pay what they bid while in uniform-price auction, smart-homes pay the same highest losing bid for every trading opportunity they get. In the three different auctions, the trading opportunities, payments, payoffs of each of the 10 smart-homes, as well as the social welfare of the microgrid are compared, as shown in Fig. 4. Vickrey auction maximizes the social welfare of $18.87(\$)$, compared with $17.68(\$)$ of discriminatory auction and $17.87(\$)$. It is worth pointing out that in the truthful bidding equilibrium of the Vickrey auction reveals another good property in the bidding behavior of individual smart-homes, which is *Individual Rationality*, meaning the payoff function is always non-negative (as shown in the bottom plot).

In Fig. 5, we investigate the influence of the reserve price on the profit of the auctioneer in a one shot Vickrey auction with different time interval sizes within the processing block. As the reserve price (normalized by the highest value) increases from 0 to 1, after certain point, the number of trading opportunities that can be successfully allocated to smart-homes decreases from 20 to 0, which corresponds to the extreme case with reserve price higher than the highest possible value.

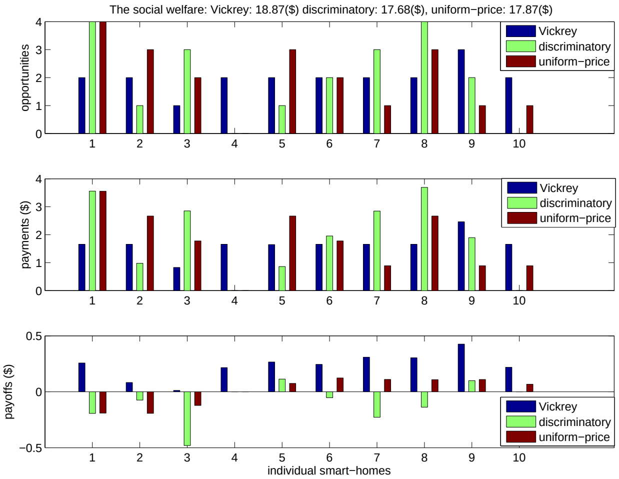

Fig. 4. The truthful bidding equilibrium of the Vickrey auction maximizes the social welfare of the entire microgrid, while keeping the individual rationality of smart-homes.

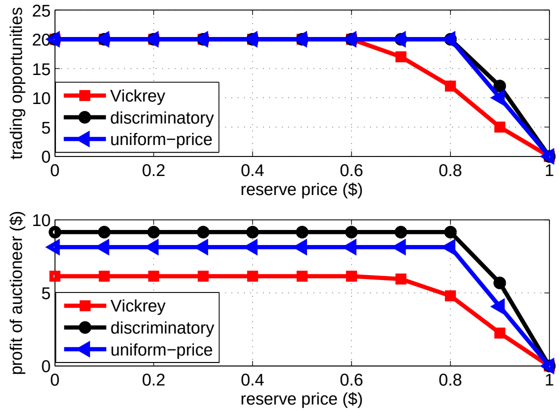

Fig. 5. As the reserve price (normalized by the highest value) increases from 0 to 1, after certain point, the number of trading opportunities that can be successfully allocated to smart-homes decreases from 20 to 0, which corresponds to the extreme case with reserve price higher than the highest possible value.

5 Conclusion

In this paper, we developed a hierarchical interactive architecture the Utility and the distributed customers in a smart grid while ensuring grid-stability and Quality-of-Service (QoS). With an abstract model consisting of one controller and multiple customers developed, we formulated a two-step decision framework for the real-time scheduling. The two-step decision framework consisted of (1) centralized controller sequential decisions and (2) distributed customer decisions. We first developed a hidden mode Markov decision process (HM-MDP) model for the controller sequential decision making. With the solution algorithm design for the HM-MDP model discussed in an earlier paper, in this paper we focused on the Vickrey auction design for distributed customers. The solution set of the Vickrey auctioning game was divided into two categories and detailed analysis on the Bayesian Nash equilibria were presented, which showed that the truthful bidding strategy was a weakly dominant Bayesian Nash equilibrium. To overcome the vulnerability of the Vickrey auction against collusion by selling-mode smart-homes, the developed Vickrey auction was extended by introducing a reserve price, which guaranteed robustness of the auction and the convergence of the auctioning game to the unique truthful bidding equilibrium.

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