

# Truthful, Practical and Privacy-aware Demand Response in the Smart Grid via a Distributed and Optimal Mechanism

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**Abstract**—High penetration of Renewable Energy Sources in modern smart grids necessitates the development of Demand Response (DR) mechanisms as well as corresponding innovative services for the emerging flexibility markets. From a game-theoretic perspective, the key requirements for a DR mechanism are: efficiency in terms of social welfare, practical applicability, scalability, privacy and incentive compatibility, in the sense of making it a dominant strategy for each user to act truthfully according to his/her real preferences, leaving no room for cheating. Previous works typically address only a subgroup of these requirements. In this paper, we propose a DR architecture, including a mechanism based on Ausubel’s clinching auction and a communication protocol, that provably guarantee both efficiency and truthful user participation. Practicality/easiness of participation is enhanced via simple queries, while scalability and user privacy are preserved via a distributed implementation. Simulation results confirm the desired properties, while also showing that the truthfulness property becomes even more important in markets where participants are not particularly flexible.

**Index Terms**—Demand Response, Auction, Flexibility, Mechanism Design, Blockchain, Incentive Compatibility, Game Theory

## NOMENCLATURE

### Setting

$\mathcal{N}$	Set of participating users
$n$	Number of participating users
$i$	Index of user
$T$	Set of timeslots
$m$	Number of timeslots in the horizon
$t$	Index of timeslot

### Flexibility Service Provider

$L$	Aggregated consumption of all users
$D$	Reduction of aggregated consumption
$a, b$	Parameters of the FSP’s reward function
$\lambda$	Per unit price for consumption reduction

### User

$q$	Consumption reduction
$\tilde{q}$	Optimal consumption reduction
$\omega$	Inelasticity parameter

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### Modified Clinching Auction

$k, \xi$	Indexes of iteration
$\varepsilon$	Price step
$\zeta$	Clinching (allocation) of consumption reduction for a user

### Appliance models

$p$	Power consumption
$p_{max}$	Power consumption upper limit
$T$	Temperature
$\eta, \theta$	Parameters of temperature dynamics
$\gamma$	EV arrival timeslot (plug-in time)
$E$	Energy required by an EV
$\delta$	Minimum charging duration of an EV

## I. INTRODUCTION

IN modern smart grids, the need to dynamically balance supply and demand, has brought a great deal of attention to the idea of Demand Response (DR). When there is a need for reducing energy consumption in real-time, an ad-hoc market is created where the operator offers to buy consumption reduction from the users. An intermediate entity is assumed, with the task to clear the ad-hoc flexibility market. We refer to this entity as the Flexibility Service Provider (FSP). Each user (consumer) is equipped with a smart meter that measures his/her consumption at all times. However, the users’ local functions (related to their flexibility/comfort levels and consumption habits) are private to each user. This makes the task of the FSP quite challenging, especially when we consider users who act strategically and may misinterpret their local function if that makes them better-off.

In real-time DR, expecting the user to manually control his/her appliances and bids in real-time is not realistic. Rather, an intelligent agent sits on each user’s side that controls the user’s DR actions and makes the user’s optimal bidding decisions while respecting the user’s energy needs. Several studies have leveraged methods from Artificial Intelligence and proposed learning algorithms for optimizing the decisions of such an energy management agent (e.g. [1]). However, strategic agent behavior can compromise the efficiency of the DR mechanism. In order to protect the system’s efficiency, a mechanism needs to be not only optimal, but also incentive compatible / truthful. This requirement is widely overlooked

in the DR literature. In the few cases where truthfulness is addressed, it comes with a sacrifice of practical implementation ability and user privacy.

In Mechanism Design terms, a mechanism is Dominant Strategy Incentive Compatible (DSIC) (or, equivalently, satisfies the truthfulness property) when it is at each user's best interest to truthfully implement his/her true preferences, regardless of what other users do (see section 10.2.2 of [2] for a more detailed analysis). In the vast majority of the DR literature users are typically modeled to myopically best-respond at each iteration of the pricing mechanism, i.e., they decide upon their preferred consumption upon receiving a price signal. As analyzed in [3], such myopic "local rationality" does not necessarily imply "global rationality", i.e., given an iterative mechanism, it is not always to the user's best interest to repeatedly best-respond. Rather, a user might be better-off by submitting false bids through the process, and such strategic behavior may compromise the mechanism's efficiency [4]. In other words, mechanisms that are not incentive compatible, are no longer optimal when strategic players are involved.

In this paper we also address this requirement, defined as the capability of the mechanism to provoke strategic users to act truthfully in accordance to their preferences, which is overlooked in most of the DR literature. Moreover, we do so via an indirect and practical mechanism, which allows for distributed, scalable and privacy-preserving implementation, in contrast to the few studies that consider incentive guarantees.

## II. RELATED WORK

In the DR literature, the end user is typically modeled as a selfish player who participates in the mechanism with the purpose of maximizing his/her own payoff. The user's preferences are widely modeled as a convex function (e.g. [5], [6], [7]). In [8] the electricity bill is minimized while the user's satisfaction is maintained above a defined threshold. In [9], a similar framework was built for deciding the charging times of EVs under forecasted prices. In [10], a spread is applied to the real-time prices in order to penalize deviations from a predefined schedule. In these studies, the bill of a user depends only on his/her own actions and it is disengaged from the actions of others. Thus, the users' DR actions might not be well coordinated.

In [11], the authors assume that consumers voluntarily provide their consumption preferences to a central entity, which optimizes the social welfare. Similarly, in [12], users estimate their energy needs and report them to an aggregator. In [13], a set of users enter into a direct-load-control contract with a load serving entity, responsible to satisfy a DR event. However, in [11]- [13], users were assumed to honestly reveal their consumption preferences.

In contrast to the studies presented so far, [5] and [6], considered users that do not reveal their local preferences, and the FSP controls their consumption indirectly by iteratively updating prices and observing the aggregated consumption. The authors use a dual decomposition method to discover the optimal prices. A scalable approach is proposed in [14], where smoothing techniques facilitate fast convergence. In

[15], the aggregator is modeled as a profit-maximizing entity and a simulated annealing algorithm was adopted for the price optimization problem. The authors in [16] configure the pricing scheme with a forecast component. In [17], the authors consider two simple billing rules and prove that best-response dynamics converges to Nash Equilibrium. In [18] and [19], pricing schemes are deployed with the objective of maximizing the fairness of the consumption allocation. In [20], the effect of the FSP's profit policy on the DR outcome was examined. However, in the studies of this paragraph, users are assumed to truthfully best-respond to each price query, and thus they don't compromise the algorithm's properties.

In mechanism design terms, the above mechanisms are not incentive compatible, because a strategic user can benefit by manipulating his/her responses. Note that the optimality guarantees of the above studies, would no longer hold in the case of strategic users. When considering strategic users the mechanism designer is confronted with a trade-off: the Vickrey-Clarke-Groves (VCG) mechanism is the unique welfare maximizing mechanism implemented in dominant (and not best-response) strategies [21], meaning that either a VCG approach is taken (like in [22], [23]) or welfare maximization is compromised (like in [24], [25], [26], [27]).

The main problem with the direct-revelation VCG approaches [22], [23] is that they require users to reveal their whole set of preferences to the FSP, while the latter makes all the calculations and decides the allocation and the rewards. This is clearly impractical, since real users cannot compactly express their preferences in closed-form mathematical functions and even when they can, they are not happy to compromise their privacy. These issues were also reported in [28] and [29], where the authors proposed that the available actions for each user were restricted to a predefined set in order to simplify the message space. However, the authors in [28] do not model the effect of the user's actions on the price (similarly to [8], [9], [10]) and the authors in [29] consider EV-charging users who are only interested in the overall energy consumption over the horizon (which is not suitable for other loads and neither for en-route charging EVs). Naturally, these kinds of approximations result in loss of efficiency.

In this paper, we opt for a VCG-like approach, so as to achieve social welfare maximization, but we omit the direct-revelation approach of the typical VCG mechanism. Instead, we design an iterative auction mechanism based on Ausubel's clinching auction, in which users are only required to make decisions regarding their consumption in the presence of price signals. The convergence of the proposed method can be dramatically accelerated, with a minimal loss of efficiency for which we also prove a theoretical upper bound. By adopting this approach, we are guaranteed the efficient and incentive-compatible VCG outcome but also allow for a scalable, distributed implementation and a privacy-preserving communication protocol.

A distinct family of studies has elaborated on how the consumption measurements of an individual user can be masked in order to protect the user's privacy (e.g. [31]). In [30] a distributed authentication method is proposed, while [32] exploits hash functions in order to serve secure data

transmission. Furthermore, [33] evolves load hiding techniques and [34] proposes obfuscation technologies towards data privacy. In [35] and [36], the authors propose privacy-preserving data aggregation methods with minimum overhead, while [37] also accounts for the case of a malicious FSP. Finally, [38] exploits adaptive key evolution, while [39] and [40] focus on the consensus problem towards reliable communication in fully distributed systems.

However, the studies of this family do not contribute to the design of the pricing scheme per se and assume that prices only depend on the aggregated consumption. This class of pricing rules can result in an optimal allocation under assumptions but it is not incentive compatible. The iterative mechanism proposed in this paper, can be implemented in configuration with a self-organized architecture that ensures privacy while in the same time is able to exploit the aforementioned systems in order to further enhance its level of security (in contrast to the direct VCG mechanism).

Summarizing the above, our proposed DR architecture: i) is suitable for a distributed implementation (unlike [22], [23]), ii) achieves the VCG outcome and does not sacrifice efficiency (unlike [24] - [27]), and iii) is incentive compatible (unlike [5], [6], [8]- [20] and [30]- [40]). In Table I, we present the four relevant requirements for a DR scheme and compare the proposed scheme to the state of the art.

TABLE I: Classification of literature based on requirements

	Optimal	Truthful	Scalable	Privacy-aware
[11] - [13]	✓	×	×	×
[18]- [20], [27]	×	×	✓	×
[5], [6], [14]- [17]	✓	×	✓	×
[22]	✓	✓	×	×
[26], [28], [29]	×	✓	✓	×
[30] - [40]	✓	×	✓	✓
This work	✓	✓	✓	✓

### III. SYSTEM MODEL

We consider a flexibility market comprised of an FSP and a set  $\mathcal{N} \triangleq \{1, 2, \dots, n\}$  of  $n$  self-interested consumers, hereinafter referred to as users. We also consider a discrete representation of time, where continuous time is divided into timeslots  $t \in \mathcal{T}$  of equal durations  $s$ , where set  $\mathcal{T} \triangleq \{1, 2, \dots, m\}$  represents the scheduling horizon. Each user possesses a number of controllable appliances, with each appliance bearing an energy demand. If the consumptions of different appliances are decoupled (independent of each other) the appliances can participate in the DR mechanism virtually as different users. Thus, we can consider one appliance per user for ease of presentation.

#### A. User's consumption and utility

The energy consumption of each user is measurable in real-time and can be shed upon request, in exchange for monetary compensation. Such a request for consumption modification is called a DR-event. In this paper we cope with real-time DR. Thus, the baseline consumption measurement is taken before the DR call, so the user cannot manipulate it since he/she does not know when a DR-event is going to occur.

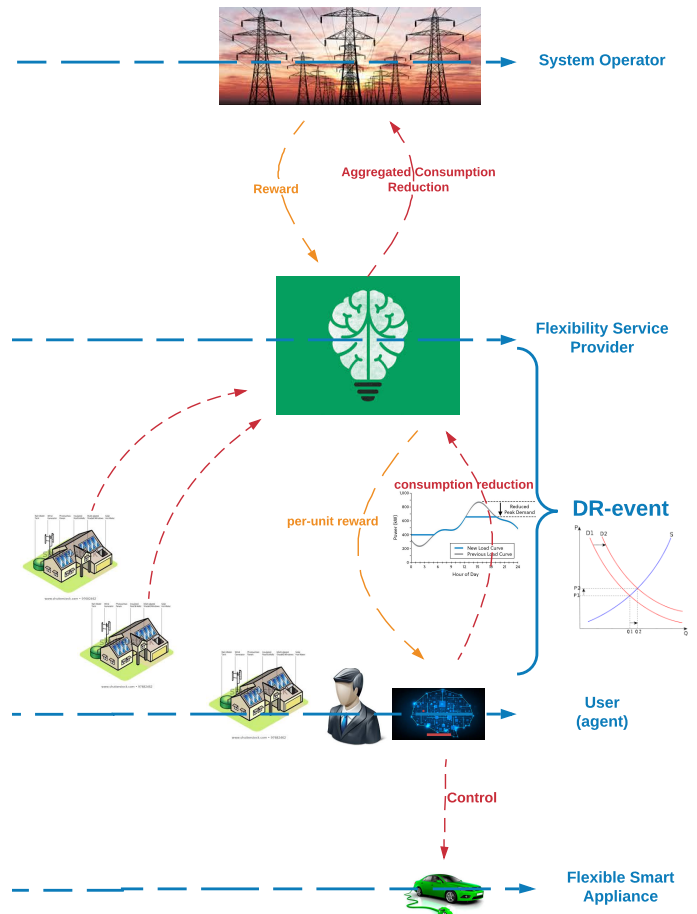


Fig. 1: System Architecture

The FSP takes on the task of providing the requested service by calling a DR-event among the users of its portfolio, which may include a micro-grid, or a local energy community [41], [42]. Upon a DR-event in timeslot  $t$ , the FSP offers a per-unit reward to the users for consumption reduction. User  $i$  can respond by reducing his/her consumption by a quantity  $q_i^t$ , assumed to be positive ( $q_i^t \geq 0$ ), without loss of generality. The decisions for  $q$  can be taken by an intelligent agent (on behalf of the actual user and according to the user's preferences) in order to disengage the actual user from real-time participation. The system's architecture is depicted in Fig. 1. The consumption reduction  $q_i^t$  is characterized by its feasible set  $Q_i$  (defined by a set of constraints on  $q_i^t$ ) and the discomfort function  $d_i(q_i^t)$  of user  $i$ . The discomfort function is private to each user and expresses the minimum compensation in monetary units that a user requires, in order to reduce his/her consumption by the corresponding amount. We make the following assumptions on the form of function  $d_i(q_i^t)$ :

**Assumption 1.** Zero consumption reduction, brings zero discomfort to the user:

$$d_i(0) = 0$$

**Assumption 2.** The discomfort function is convex, so that additional increase of  $q_i^t$  brings increasing discomfort to the

user:

$$\begin{aligned} q_i A^t \geq q_i B^t &\Leftrightarrow d_i(q_i A^t + \varepsilon) - d_i(q_i B^t + \varepsilon) \\ &\geq d_i(q_i A^t) - d_i(q_i B^t), \forall \varepsilon, q_i A^t, q_i B^t > 0. \end{aligned}$$

Detailed example appliance models (including operational constraints) are described in Section VII. The theoretical results to be presented in the following sections are valid for any user model that satisfies the assumptions above. A user's utility is defined as the difference between his/her discomfort and the reward reward  $r_i(q_i^t)$  he/she receives:

$$U_i = \sum_{t \in \mathcal{T}} (r_i(q_i^t) - d_i(q_i^t)) \quad (1)$$

In order to offer the rewards  $r_i(q_i^t)$ , the FSP draws on the reward offered by the operator requesting the reduction, as described in the following subsection.

### B. DR-event and the FSP

Let  $L^t$  denote the aggregated consumption of all users in  $\mathcal{N}$ , as seen by the operator, within a certain time interval  $t$ . The energy cost is modeled as a quadratic function of  $L^t$ , (like in [5] - [7], [14], [17], [22]):

$$C(L^t) = c_1 \cdot L^t + c_2 \cdot (L^t)^2$$

Upon a DR-event at  $t$ , let  $D^t$  denote the reduction from baseline consumption  $L_B^t$  to consumption  $L_B^t - D^t$ . The respective cost reduction is:

$$\begin{aligned} C(L_B^t) - C(L_B^t - D^t) &= \\ c_1 \cdot L_B^t + c_2 \cdot (L_B^t)^2 - c_1 \cdot (L_B^t - D^t) - c_2 \cdot (L_B^t - D^t)^2 \end{aligned}$$

which reads:

$$C(L_B^t) - C(L_B^t - D^t) = (c_1 + 2 \cdot c_2 \cdot L_B^t) \cdot D^t - c_2 \cdot (D^t)^2$$

We set  $a = c_1 + 2 \cdot c_2 \cdot L_B^t$  and  $b = c_2$ . The cost benefit  $C(L_B^t) - C(L_B^t - D^t)$  is denoted as a reward function  $R(D^t)$ :

$$R^t(D^t) = a \cdot D^t - b \cdot (D^t)^2, D^t \in [0, L_B^t], \quad (2)$$

where  $a, b$  are positive parameters with  $a \geq 2bL_B^t$  so that it is an increasing function in the range of permitted values. The proposed DR architecture is open to any other choice of  $R^t(D^t)$ , provided it is an increasing and concave function. Thus, we assume that upon a DR-event, the operator offers a marginal per-unit reward for a reduction of  $D^t$  units:

$$\mu = \frac{d(R^t(D^t))}{d(D^t)} \quad (3)$$

## IV. PROBLEM FORMULATION

We would like to facilitate the allocation of consumption reduction among users so as to maximize social welfare. Social welfare is defined as the difference between the revenues  $R^t(D^t)$  that the FSP receives from the operator, as defined in Eq. (2), and the sum of the discomforts caused to its users. This problem is formulated as:

$$\underset{q_i^t \in Q_i, i \in \mathcal{N}}{\text{maximize}} \quad \left\{ R^t(D^t) - \sum_{i \in \mathcal{N}} d_i(q_i^t) \right\} \quad (4)$$

$$\text{subject to} \quad D^t = \sum_{i \in \mathcal{N}} q_i^t. \quad (5)$$

Problem (4) is a convex optimization problem and could be solved efficiently if the local functions  $d_i(q_i^t)$  were known (or truthfully disclosed). However,  $d_i(q_i^t)$  of each user is not known and thus, problem (4) is typically solved via dual decomposition in the DR literature. In this approach, the FSP iteratively increases a per-unit reward  $\lambda$  asking the users their consumption reduction  $q_i^t(\lambda)$  at each per-unit reward  $\lambda$  (auction query). At each iteration, each user  $i$  responds with his/her preferred  $q_i^t(\lambda)$ . A truthful (locally optimal) response by user  $i$ , denoted as  $\tilde{q}_i^t(\lambda)$ , is the one that maximizes  $i$ 's utility for reward  $\lambda$ . This is mathematically formulated as the solution to maximization problem (6):

$$\tilde{q}_i^t(\lambda) = \underset{q_i^t \in Q_i, i \in \mathcal{N}}{\text{argmax}} \{ \lambda \cdot q_i^t - d_i(q_i^t) \} \quad (6)$$

Clearly,  $\tilde{q}_i^t(\lambda)$  is non-decreasing in  $\lambda$ , since  $q_i^t \geq 0$ . The auction terminates when  $\lambda$  reaches a value for which  $\sum_{i \in \mathcal{N}} \tilde{q}_i^t(\lambda) = D^t(\lambda)$ . The final price is called the market-clearing price and is denoted by  $\lambda_{mc}$ . The allocation at  $\lambda_{mc}$  is efficient if the users truthfully report their  $q_i^t$  at each query. However, truthful report may not be the best strategy for every user. To illustrate this, we present the following example:

### Illustrative Example

Consider two users and a given timeslot  $t$ . User 1 operates a load of 10 kW while user 2 operates a 50 kW load. Their discomfort function is  $d_i(q_i^t) = \omega_i \cdot (q_i^t)^2, i \in \{1, 2\}$ , where their true flexibility parameters are  $\omega_1 = \omega_2 = 0.1$ . The reward function is  $R^t(D^t) = 5 \cdot (D^t)$ . Should they act according to their true discomfort function parameters, their utilities (given by Eq. 1) at equilibrium would be  $U_1 = U_2 = 4.875$ . In case User 2 acts untruthfully according to  $\omega_2^{fake} = 0.2$ , his/her utility at equilibrium will be  $U_2 = 7$ . Therefore, the best strategy for User 2 is to be untruthful. ■

The previous *example* demonstrates how the market-clearing approach builds on the assumption that users behave myopically, by truthfully solving (6) at each iteration. The problem is that if we relax the truthfulness assumption and consider strategic users, market-clearing methods no longer result in efficient allocations. Thus, it is very important to design a mechanism that is not only efficient but also incentive compatible.

The Vickrey-Clarke-Groves (VCG) mechanism is the unique mechanism that is simultaneously truthful and efficient [21]. The VCG payment rule is the so called "Clarke pivot rule", which rewards each user  $i$  with an amount equal to the difference that  $i$ 's presence makes in the welfare of other users. In the direct VCG mechanism, users are asked to declare their local functions  $d_i(q_i^t)$  to the FSP (like in [22]). Because of the Clarke pivot rule, it is a dominant strategy for each user to make a truthful declaration [43]. In order to calculate the VCG rewards, problem 4 is solved  $|\mathcal{N}|+1$  times (one time with each user in  $\mathcal{N}$  absent to calculate the payments, plus one time with all users present to calculate the allocation). The major drawback of the direct VCG mechanism is the requirement that the users disclose their discomfort functions  $d_i(q_i^t)$  to the FSP. This raises important issues such as privacy and difficulty of

implementation. In the next section, we propose a modification of Ausubel's Clinching auction [44], allowing for a distributed implementation of VCG, designed to tackle these issues.

### V. AUSUBEL'S CLINCHING AUCTION FOR DR-EVENT PARTICIPATION

The Clinching Auction (CA) is a well-known ascending price auction that halts when demand equals supply. However, in contrast to most auctions, allocation and rewards are not cleared exclusively at the final iteration. Rather, the goods (consumption reduction in our context) are progressively allocated as the auction proceeds and payments are also progressively built, while the auction design guarantees that the final allocation and payments coincide with the ones obtained through VCG. Thus, both allocation efficiency and incentive compatibility are achieved, while the aforementioned privacy and implementation drawbacks of the direct-VCG mechanism are effectively addressed.

In order for the CA to work in our setting, first we need to reverse the price trajectory. In the proposed Modified Clinching Auction (MCA), the FSP begins with a per-unit reward  $\lambda = \lambda_{max}$  and in each iteration  $k$  the price  $\lambda^k$  is reduced by a small positive number  $\varepsilon$ . The size of  $\varepsilon$  adjusts the discretization level of MCA. By Eq. 3, reward  $\lambda_{max}$  is  $\frac{d(R^t(0))}{d(\Delta L^t)} = a$ , which, as analyzed in Section III, is the highest value possible given that  $R^t$  is concave. Users respond by bidding their preferred reduction  $\tilde{q}_i^t(\lambda)$  for each  $\lambda$ . We represent the user's response at  $\lambda$  as the solution to the user utility maximization problem (which is formally defined in Eq. 6 of the previous section).

The user's objective function is concave in  $q_i^t$ , since  $\lambda \cdot q_i^t$  is linearly increasing and  $d_i(q_i^t)$  is convex by Assumption 2. Also, the solution  $q_i^t$  is increasing in  $\lambda$ , which means that the user's response  $\tilde{q}_i^t$  gradually decreases as  $\lambda$  decreases. For the MCA, we relax constraint (5) to the inequality:

$$D^t \geq \sum_{i \in \mathcal{N}} q_i^t \quad (7)$$

Consider an arbitrary iteration  $k$  of the MCA and let  $D^t(\lambda^k)$  denote the operator's desired reduction for per-unit reward  $\lambda^k$ . The central idea of the MCA is the following: if there is a set  $\mathcal{N}^j \subset \mathcal{N}$  for which we have

$$D^t(\lambda^k) - \sum_{j \in \mathcal{N}^j} \tilde{q}_j^t(\lambda^k) > 0 \quad (8)$$

then we allocate a reduction equal to  $\zeta_i^k = D^t(\lambda^k) - \sum_{j \in \mathcal{N}^j} \tilde{q}_j^t(\lambda^k)$  to each user  $i \notin \mathcal{N}^j$  at a per-unit reward  $\lambda^k$ . We then say that user  $i$  "clinched"  $\zeta_i^k$  units. The MCA auction terminates when set  $\mathcal{N}^j$  that satisfies condition (8) and set  $\mathcal{N}$ , are equal, that is, constraint (7) is satisfied. After that, it allocates the remaining  $D^t(\lambda^{(k-1)})$  proportionally to the users that bid in the second-to-last iteration. Algorithm 1 below, describes the proposed MCA.

We are now in a position to prove the optimality of MCA in terms of social welfare performance:

**Theorem 1.** *The social welfare loss at the final allocation of MCA is within  $\frac{\varepsilon^2 + \lambda_{max} \cdot \varepsilon}{2b}$  of the maximum possible.*

### Algorithm 1 MCA : Modified Clinching Auction

- 1: Initialize  $\lambda^0 = \lambda_{max}$ ,  $q_i^t(\lambda_{max})$ ,  $D^t(\lambda_{max})$ ,  $k = 0$
- 2: **while**  $D^t(\lambda^k) < \sum_{i \in \mathcal{N}} \tilde{q}_i^t(\lambda^k)$  **do**
- 3:   **if** there exists  $\mathcal{N}^j : \sum_{j \in \mathcal{N}^j} \tilde{q}_j^t(\lambda^k) < D^t(\lambda^k)$  **then**
- 4:     clinched units  $\zeta_i^k = D^t(\lambda^k) - \sum_{j \in \mathcal{N}^j} \tilde{q}_j^t(\lambda^k)$  for all  $i \notin \mathcal{N}^j$  at per-unit reward  $\lambda^k$
- 5:   **else**
- 6:     set  $\lambda^{(k+1)} = \lambda^k - \varepsilon$  and  $k = k + 1$
- 7:     ask each user a reduction query for  $\lambda^k$  and collect the responses  $q_i^t(\lambda^k)$
- 8:     ask the operator for the desired total reduction  $D^t(\lambda^k)$  at per-unit reward  $\lambda^k$
- 9:   **end if**
- 10: **end while**
- 11: Clinch units  $\zeta_i^k = \left( q_i^t(\lambda^{k-1}) - \sum_{\xi=0}^{k-1} \zeta_i^\xi \right) \cdot \frac{D^t(\lambda^{k-1})}{\sum_{i \in \mathcal{N}} q_i^t(\lambda^{k-1})}$  at per-unit reward  $\lambda^{k-1}$ , for each  $i \in \mathcal{N}$

*Proof.* The Proof is given in Appendix A. □

Since we cope with a real-time application, the trade-off between the mechanism's optimality and its computational time is of special importance. The latter directly relates to the price-step  $\varepsilon$ , which means that Theorem 1 gives a quantification of the trade-off described. In practice, for the relevant use cases of price-anticipating users (described in the introduction), the computational complexity of the MCA is small, which allows for a very small choice of  $\varepsilon$ . To emphasize this, it is useful to state the following corollary to Theorem 1.

**Corollary 1.** *for  $\varepsilon \ll 1$ , the welfare loss grows linearly with  $\varepsilon$ .*

Because the MCA includes a price-sensitive response also at the operator's side, we have to verify that the properties of efficiency and incentive compatibility still hold. This is proved in the following Propositions.

**Proposition 1.** *Truthful bidding is a dominant strategy in MCA.*

*Proof.* The proof is given in Appendix B. □

Furthermore, the following properties of the VCG mechanism hold also for the MCA:

**Proposition 2.** *MCA is individually rational, weakly budget-balanced, and achieves the maximum revenue for the FSP among all efficient and individually rational mechanisms.*

*Proof.* The proof is given in Appendix C. □

### VI. PRIVACY-PRESERVING DISTRIBUTED IMPLEMENTATION

In the MCA auction users are only required to respond to a specific sequence of queries, instead of communicating their discomfort function. Thus, each participant solves an optimization problem in parallel, while the mechanism still achieves the VCG outcome (and its nice properties). This allows the exploitation of blockchain services towards a DR

architecture which is not only efficient and truthful but also privacy-aware. In this section, we demonstrate how exactly the proposed optimal and incentive compatible mechanism can be configured with a scalable and privacy-preserving communication protocol that instantiates blockchain services. For this purpose, we exploit [45].

The proposed DR architecture exploits blockchain services [46], which are based on Distributed Hash Tables (DHT) [47] technologies, in order to execute MCA in a distributed fashion. In this context, users do not inform the FSP about their answers to the MCA's queries. Instead, the necessary aggregations are realized via a DHT, which is based on the scheme proposed by Kademia [45]. Each user (node) is identified by a number (nodeID) that can be seen as a point in a specific virtual space. The nodeIDs do not serve only as identification, but they are also used for answering data base queries. Each piece of information is given as input to a hash function whose output belongs to the virtual space. Each node is responsible for a sub space of this virtual space according to its nodeID. Furthermore, participating nodes create and dynamically maintain routing tables in a bottom-up and self-organized way. Thus, they can collectively reach any point of this virtual space, by exploiting their routing tables, in order to store and get information. The distributed execution of MCA (DE-MCA) takes place through the following processes (see Algorithm 1 for the centralized version):

*Process A - Data insertion:* Each node  $i$  stores its bid  $\tilde{q}_i^t(\lambda^k)$  in another random node  $w$  through the use of the DHT system [47]. In more detail,  $i$  hashes its id and stores  $\tilde{q}_i^t(\lambda^k)$  and  $k$  in node  $w$  which is responsible for this id, based on the Kademia architecture. It is highlighted that  $w$  is different for each  $i$  and  $k$ , as it is derived from the output of the hash function that Kademia uses. This means that the set of nodes which are responsible for a specific data set is not determined from the data set owners. Thus, collusion of a relatively small number of malicious users to compromise privacy will fail.

*Process B - Calculation of sums:* The MCA algorithm requires the calculation of  $n+1$  different sums at each iteration  $k$ . These are the  $n$  sums noted as  $\sum_{j \in \mathcal{N}^j} \tilde{q}_j^t(\lambda^k)$  (one for each user absent) and the sum  $\sum_{i \in \mathcal{N}} \tilde{q}_i^t(\lambda^k)$  of all user bids (see Algorithm 1). The proposed system exploits a tree structure and develops a distributed algorithm in order to calculate these sums. To do so, each node  $w$  that participates in the calculation requests from the subset of nodes in its routing tables, that dispose lower nodeID from it, to inform  $w$  on possible data values which they dispose in order to send them to  $w$ . The term "possible data values" refers to the aggregation of bids (up to  $w$ ) for iteration  $k$  of MCA that is executed at that time instance. This process continues recursively until node  $MAX$ , which is the node with the highest id acquires the desirable data and calculates the sum  $\sum_{i \in \mathcal{N}} \tilde{q}_i^t(\lambda^k)$ . At this point, this node also requests and receives  $D^t(\lambda^k)$  and checks the termination condition of MCA. If the termination condition doesn't hold,  $MAX$  proceeds by broadcasting  $\sum_{i \in \mathcal{N}} \tilde{q}_i^t(\lambda^k)$  and  $D^t(\lambda^k)$  to all nodes by using the aforementioned Kademia tree.

*Process C - Calculation of  $\zeta_i^k(\lambda^k)$ :* Each node  $w$  cal-

culates  $\zeta_i^k(\lambda^k)$  by subtracting from the broadcasted sum  $\sum_{i \in \mathcal{N}} \tilde{q}_i^t(\lambda^k)$ , the value that is stored in it. Note that this is not its own  $\tilde{q}_i^t(\lambda^k)$  value, and it doesn't know whose it is. If the result is negative then it sets  $\zeta_i^k(\lambda^k) = 0$ .

*Process D - Tuple update:* It is highlighted here that in each iteration of MCA (e.g. the next iteration  $k+1$ ) a different instance of Kademia tree is created, so that  $\zeta_i^{k+1}(\lambda^{k+1})$  is stored at a new node  $w^{k+1}$ , other than  $w^k$ . Thus, even in the case that a set of nodes are malicious, data privacy is not compromised. The tuple  $A_i^k = \{\sum_{\xi=1}^k \zeta_i^\xi(\lambda^\xi), \lambda^\xi \cdot \sum_{\xi=1}^k \zeta_i^\xi(\lambda^\xi)\}$ , containing the allocation and payments of user  $i$  until iteration  $k$ , is updated and passed from node  $w^k$  to  $w^{k+1}$ .

*Process E - Final allocation and payments:* At the final iteration, the updated tuples  $A_i^z$  are communicated to the FSP. Note that the FSP receives only the final allocation and payments for each user, i.e. only the sum  $\sum_{k=1}^z \zeta_i^k(\lambda^k)$  and not the intermediate values  $\zeta_i^k(\lambda^k)$ . In this way the aforementioned architecture ensures that the FSP and every other node that participates in the system do not have the data to estimate the local discomfort function  $d_i(\cdot)$  of user  $i$ .

In Algorithm 2, the distributed execution of MCA is described. In case of a malicious FSP (i.e. with no hesitations to break the law), more strict privacy assumptions are needed, but this case is outside the scope of the present work. The interested reader can refer to the recent literature of privacy-preserving aggregation for the smart grid [30]- [38].

Since we cope with real-time DR it is important to note that, except for line 18 (distributed calculation of sum), all other operations of DE-MCA require constant time. Also, as is well known in DHTs, the latency of line 18 increases logarithmically with the number of users. This results in a very scalable implementation of the VCG mechanism, suitable for real-time DR. We also verify this property in the next section.

## VII. USER MODELS & PERFORMANCE DEMONSTRATION

In this section, we present detailed appliance models taken from the literature and then use simulations to demonstrate the advantages of the MCA and verify its properties. We also compare MCA with the marginal cost pricing method [6] in terms of truthfulness and FSP's profits and with the direct-revelation VCG method [22] in terms of scalability. Simulations were run in Matlab R2018b.

### A. Detailed appliance models

The first model is taken from [6] and includes appliances that control the temperature of an environment, such as HVAC units. The user's most preferable temperature is denoted by parameter  $T_i^{pref}(t)$  and was taken in our experiments to be uniformly distributed in the interval [75F,79F]. The actual room temperature, denoted by  $T_i^{in}(t)$ , evolves according to

$$T_i^{in}(t) = T_i^{in}(t-1) + \eta \cdot [T_i^{out}(t) - T_i^{in}(t-1)] + \theta \cdot (p_{i,HVAC}^t - q_{i,HVAC}^t) \quad (9)$$

where  $p_{i,HVAC}^t$  is the user's measurable power consumption before the DR-event occurrence and  $q_{i,HVAC}^t$  is the curtailment resulting from the DR-event. Clearly, we have

$$p_{i,HVAC}^t - q_{i,HVAC}^t \geq 0, \quad (10)$$

**Algorithm 2** DE-MCA : Distributed Execution of Modified Clinching Auction

- 1: FSP sets  $\varepsilon$ , initializes  $\lambda^0 = \lambda_{max}$ ,  $k = 0$ , tuples  $A_i^0 = \{0, 0\}$  and communicates them to all nodes
- 2: Each node  $i$  receives  $\lambda^0$  and calculates  $\tilde{q}_i^t(\lambda^0)$
- 3: Instance 0 of Kademia tree is created (its root is noted as  $MAX^0$ )
- 4: Data insertion (each node  $i$  puts  $\tilde{q}_i^t(\lambda^0)$  to instance 0 of Kademia tree, see *Process A*)
- 5: Distributed calculation of  $\sum_{i \in \mathcal{N}} \tilde{q}_i^t(\lambda^k)$  which ends at node  $MAX^0$  (see *Process B*)
- 6: Node  $MAX^0$  requests  $D^t(\lambda^k)$  from FSP and checks the termination condition
- 7: **while**  $D^t(\lambda^k) < \sum_{i \in \mathcal{N}} \tilde{q}_i^t(\lambda^k)$  **do**
- 8: Node  $MAX^k$  broadcasts  $\sum_{i \in \mathcal{N}} \tilde{q}_i^t(\lambda^k)$  to all nodes
- 9: Each node  $w^k$  in Kademia tree, (where  $w^k \neq i$ ) calculates  $\zeta_i^k(\lambda^k)$  (see *Process C*)
- 10: Node  $w^k$  updates the tuple  $A_i^k$
- 11: Node  $MAX^k$  sends to FSP signal to set  $k = k + 1$
- 12: FSP sets  $k = k + 1$  and  $\lambda^k = \lambda^{k-1} - \varepsilon$
- 13:  $k^{th}$  Kademia tree instance is created
- 14: Each node  $w^{k-1}$  passes tuple  $A_i^{k-1}$  to node  $w^k$  (*Process D*)
- 15: Node  $MAX^k$  communicates  $\lambda^k$  to all nodes
- 16: User  $i$  receives  $\lambda^k$  and calculates  $\tilde{q}_i^t(\lambda^k)$
- 17: Data insertion (each user  $i$  puts  $\tilde{q}_i^t(\lambda^k)$  to instance  $k$  of Kademia tree, see *Process A*)
- 18: Distributed calculation of  $\sum_{i \in \mathcal{N}} \tilde{q}_i^t(\lambda^k)$  at node  $MAX^k$  (see *Process B*)
- 19: Node  $MAX^k$  requests  $D^t(\lambda^k)$  from FSP and checks the termination condition
- 20: **end while**
- 21:  $MAX^k$  receives  $D^t(\lambda^k)$  and broadcasts  $\sum_{i \in \mathcal{N}} \tilde{q}_i^t(\lambda^k)$  and  $D^t(\lambda^k)$  to all nodes
- 22: Each node  $w^k$  calculates  $\zeta_i^k(\lambda^k) = (\tilde{q}_i^t(\lambda^k) - \sum_{\xi=0}^k \zeta_i^\xi) \cdot \frac{D^t(\lambda^k)}{\sum_{i \in \mathcal{N}} \tilde{q}_i^t(\lambda^k)}$  and updates tuple  $A_i^k$
- 23: All nodes communicate  $A_i^k$  to FSP (*Process E*)

and we also have the operational constraint

$$p_{i,HVAC}^t \leq p_{i,max}^t, \quad (11)$$

In the experiments  $p_{i,max}^t$  was set to 5 kW. Outdoors temperature  $T^{out}(t)$  was the same for all users and represented a typical summer day in Athens. Parameters  $\eta$  and  $\theta$  were set to 0.9 and 3, respectively. The discomfort for such users was defined as the square difference between actual and desired temperatures:

$$d_i^{temp}(q_i^t) = \omega_{i,HVAC}^{temp} \cdot \left( T_i^{in}(t) - T_i^{pref}(t) \right)^2 \quad (12)$$

where parameter  $\omega_{i,HVAC}^{temp}$  expresses the user's inelasticity in timeslot  $t$  and was randomly selected in the range [0.10, 0.50].

The second model represents temporally flexible loads (e.g., EVs) and is taken from [16]. The EV is plugged-in at timeslot  $\gamma_i$  (uniformly selected in the interval [3,9], for one third of

the users and in the interval [14,20] for the remaining two thirds). Each EV charges at power  $p_{i,EV}^t$  and has a total demand of  $E_{i,EV}$  kWhs, where  $E_{i,EV}$  was uniformly selected in the interval [6,36]. The user wants the EV to be charged as soon as possible and any delay would bring discomfort. This model accurately represents en-route charging EVs. The desired charging duration, denoted as  $\delta_i$ , was set to  $\delta_i = 3$  timeslots for all users. The upper power limit  $p_{i,max}^t$ , was selected as  $p_{i,max}^t = \frac{E_{i,EV}}{\delta_i}$ . That is, if no DR-events occurred, each user would charge his/her EV in 3 consequent timeslots. An EV operational constraint is given as

$$p_{i,EV}^t \leq p_{i,max} \quad (13)$$

The EV cannot be charged before arrival:

$$p_{i,EV}^t = 0, t < \gamma_i \quad (14)$$

and must be fully charged before leaving:

$$\sum_{t \in \mathcal{T}} p_{i,EV}^t \geq E_{i,EV}. \quad (15)$$

During a DR-event a user may choose to curtail  $q_{i,EV}^t$  units and shift charging to a later timeslot. This delayed charging (for timeslots after  $\gamma_i + \delta_i - 1$ ), comes with a discomfort defined as

$$d_{i,EV}^{wait}(q_{i,EV}^t) = \sum_{t \in \{\mathcal{T} | t \geq \gamma_i + \delta_i\}} [(\omega_{i,EV}^{wait})^{t - \gamma_i - \delta_i + 1} \cdot p_{i,EV}^t] \quad (16)$$

where parameter  $\omega_{i,EV}^{wait}$  expresses the user's inelasticity and was uniformly selected in [1, 1.5].

### B. Simulation Results

Over a time horizon of 24 timeslots, with a duration of 15 minutes for each timeslot and for a setting of 50 users, we simulated a DR event in timeslot 17 (where there was a peak in the aggregated consumption). The parameters of the reward function were set to  $a = 3$  and  $b = 0.05$ . We used step  $\varepsilon = 10^{-3}$  in the MCA algorithm. Fig. 2 depicts the aggregated consumption along all 24 timeslots. As the figure shows, there is a consumption curtailment in timeslot 17 and a consequent shift of consumption to timeslot 20. Note that it could not be shifted to timeslots 18 or 19 because constraints (11) and (13) where already tight for these timeslots.

Next, we investigate the effect that cheating has on the FSP's profits, denoted by  $\Pi^{truthful}$  for the case where users act truthfully and by  $\Pi^{cheat}$  for the case where they act according to what brings them the highest utility. We plot the ratio  $\Pi^{cheat} / \Pi^{truthful}$  for different values of users' elasticities  $\{\omega_{i,HVAC}^{temp}, \omega_{i,EV}^{wait}\}$ . To do so, for each experiment we multiply the users' elasticity parameters by a positive factor  $\omega_f$ . Higher values of  $\omega_f$  indicate more inelastic users. Fig. 3 shows that the ratio  $\Pi^{cheat} / \Pi^{truthful}$  is maximized and is equal to 1 for the MCA, verifying our theoretical results. For the marginal cost pricing method [6], the FSP's profit loss due to untruthfulness rises with  $\omega_f$  (i.e., when users are less elastic), indicating that our scheme's truthfulness property becomes more important in markets where participants are not particularly flexible.

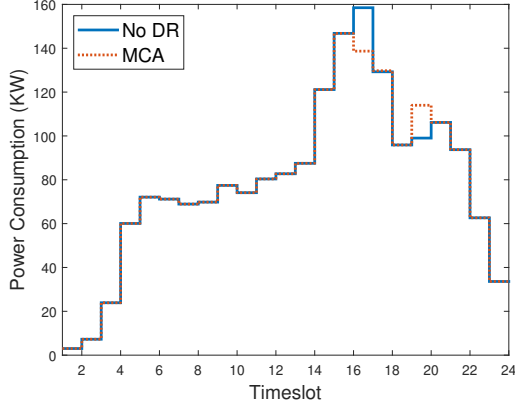


Fig. 2: Aggregated consumption as a function of time with and without the DR-event

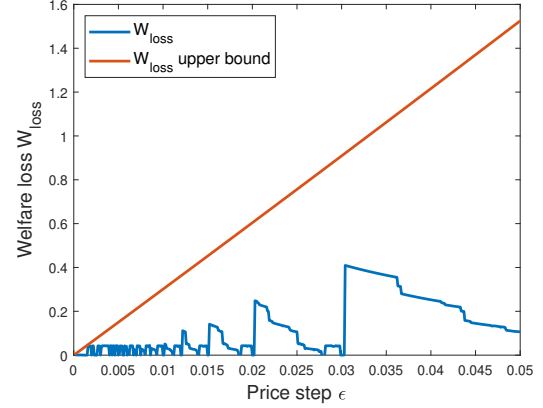


Fig. 4: Proportional welfare loss of MCA as a function of the price step  $\varepsilon$

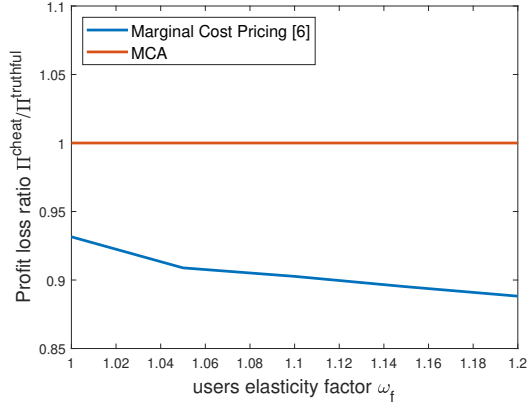


Fig. 3: Ratio  $\Pi^{cheat}/\Pi^{truthful}$  as a function of  $\omega_f$

Next, we simulated the DR-event for different values of the step  $\varepsilon$ , measuring the proportional welfare loss

$$W_{loss} = \frac{W_{opt} - W_{MCA}}{W_{opt}}, \quad (17)$$

where  $W_{opt}$  is the optimal welfare and  $W_{MCA}$  is the welfare achieved by the MCA. The simulation results in Fig. 4 verify Corollary 1, which states that for small values of  $\varepsilon$  the upper bound on the welfare loss grows linearly with  $\varepsilon$ .

Finally, we compare MCA to the direct-revelation VCG method (proposed in [22]), in terms of scalability with respect to the number of users. Simulations are carried out on an Intel Core i7 4GHz, 64-bit, 16GB RAM, computer. The computational time of the method in [22] rises very quickly, which makes it impractical for real-time applications. In contrast, MCA scales remarkably well to any number of users, since the algorithm's convergence time does not depend on the size of set  $\mathcal{N}$ . In order to evaluate the latency of DE-MCA we assumed that the data network introduces a network delay (between any two nodes) that follows a uniform distribution between 5ms and 15ms. Fig. 6 depicts the latency introduced by DE-MCA. It is defined as the total time overhead that the proposed distributed implementation introduces due to data network delays between any two data network nodes. As

it is known theoretically, in DHT technologies, this latency increases logarithmically with the number of users. This is verified in Fig. 6. In comparison to the timeslot duration (e.g. 15 minutes, which is a typical granularity for measurements and clearing of the balancing market), these results show that the proposed system is both scalable and efficient.

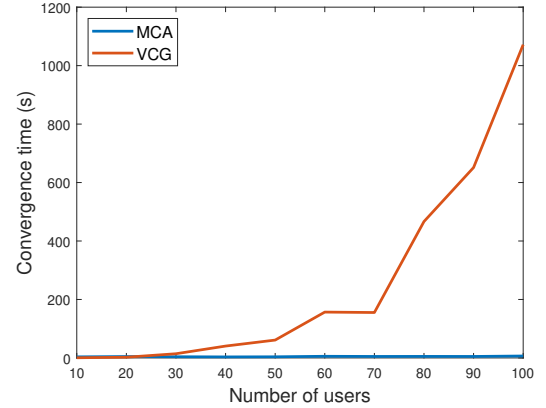


Fig. 5: Convergence time of MCA and VCG, as a function of the number of users

### C. Incentive Compatibility and the case of inelastic appliances

In this subsection we discuss the property of incentive compatibility. We verify the theoretical result of Proposition 1 and also experimentally study incentive compatibility in the case of inflexible appliances (where our Assumptions are not satisfied). We assume that one user misinterprets his/her discomfort by manipulating his/her  $\omega_{i,EV}^{wait}$ . The untruthful user is indexed by  $ch$  (for cheater). The cheater's utility  $U_{ch}$  is maximized for a certain choice of  $\omega_{ch}$ . Fig. 7 shows  $U_{ch}$  as a function of  $\omega_{ch}$ .

The black vertical line represents the focal user's real  $\omega_{i,EV}^{wait}$ , denoted as  $\omega_{real}$ . For the MCA, the user's optimal choice of  $\omega$  (where  $U_{ch}$  is maximized) coincides with  $\omega_{real}$ , which means that the user's best strategy is to act truthfully, in contrast to the marginal cost pricing method.



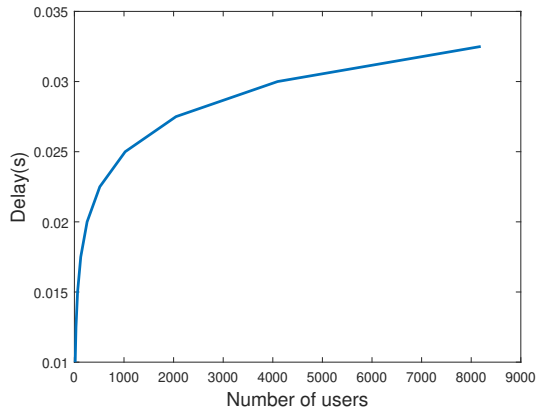


Fig. 6: Delay (latency) of privacy preserving protocol as a function of the number of participating users

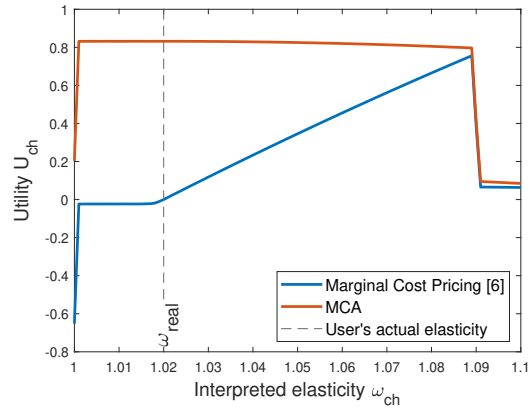


Fig. 7: Focal user's utility as a function of  $\omega_{ch}$

The result of Fig. 7 was expected, since it was already proven in Proposition 1. Although we cannot state a similarly strong theoretical guarantee for inflexible users, nevertheless our simulations show similar results. We study the case where an appliance is inflexible (Type 2 appliances of [14]), in the sense that it can only be turned on or off, but its consumption cannot take intermediate values:

$$p_{i,incl}^t \in \{0, p_{i,max}^t\}, \quad (18)$$

and thus,

$$q_{i,incl}^t \in \{0, p_{i,max}^t\}. \quad (19)$$

The user's discomfort for turning his/her load off, is denoted by  $d_{i,incl}^{off}$ . Thus, the user's discomfort function takes the form:

$$d_{i,incl}(q_{i,incl}^t) = \begin{cases} 0, & q_{i,incl}^t = 0 \\ d_{i,incl}^{off}, & q_{i,incl}^t > 0 \end{cases} \quad (20)$$

This kind of appliances violate Assumption 2. In fact, the form of the user's valuation exhibits complementarity (the user can either curtail all  $p_{i,max}^t$  kWhs, but cannot make use of an allocation that is smaller than  $p_{i,max}^t$ ). In the presence of such complementarities there is no tractable iterative auction that can achieve incentive compatibility [48]. We present an extension of MCA that accommodates inflexible users and

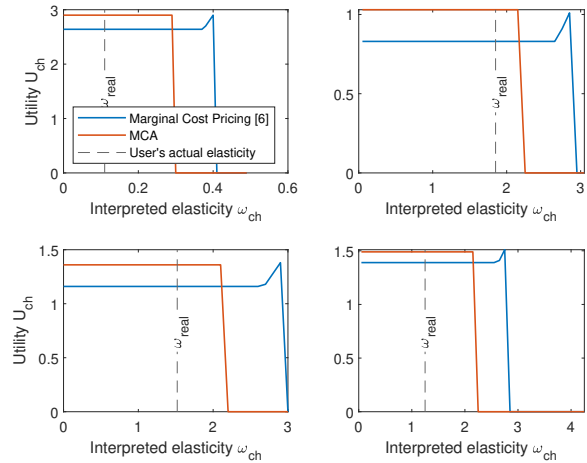


Fig. 8: Users' Utility as a function of user's interpreted elasticity  $\omega$

evaluate it. Although we can no longer guarantee incentive compatibility, nevertheless simulation results show that, in practice, truthful bidding is still the best choice for each user.

Let  $\mathcal{I}$  denote the set of inflexible users. Also, let  $\varkappa$  denote the number of iterations until the auction halts (see Appendix A). The first step is to run the MCA algorithm. Then, we grant the MCA allocations  $\zeta_i^k, \forall k$  only to elastic users  $i \notin \mathcal{I}$ . The remaining reduction  $\sum_{k=1}^{\varkappa} \sum_{i \in \mathcal{I}} \zeta_i^k$ , will be reallocated amongst the inflexible users, in a way that respects constraints (19). This is an instance of the knapsack problem. In order not to compromise the computational time guarantees of our real-time auction, we use a simple heuristic to solve it. Inflexible users are sorted in increasing order of their ‘‘bang-for-buck’’ i.e. their  $d_{i,incl}^{off}/p_{i,max}^t$ . We allocate  $q_{i,incl}^t = p_{i,max}^t$  to user  $i \in \mathcal{I}$ , in increasing order of the sorted list, until  $\sum_{i \in \mathcal{I}} q_{i,incl}^t \geq \sum_{k=1}^{\varkappa} \sum_{i \in \mathcal{I}} \zeta_i^k$ . The procedure is depicted in Algorithm 3.

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#### Algorithm 3 Extended Modified Clinching Auction

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- 1: Run the MCA algorithm
  - 2: set  $q_{i,incl}^t = 0, \forall i \in \mathcal{I}$
  - 3: sort users  $i \in \mathcal{I}$ , in increasing order of  $d_{i,incl}^{off}/p_{i,max}^t$
  - 4: set  $q_{i,incl}^t = p_{i,max}^t$ , for user  $i \in \mathcal{I}$ , in increasing order of the sorted list, until  $\sum_{i \in \mathcal{I}} q_{i,incl}^t \geq \sum_{k=1}^{\varkappa} \sum_{i \in \mathcal{I}} \zeta_i^k$ .
- 

In Fig. 8, we present indicative results for various values of  $p_{i,max}$  and  $d_{i,incl}^{off}$ , regarding truthfulness in the extended MCA. More specifically, we tested how well a user does (in terms of utility  $U_i$ , see Eq. 6), by interpreting his/her elasticity with various (untruthful) values  $\omega_{ch}$ . The user's actual discomfort for curtailing  $p_{i,max}$  units is marked with a vertical dotted line. From the figure, it becomes clear that the user already achieves his/her maximum possible utility, by truthfully interpreting his/her discomfort and has nothing to gain by playing untruthfully. This is, again, in contrast to the marginal cost pricing approach [6].

## VIII. CONCLUSION

In this paper we considered a setting of strategic, intelligent users and an FSP seeking to incentivize them in order to curtail part of their consumption in response to a real-time DR-event. We showcased the inefficiency of previous state-of-the-art approaches, which either do not consider user incentives, or adopt a direct-revelation approach, respectively leading to either lack of truthfulness and consequent inefficiency, or to lack of privacy and scalability. To overcome these shortcomings, we presented a novel iterative auction mechanism that implements the truthful and efficient VCG outcome but also allows for a distributed implementation and a privacy-preserving communication protocol. For this purpose, we identified a suitable mechanism from the field of mechanism design (Ausubel's Clinching auction) and modified it for a setting with continuous items (energy), where the number of items is not fixed but bears a cost function (reward function in our case). We extended the properties of the original mechanism to the modified mechanism that we propose. Furthermore, we proved a theoretical upper bound for the efficiency loss caused by an increase in the price step, which relates to a decrease in the mechanism's computational time.

Our theoretical and simulation results verified that the proposed scheme combines the desired properties with very good performance and small overhead. Moreover, we also implemented appliances that can only be turned on or off without the ability to adjust their power consumption. In our simulations, the proposed mechanism was shown to work very well in the DR setting, even with these types of loads, despite the fact that they do not satisfy the necessary assumptions.

### APPENDIX A

#### PROOF OF THEOREM 1

The value of  $\lambda$  at which  $D^t = \sum_{i \in \mathcal{N}} \tilde{q}_i^t$  is denoted as  $\lambda_{mc}$ , which gives

$$D^t(\lambda_{mc}) = \sum_{i \in \mathcal{N}} \tilde{q}_i^t(\lambda_{mc}). \quad (21)$$

Let  $\varkappa$  denote the number of iterations until the auction halts, that is,

$$\varkappa = \lceil \frac{\lambda_{max} - \lambda_{mc}}{\varepsilon} \rceil, \quad (22)$$

where  $\lceil \cdot \rceil$ , denotes the rounding to the nearest integer above. We have

$$\lceil \frac{\lambda_{max} - \lambda_{mc}}{\varepsilon} \rceil \geq \varkappa \geq 1 + \lceil \frac{\lambda_{max} - \lambda_{mc}}{\varepsilon} \rceil. \quad (23)$$

After the last clinchings (line 11 of Algorithm 1) we have efficiently allocated  $D^t(\lambda^{\varkappa-1})$  reduction units to the users. The remaining  $D^t(\lambda_{mc}) - D^t(\lambda^{\varkappa-1})$  are not allocated and this causes the loss of welfare  $W_{loss}$ , which is depicted as the grey area in Fig. 9, where the red line represents  $D^t(\lambda)$  and the blue line represents  $\sum_{i \in \mathcal{N}} \tilde{q}_i^t(\lambda)$ .

Since we remain agnostic of the closed form of  $\sum_{i \in \mathcal{N}} \tilde{q}_i^t(\lambda^k)$ , we assume the worst case and calculate an upper bound on the sum of the gray plus the yellow area:

$$W_{loss} \geq \lambda_{mc} \cdot (D^t(\lambda_{mc}) - D^t(\lambda^{\varkappa-1})) + \frac{1}{2}(\lambda^{\varkappa-1} - \lambda_{mc}) \cdot (D^t(\lambda_{mc}) - D^t(\lambda^{\varkappa-1})). \quad (24)$$

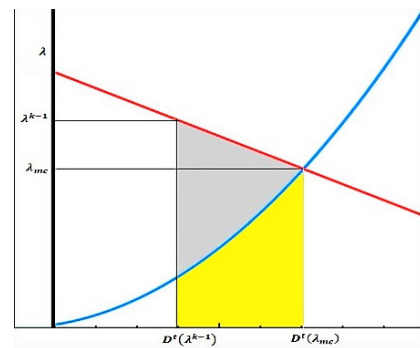


Fig. 9:  $D^t(\lambda)$  and  $\sum_{i \in \mathcal{N}} q_i^t(\lambda)$  as a function of  $\lambda$

By substituting  $D^t(\lambda) = \frac{a-\lambda}{2b}$ , from Eq. 3, we get

$$W_{loss} \geq \frac{\lambda_{mc} \cdot (\lambda^{\varkappa-1} - \lambda_{mc})}{4b} + \frac{\lambda^{\varkappa-1} \cdot (\lambda^{\varkappa-1} - \lambda_{mc})}{4b} \geq \frac{(\lambda^{\varkappa-1})^2 - (\lambda_{mc})^2}{4b}. \quad (25)$$

By further substituting  $\lambda^{\varkappa-1} = \lambda_{max} - \varepsilon \cdot (\varkappa - 1)$  and also substituting  $\varkappa$ , using the left inequality when  $\varkappa$  appears with a minus sign and the right inequality when it appears with a plus sign, we finally obtain

$$W_{loss} \geq \frac{\varepsilon^2 + \lambda_{max} \cdot \varepsilon}{2b} \quad (26)$$

### APPENDIX B

#### PROOF OF PROPOSITION 1

Fix an iteration  $k$  and assume that user  $i$  bids  $q_{i,false}^t(\lambda^k) \neq \tilde{q}_i^t(\lambda^k)$  in that iteration. From step 4 of MCA, we see that  $\zeta_i^k$  does not depend on  $q_i^t$  but only on the other users' bids  $q_j^t, j \neq i$ . Thus, user  $i$ 's bid can affect  $i$ 's allocation only by changing the  $\lambda$  at which the termination condition holds. This means that a false bid  $q_{i,false}^t(\lambda^k)$  will make a difference to  $i$ , only if  $k$  is the last iteration. However, by definition of  $\tilde{q}_i^t(\lambda^k)$  (see Eq. 6), any bid  $q_{i,false}^t(\lambda^k) \neq \tilde{q}_i^t(\lambda^k)$  brings strictly lower utility to user  $i$  at any iteration  $k$ . Thus, truthful bidding brings the highest utility to user  $i$ .

### APPENDIX C

#### PROOF OF PROPOSITION 2

The MCA auction is welfare maximizing (by Theorem 1, for  $\varepsilon$  small enough) and truthful (by Proposition 1). Moreover, the class of VCG mechanisms is the unique class that simultaneously achieves these two properties [21]. Since MCA terminates with the VCG allocation and payments, it inherits the property of individual rationality.

Regarding the weak budget balance property, it suffices to show that our setting exhibits the no single-agent effect [2] 10.4.4. This is true if the aggregated utility of  $n-1$  users does not improve by adding a  $n$ -th user to the system. This property holds in single-sided auctions with monotonous preferences, since dropping a user only reduces the competition for the remaining users, thus making them better-off. Moreover, by [49], the VCG mechanism maximizes the auctioneer's utility,

which means that the FSP buys flexibility units from the users at the lowest possible price (among all efficient and individually rational mechanisms).

## REFERENCES

- [1] F. Ruelens, B. J. Claessens, S. Vandael, B. De Schutter, R. Babuška and R. Belmans, "Residential Demand Response of Thermostatically Controlled Loads Using Batch Reinforcement Learning", in *IEEE Transactions on Smart Grid*, vol. 8, no. 5, pp. 2149-2159, Sept. 2017.
- [2] Y. Shoham, K. Leyton-Brown, "Multiagent Systems", Cambridge University Press, 2009
- [3] N. Nisan, M. Schapira, G. Valiant, A. Zohar, "Best-response mechanisms", *Proc. ICS*, pp. 155-165, 2011.
- [4] R. Johari, S. Mannor, and J. Tsitsiklis, "Efficiency loss in a network resource allocation game: The case of elastic supply", *IEEE Trans. On Automatic Control*, vol. 50, no. 11, pp. 1712-1724, Nov. 2005.
- [5] P. Samadi, A. H. Mohsenian-Rad, R. Schober, V. W. S. Wong and J. Jatskevich, "Optimal Real-Time Pricing Algorithm Based on Utility Maximization for Smart Grid", 2010 First IEEE International Conference on Smart Grid Communications, Gaithersburg, MD, 2010, pp. 415-420.
- [6] N. Li, L. Chen and S. H. Low, "Optimal demand response based on utility maximization in power networks", 2011 IEEE Power and Energy Society General Meeting, Detroit, MI, USA, pp. 1-8, 2011.
- [7] L. Gkatzikis, I. Koutsopoulos, and T. Salonidis, "The role of aggregators in smart grid demand response markets", *IEEE Journal on Selected Areas in Communications*, vol. 31, no. 7, pp. 1247-1257, Jul. 2013.
- [8] S. Althaher, P. Mancarella and J. Mutale, "Automated Demand Response From Home Energy Management System Under Dynamic Pricing and Power and Comfort Constraints", in *IEEE Transactions on Smart Grid*, vol. 6, no. 4, pp. 1874-1883, July 2015.
- [9] Z. Wang and R. Paranjape, "Optimal Residential Demand Response for Multiple Heterogeneous Homes With Real-Time Price Prediction in a Multiagent Framework", in *IEEE Transactions on Smart Grid*, vol. 8, no. 3, pp. 1173-1184, May 2017.
- [10] G. Tsaousoglou, P. Makris, E. Varvarigos, "Electricity market policies for penalizing volatility and scheduling strategies: The value of aggregation, flexibility, and correlation", *Sust. Energy, Grids and Networks (SEGAN)*, vol.12, pp. 57-68, Dec. 2017.
- [11] M. Ahmadi, J. M. Rosenberger, W. J. Lee and A. Kulvanitchaiyanunt, "Optimizing Load Control in a Collaborative Residential Microgrid Environment", in *IEEE Transactions on Smart Grid*, vol. 6, no. 3, pp. 1196-1207, May 2015.
- [12] D. T. Nguyen and L. B. Le, "Joint Optimization of Electric Vehicle and Home Energy Scheduling Considering User Comfort Preference", in *IEEE Transactions on Smart Grid*, vol. 5, no. 1, pp. 188-199, Jan. 2014.
- [13] O. Erdiñç, A. Taşcıkaraoğlu, N. G. Paterakis, Y. Eren and J. P. S. Catalão, "End-User Comfort Oriented Day-Ahead Planning for Responsive Residential HVAC Demand Aggregation Considering Weather Forecasts", in *IEEE Transactions on Smart Grid*, vol. 8, no. 1, pp. 362-372, Jan. 2017.
- [14] S. Mhanna, A. C. Chapman and G. Verbič, "A Fast Distributed Algorithm for Large-Scale Demand Response Aggregation", in *IEEE Transactions on Smart Grid*, vol. 7, no. 4, pp. 2094-2107, July 2016.
- [15] L. P. Qian, Y. J. A. Zhang, J. Huang and Y. Wu, "Demand Response Management via Real-Time Electricity Price Control in Smart Grids", in *IEEE Journal on Selected Areas in Communications*, vol. 31, no. 7, pp. 1268-1280, July 2013.
- [16] A. H. Mohsenian-Rad and A. Leon-Garcia, "Optimal Residential Load Control With Price Prediction in Real-Time Electricity Pricing Environments", in *IEEE Transactions on Smart Grid*, vol. 1, no. 2, pp. 120-133, Sept. 2010.
- [17] P. Jacquot, O. Beaudé, S. Gaubert and N. Oudjane, "Demand response in the smart grid: The impact of consumers temporal preferences", 2017 IEEE International Conference on Smart Grid Communications (SmartGridComm), Dresden, pp. 540-545, 2017.
- [18] G. Tsaousoglou, N. Eftymiopoulos, P. Makris, E. Varvarigos, "Personalized real time pricing for efficient and fair demand response in energy cooperatives and highly competitive flexibility markets", *Journal of Modern Power Systems and Clean Energy* vol. 7, Issue 1, pp. 151-162, Jan. 2019.
- [19] K. Steriotis, G. Tsaousoglou, N. Eftymiopoulos, P. Makris, E. Varvarigos, "A novel behavioral real time pricing scheme for the active consumers' participation in emerging flexibility markets", *Sust. Energy, Grids and Networks (SEGAN)*, vol.16, pp. 14-27, Dec. 2018.
- [20] K. Steriotis, G. Tsaousoglou, N. Eftymiopoulos, P. Makris and E. Varvarigos, "Development of real time energy pricing schemes that incentivize behavioral changes", 2018 IEEE International Energy Conference (ENERGYCON), Limassol, Cyprus, pp. 1-6, 2018.
- [21] J. Green, J.J. Laffont, "Characterization of Strongly Individually Incentive Compatible Mechanisms for the Revelation of Preferences for Public Goods", *Econometrica*, vol.45, pp.427-438, 1977.
- [22] P. Samadi, A. H. Mohsenian-Rad, R. Schober, V. W. S. Wong, "Advanced demand side management for the future smart grid using mechanism design", *IEEE Transactions on Smart Grid*, vol. 3, no. 3, pp. 1170-1180, Sep. 2012.
- [23] E. Nekouei, T. Alpcan and D. Chattopadhyay, "Game-Theoretic Frameworks for Demand Response in Electricity Markets", in *IEEE Transactions on Smart Grid*, vol. 6, no. 2, pp. 748-758, March 2015.
- [24] N. Yaagoubi and H. T. Mouftah, "User-Aware Game Theoretic Approach for Demand Management", in *IEEE Transactions on Smart Grid*, vol. 6, no. 2, pp. 716-725, March 2015.
- [25] J. Ma, J. Deng, L. Song and Z. Han, "Incentive Mechanism for Demand Side Management in Smart Grid Using Auction", in *IEEE Transactions on Smart Grid*, vol. 5, no. 3, pp. 1379-1388, May 2014.
- [26] A. C. Chapman and G. Verbič, "An Iterative On-Line Auction Mechanism for Aggregated Demand-Side Participation", in *IEEE Transactions on Smart Grid*, vol. 8, no. 1, pp. 158-168, Jan. 2017.
- [27] G. Tsaousoglou, K. Steriotis, N. Eftymiopoulos, K. Smpoukis and E. Varvarigos, "Near-optimal demand side management for retail electricity markets with strategic users and coupling constraints", *Sustainable Energy, Grids and Networks*, Sep. 2019.
- [28] S. Li, W. Zhang, J. Lian and K. Kalsi, "Market-based coordination of thermostatically controlled loads-Part I: A mechanism design formulation", 2016 IEEE Power and Energy Society General Meeting (PESGM), Boston, MA, pp. 1-11, 2016.
- [29] E. Bitar and Y. Xu, "Deadline Differentiated Pricing of Deferrable Electric Loads", in *IEEE Transactions on Smart Grid*, vol. 8, no. 1, pp. 13-25, Jan. 2017.
- [30] H. J. Jo, I. S. Kim and D. H. Lee, "Efficient and Privacy-Preserving Metering Protocols for Smart Grid Systems", in *IEEE Transactions on Smart Grid*, vol. 7, no. 3, pp. 1732-1742, May 2016.
- [31] F. Knirsch, G. Eibl and D. Engel, "Error-Resilient Masking Approaches for Privacy Preserving Data Aggregation", in *IEEE Transactions on Smart Grid*, vol. 9, no. 4, pp. 3351-3361, July 2018.
- [32] P. Gope and B. Sikdar, "Lightweight and Privacy-Friendly Spatial Data Aggregation for Secure Power Supply and Demand Management in Smart Grids", in *IEEE Transactions on Information Forensics and Security*, vol. 14, no. 6, pp. 1554-1566, June 2019.
- [33] D. Egarter, C. Prokop and W. Elmenreich, "Load hiding of household's power demand", 2014 IEEE International Conference on Smart Grid Communications (SmartGridComm), Venice, 2014, pp. 854-859.
- [34] A. Awad, P. Bazan and R. German, "Privacy Aware Demand Response and Smart Metering", 2015 IEEE 81st Vehicular Technology Conference (VTC Spring), Glasgow, 2015, pp. 1-5.
- [35] P. Gope and B. Sikdar, "An Efficient Data Aggregation Scheme for Privacy-Friendly Dynamic Pricing-Based Billing and Demand-Response Management in Smart Grids", in *IEEE Internet of Things Journal*, vol. 5, no. 4, pp. 3126-3135, Aug. 2018.
- [36] P. Gope and B. Sikdar, "An Efficient Privacy-Friendly Hop-by-Hop Data Aggregation Scheme for Smart Grids", in *IEEE Systems Journal*. doi: 10.1109/JSYST.2019.2899986
- [37] A. Braeken, P. Kumar, A. Martin, "Efficient and Privacy-Preserving Data Aggregation and Dynamic Billing in Smart Grid Metering Networks" in *Energies*, vol. 11 no. 8, pp. 2085, 2018
- [38] H. Li, X. Lin, H. Yang, X. Liang, R. Lu and X. Shen, "EPPDR: An Efficient Privacy-Preserving Demand Response Scheme with Adaptive Key Evolution in Smart Grid", in *IEEE Transactions on Parallel and Distributed Systems*, vol. 25, no. 8, pp. 2053-2064, Aug. 2014.
- [39] R. Olfati-Saber, J.A. Fax, R.M. Murray, "Consensus and Cooperation in Networked Multi-Agent Systems", *Proc. IEEE*. vol. 95, pp. 215-233, 2007.
- [40] R. Olfati-Saber, R.M. Murray, "Consensus Problems in Networks of Agents With Switching Topology and Time-Delays", *IEEE Transactions on Automatic Control* vol. 49, pp. 1520-1533, 2004.
- [41] P. Makris, N. Eftymiopoulos, V. Nikolopoulos, A. Pomazanskyi, B. Irmischer, K. Stefanov, K. Pancheva, E. Varvarigos, "Digitization

Era for Electric Utilities: A Novel Business Model Through an Inter-Disciplinary S/W Platform and Open Research Challenges”, *IEEE Access*, vol.6, pp. 22452-22463, 2018.

- [42] I. Mamounakis, N. Efthymiopoulos, G. Tsaousoglou, D. J. Vergados, P. Makris and E. Varvarigos, "A novel pricing scheme for virtual communities towards energy Efficiency", 2018 IEEE International Energy Conference (ENERGYCON), Limassol, Cyprus, pp. 1-6, 2018.
- [43] V. Krishna, "Auction Theory", New York: Academic, 2002.
- [44] L. M. Ausubel, "An efficient ascending-bid auction for multiple objects", in *American Economic Review*, vol 94, no.5, pp. 1452-1475, 2004.
- [45] P. Maymounkov, D. Mazières, "Kademlia: A Peer-to-Peer Information System Based on the XOR Metric", *Peer-to-Peer Systems, IPTPS 2002. Lecture Notes in Computer Science*, vol 2429, 2002.
- [46] G. Zyskind, O. Nathan and A. Pentland, "Decentralizing Privacy: Using Blockchain to Protect Personal Data", 2015 IEEE Security and Privacy Workshops, San Jose, CA, 2015, pp. 180-184.
- [47] G. Xylomenos, C. N. Ververidis, V. A. Siris, N. Fotiou, C. Tsilopoulos, X. Vasilakos, K. V. Katsaros, G. C. Polyzos, "A survey of information-centric networking research", *IEEE Communications Surveys and Tutorials*, vol. 16 no. 2, pp.1024-1049, 2014.
- [48] F. Gul and E. Stacchetti, "Walrasian equilibrium with gross substitutes" *Journal of Economic Theory*, vol 87 no 1, pp. 95-124, 1999.
- [49] V. Krishna and M. Perry, "Efficient Mechanism Design", *Game Theory and Information*, University Library of Munich, Germany, <https://EconPapers.repec.org/RePEc:wpa:wuwpga:9703010>.



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