Optimal Targeting and Contract Offering for Load Curtailment in Nega-Watt Markets

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Abstract—This paper models and analyzes Nega-Watt markets. In the proposed setting a utility operator wants to curtail some amount of demanded load during peak hours in order to save energy generation costs. The problem for the operator is twofold: (i) select the consumers, and (ii) determine the amounts of load to be curtailed by each one of them. The major novelty in this setup stems from the arising uncertainty due to consumer non-engagement. Even if an a priori agreement is reached between the operator and a consumer about the load to be curtailed, the consumer may not succeed to curtail the load. The second element that makes our problem formulation different from other markets is the incentive design per se. We argue that the operator needs to employ a two-branch incentive, that is, provide consumers with a reward if they actually curtail the load and charge them a fine if they do not. We employ this dual-mode incentive into various game-theoretic mechanisms such as bilateral negotiation and different types of Stackelberg mechanisms that result in selecting the consumers and the amounts of load to curtail. We define equilibrium points for the mechanisms and compute the resulting contractual agreements between the operator and each selected consumer for load curtailment. Our results reveal interesting insights about the impact of the competition arising among consumers and the consumer-operator interaction on the expected benefits for the operator and the consumers.

I. INTRODUCTION

A. Concept and motivation

The concept of smart grid has begun to materialize in recent years, leading to more flexible and reliable power distribution systems. In this context, demand-response (DR) methods constitute a core element, aiding in peak-load alleviation by controlling consumer loads either directly (e.g. with intelligent scheduling of power demands) or indirectly (e.g. through time-varying pricing schemes). Also, advanced market-driven methods coordinate energy flow spanning the wholesale markets at the power generation level, the power distribution level and the consumer. In a wholesale energy market, wholesale prices are time-varying and are determined by the marginal energy generation cost, depending on the type or the number of power generation facilities that need to be activated. Utility operators purchase energy at the wholesale market at time-varying prices and resell it to consumers at fixed tariffs. These market-driven methods promise substantial benefits for the consumers (e.g. electricity bill savings), as well as for the operators (e.g. lower wholesale prices), and they aid in better control of the system.

This paper studies and analyzes a Nega-Watt market, in which a utility operator wishes to curtail some amount of load during a peak-demand time. A Nega-Watt is defined as a unit of power that is curtailed and is therefore not consumed by the consumer. The term was coined by Amory Lovins in 1989 [2]. With the term “Nega-Watt markets” we refer to electricity markets that apply demand response programs that compensate consumers for the nega-watts they offer. Some DR programs that are applied in today’s energy markets enable end-user participation in the wholesale market as well. The market players at the wholesale market are the energy generation companies and the large-scale consumers. The latter trade Nega-Watts (i.e. amounts of power saved) in a similar manner as supply companies do with generated Watts. Towards this direction, in 2011 the Federal Energy Regulatory Commission (FERC) updated a regulation according to which the Nega-Watts may have the same market prices as real MWs of generated electricity. Some real-life examples of Nega-Watt markets are the New England Independent System Operator (NE ISO) [3], the New York ISO (NYISO) [4], and the Pennsylvania-Jersey-Maryland (PJM) market [5].

The operator buys energy at volatile wholesale prices, which are equal to the marginal energy generation cost, and resells it to the consumers at a fixed retail price. At peak times, when the marginal generation cost is high, wholesale prices exceed by far the retail ones and the operator incurs losses. In order to reduce the load and thus mitigate losses, the operator can resort to DR methods. Then, benefits of load curtailment are two-fold: (i) The amount of load to be bought at the wholesale market is lower, hence the loss becomes lower. (ii) If the reduction of load is high enough, then the marginal generation cost and thus the wholesale price can also be reduced, if the remaining demand is supplied by less costly energy generators.

The most important challenge in such a setup is the arising uncertainty about real occurrence of load curtailment which stems from potential non-conformance of the consumer to the agreement. That is, even if an a priori agreement is reached between the operator and a user about the load to curtail, it is entirely up to the user to consume the load or not. Indeed, the consumer may not conform to this agreement and consume the load that was deemed to be curtailed. This may occur if the consumer ultimately needs the load, she is not familiarized
with the DR procedures or it may occur due to other subjective and user behavioral factors. We capture this uncertainty for the user through the definition of a conformance probability, i.e. a probability of actually performing load reduction.

This uncertainty about load curtailment introduces a novel twist to the problem. Competing consumers offer their Negative-Watt procurement option, and consumer selection naturally arises due to the heterogeneity of consumers in terms of valuations and probability of conforming to load curtailment. In the most general case, the operator needs to select the consumers and the portion of load to curtail from each consumer. Even if a consumer is selected, she cannot actually commit to deliver the promised good, i.e. the curtailed load. The problem that now applies is how to optimally perform the necessary load reduction, i.e. which consumers to target, how to incentivise them etc. This calls for the design of novel incentive mechanisms that shape consumer participation and conformance to load curtailment. In such a case, the operator needs to employ a two-branch incentive, that is, a reward if consumers actually curtail the load and a fine if they do not.

Note that the setting would be exactly the same if we assumed a retailer that is also an aggregator, which buys energy at volatile wholesale prices (e.g. from the spot market) and resells it to users at fixed retail prices. Again, it would be occasionally beneficial for such an aggregator to curtail part of the total demand of his consumers. In that case though, the aggregator would need to appropriately distribute among them the reward he would obtain from load curtailment. In section V we study the case of multiple consumers with different curtailment capabilities and propose a mechanism to allocate the desired amount of load curtailment among them. This mechanism can also be employed in the case of an aggregator.

\section{Related Work}

DR methods use two types of incentives to motivate participation in electricity markets: price-based and reward-based. The former ones refer to dynamic retail pricing schemes that guide consumers towards reducing their demand when prices are high, thus reducing their electricity bill. The works \cite{6}–\cite{8} present incentive-based consumption scheduling solutions towards this goal. Reward-based incentives give financial incentives to users for curtailing their load during peak-demand \cite{9}–\cite{13}. The authors in \cite{9}–\cite{10} deal with incentive-based DR programs that impose penalties to customers in case they do not conform to load reduction. In \cite{11}–\cite{13} users submit their bids or supply functions, and the operator decides on a market-clearing price for maximizing total market benefit.

A hierarchical market model for smart grids is proposed in \cite{14}, where the aggregators act as intermediaries between the operator and home users. Aggregators sell DR services to the operator and provide compensation to end-users to modify their consumption pattern. In \cite{15} the authors propose a Stackelberg game between utility companies and end-users to maximize the revenue of each utility company and the payoff of users. The authors in \cite{16} deal with two types of curtailment contracts, namely automated contracts that require fixed load curtailments from enrolled consumers and voluntary contracts that allow the amount of load curtailment to vary along with the consumer opportunity cost. The authors in \cite{17} propose a contract design for a buyer who wishes to procure energy and a seller that produces energy from conventional or renewable generators. They assume that the buyer determines the energy quantity and payment. The buyer offers a set of contracts to the seller and then the seller chooses one based on her private type, i.e. production technology and cost. Contract-based mechanisms are also studied in a different context by authors in \cite{18} to motivate the collaboration of smart-phone users on data acquisition and computing application tasks.

\textit{Uncertainty in resource supply} has been studied in a general framework in \cite{19}. Two suppliers are considered producing a good, an expensive and reliable, and a cheaper but unreliable. The buyer decision is on the appropriate amounts of good to purchase from each one, after they specify prices for different portions of purchase of the good allocated to them. Uncertainty is modeled with a probability of carrying out the order. In DR literature, uncertainty has been mainly studied in terms of residential user behavior in response to real-time prices and weather conditions \cite{20}. The authors in \cite{21} handle uncertain wind power and DR reserves by means of a stochastic optimal power flow model, but they focus on uncertainty caused by temperature forecasting error only. Contrary to the above, our work addresses uncertainty at the \textit{demand-side}, which is heavily dependent on the user through the valuation she places on the load and on the incentives provided. The innovative side of our work is that it brings together all the aspects mentioned above in the user and operator utility functions.

DR programs are offered in today’s energy markets, either directly or by ISOs and energy utilities. In several such cases therein, the operator imposes fines to consumers if they fail to fulfill load reduction; e.g. in the NYISO day-ahead demand response program the deviations from day-ahead schedules are settled at the higher of day-ahead or real-time price; also, in Southern California Edison optional binding mandatory Curtailment Program penalties are applied if the customer fails to achieve the required load reduction of up to 15\% \cite{22}, \cite{23}. In this work, we take a step ahead introducing different models for meaningful operator-user interaction assuming rational, self-interested parties. The modes of interaction proposed aim to bring uncertainty in the foreground and extract interesting guidelines towards designing Nega-Watt markets.

\section{Our contribution}

In this work, we model and study various modes of interaction between the operator and the users in a Nega-Watt market. We study ways in which a contractual agreement between the operator and each selected user can be reached for load curtailment, and the incurred incentives. To the best of our knowledge, this is the first work that attempts to study such a market. The novel aspects of our contribution are as follows:

\begin{itemize}
  \item We model the uncertainty introduced by the user in load curtailment through defining user conformance probability that depends on her valuation and on provisioned incentives.
  \item This probability is incorporated in appropriately defined utility functions which capture the expected benefit stemming from the curtailment for the users and the operator.
\end{itemize}
• We incorporate two-branch incentive mechanisms in the utility functions in the form of rewards and fines, depending on whether consumers perform load reduction or not.

• We study different models of interaction between the operator and the consumers in Nega-Watt markets for the basic case of one unit of load curtailment, such as: (i) bilateral negotiation between one operator and one user that characterizes the conflict of interest between the two entities, (ii) Stackelberg-game interactions with the operator as leader and the user as follower that captures instances in which the operator drives the market. We extend these models to multiple users so as to capture the inherent competition among them in being selected for load curtailment.

• We extend the models to consumers with different curtailment capabilities and multiple load units to be curtailed, and we propose appropriate mechanisms to allocate load curtailment among the selected consumers.

• We analyze all mechanisms introduced and derive interesting intuitions and guidelines related to the competition among consumers and between consumers and the operator, and its impact on expected derived utility for involved entities. These guidelines also shed light into market design.

The models of interaction above and the resulting rewards, fines and amounts of load for curtailment may be seen as the contractual agreement between the operator and a selected consumer for load curtailment. The rest of the paper is organized as follows. In section II we present the base model for one unit of load curtailment and multiple consumers, and in section III we develop the fundamental game-theoretic market mechanisms. In section IV we study a direct extension of the model with multiple load units to be curtailed, and in section V we further enrich our model with different curtailment capabilities by consumers. In section VI we numerically evaluate our mechanisms, and conclude in section VII. The terms “consumer” and “user” are used with the same meaning).

II. THE BASE MODEL: ONE UNIT OF LOAD TO CURTAIL

In the base model, we consider one operator and a set \( N \) of \( N \) consumers that participate in the market. We fix attention to a specific time instance when the operator wishes to curtail one unit of load. We assume that the total load is known (some uncertainty in total demand is ignored), and that user inform the operator in advance (e.g. the previous day) about their demand throughout the day. The precise amount of load represented by a unit of load to be curtailed is fixed and known in advance. In order to capture plausible real-life scenarios, the unit of load to be curtailed is considered to be large enough so that it is meaningful for the consumer to participate in the market, e.g. of the order of 1 or few MWs. Without loss of generality, in the base model we assume that the operator will select only one user out of the \( N \) ones that declared they are willing to curtail load. This implies that the plausible users to participate are industries or other types of big consumers. Note however that the approach does not place limitations on the types of users, e.g. multiple smaller-scale consumers could also be selected, perhaps through a proxy aggregator entity that would aggregate the small-load curtailments of users to the required unit of load to curtail.

**Incentives:** The operator uses a two-branch incentive depending on whether each selected user curtails her promised unit of load or not. If the user curtails her load, the operator provides her with a reward \( r \), while if the user does not reduce the load, she pays a fine \( f \). The uncertainty on whether a consumer \( i \) will reduce the load or not is captured through a conformance probability \( s_i(\cdot) \), to be defined in sequel.

**Curtailment contract:** The operator makes a contract with the consumer that is selected for load curtailment. The vector \((r, f)\) forms the contractual obligations of each party and is mutually agreed in advance before curtailment takes place.

**Consumer:** Each consumer \( i \) is characterized by a parameter \( v_i > 0 \) that models her valuation for the unit of load under tentative curtailment. The valuation reflects the importance of that unit of load for her, and it may depend on various factors such as the user consumption profile or time of day. A selected user \( i \) that ultimately curtails her load receives a reward \( r_i \), otherwise she pays a fine \( f_i \). In the latter case, the user still enjoys valuation \( v_i \) but she also has to pay the electricity bill for the load at the fixed retail price \( p \) per unit of load. It is reasonably assumed that the valuation exceeds the retail price, and thus the user has a positive net benefit when consuming the load. Both quantities are of the same order of magnitude.

**Conformance probability:** The conformance probability \( s_i(\cdot) \) for user \( i \) is a function of valuation \( v_i \), reward \( r_i \) and fine \( f_i \). For larger values of \( r_i \) and \( f_i \) the user strives more to conform to achieving the curtailment.\(^2\) Also, the user is more likely to perform the curtailment if the load is of low importance to her. Hence, \( s_i(\cdot) \) is taken to be increasing in \( r_i \), \( f_i \) and decreasing in \( v_i \). Further, as the value of reward or fine increases, a unit of additional increase in reward or fine is expected to have diminishing impact on the conformance probability. This essentially implies that \( s_i(\cdot) \) should be a concave function of \( r_i \) and \( f_i \). Our model and subsequent analysis work in general for all functions \( s_i(\cdot) \) with the properties above. However, in order to perform the mathematical analysis in the sequel, we select

\[
s_i(r_i, f_i) = \frac{r_i}{2(r_i + \Delta r \cdot \frac{v_i}{p})} + \frac{f_i}{2(f_i + \Delta r \cdot \frac{v_i}{p})}.
\]

(1)

In the expression above, recall that \( p \) is the price per MWh, and thus it is of the order of $100; see Section VI. Thus, \( v \) is also of the order of $100, and reasonable values of \( r \) and \( f \) will be of the same order. We also select a small value for the sensitivity factor \( \Delta r \), so that it does not dominate the denominator. In particular, we take \( \Delta r = 10 \). Implicitly we assume that \( r \) and \( f \) are also expressed in dollars. The expected net benefit of user \( i \), \( U_i(\cdot) \) for a unit of load curtailment, is,

\[
U_i(r_i, f_i) = r_i s_i(r_i, f_i) + (v_i - f_i)(1 - s_i(r_i, f_i)).
\]

(2)

The consumer is willing to participate in the market selection process about load curtailment if her expected net benefit exceeds the one she would obtain if she did not participate. Thus, the participation constraint for the user is

\[
U_i(r_i, f_i) \geq v_i - p.
\]

\(^2\)According to policy makers, the design of a successful demand response program, among others, needs to include penalties for non-conformance [24]
**Operator:** Assume that the total demand is \( d \). If the selected user does not perform the curtailment, the operator will buy load \( d \) at a wholesale electricity price \( C \) and resell it to users at fixed price \( p \). The operator receives the amount of fine \( f_i \) from the user due to user non-conformance in load reduction. Contrarily, if the user performs load curtailment, the operator needs to buy load \( d - 1 \) at a wholesale electricity price \( C' \) that is possibly lower than \( C \), while it offers reward \( r_i \) to the user. The operator expected net payments to others, i.e. generators, if user \( i \) is selected to curtail one unit of load is,

\[
L_{op}(r_i, f_i) = \left[ r_i + (C' - p)(d - 1)\right] s_i(r_i, f_i) + \left[ (C - p)d - f_i \right](1 - s_i(r_i, f_i)). 
\]

(4)

The operator benefits from user recruitment for load curtailment if its expected payment is less or equal to the one it would pay if users did not participate in the market. The participation constraint for the operator is thus,

\[
L_{op}(r_i, f_i) \leq (C - p)d.
\]

(5)

The operator and user participation constraints define a feasible region for \((r_i, f_i)\) which we denote by \( \mathcal{R}(r_i, f_i) \).

**Remark 1:** The operator is assumed to know user valuations. This is realistic for large-scale consumers (e.g. industries) with known consumption profiles or it can be based on some prior operator–user interaction. This assumption is an essential first step towards understanding structural properties of the problem and the outcomes of the interaction.

**Remark 2:** When expression (1) is entered in (2)-(4), meaningful monotonicity properties are seen, i.e. user net benefit is increasing in \( r \) and operator net payment is decreasing in \( f \) respectively. Also, the lower the valuation of the user is, i.e. the more confident she is about load curtailment, the higher is the fine that she is willing to pay in case of failure.

III. BASIC FULL-INFORMATION GAME THEORETIC MARKET MECHANISMS

In this section we study different game-theoretic modes of interaction between the operator and the users. Our aim is, through comparison of these fundamental models to identify valuable intuitions about the market and about the impact of competition on the expected utilities of consumers and on the expected payment by the operator. All entities are rational, self-interested ones that aim at optimizing their expected net utility or payment. In order to better understand the interactions, we begin with the simple case of one large-scale user interacting with the operator. We then extend that to \( N \) interacting users. The selected user out of the \( N \) ones is going to contract with the operator for tentative load curtailment.\(^3\)

A. One consumer and one operator

Consider that the operator wants to curtail one unit of load and only one user participates in the market. This situation may arise if other consumers fail to participate because of high valuations or other reasons, or in case the operator chooses to interact in a point-to-point fashion with a certain consumer, e.g. a large industrial one. We consider two modes of interaction: (i) a Bilateral negotiation between the consumer and the operator, and (ii) a leader-follower Stackelberg game, where the operator acts as leader and the consumer acts as follower. As will be seen in section III-A1, the equilibrium point of each interaction specifies the terms of the contract between the operator and the consumer for one unit of load curtailment. In this subsection, we drop index \( i \) from notation.

1) Iterative bilateral negotiation: In bilateral negotiation we assume that the consumer and the operator have equal negotiation power. The entities negotiate over the values of the reward and the fine. The negotiation is carried out in rounds. At each round, the operator suggests an amount of reward in case of load curtailment, and the user responds by agreeing with the proposed reward and by suggesting an amount of fine in case of non-conformance to load curtailment. At each round, each entity makes the suggestion in a best-response fashion, i.e. so that it optimizes its expected net utility or payment, given the suggestion of the other entity.

Within the feasible negotiation region \( \mathcal{R}(r_i, f_i) \), the operator expected profit and the consumer expected net benefit are concave functions. By applying KKT first- and second-order optimality conditions to equations (2) and (4), we can uniquely derive the best response strategies, which are as follows. For a fixed \( r \) offered by the operator, the best-response function for the consumer is \( F_u(r) = \arg \max f U(r, f) \) subject to constraint (3). For a fixed \( f \) from the user, the best-response function of the operator is \( F_{op}(f) = \arg \min r L_{op}(r, f) \) subject to constraint (5). Best-response strategies characterize the iterative bilateral negotiation. The negotiation process amounts to a sequence of best-responses applied interchangeably by the operator and the consumer and is summarized as follows.

- **STEP 0:** Initialization. Set iteration count \( n = 0 \). The operator starts the negotiation by choosing an arbitrary amount of reward \( r^{(0)}, n \leftarrow n + 1 \).
- **STEP 1:** Consumer responds with best-response fine \( f^{(n)} = \arg \max f U(r^{(n-1)}, f) \).
- **STEP 2:** Operator responds with best-response reward \( r^{(n)} = \arg \min r L_{op}(r, f^{(n)}) \).
- **STEP 3:** If \( |r^{(n)} - r^{(n-1)}| < \varepsilon \), STOP. Else, go to Step 1.

Here \( \varepsilon \) is a small number to signify convergence. By using Brower’s theorem, it can be shown that the sequence of best-responses above has a fixed point \((r^*, f^*)\) to which it converges. This point is a Nash Equilibrium point (NEP) of the negotiation, since none of the entities can further improve its net utility (or payment) by modifying its strategy, while the other player keeps its strategy unchanged. All our experiments converge to the same point independently of the initial point. The NEP provides the contractual obligations of the operator and the consumer in terms of revenue and fine respectively.

**Remark 3:** We abide to the rule that the user suggests the fine and the operator responds with the reward. Having instead the user computing the reward and the operator responding with the fine would lead to a situation where in each iteration the expected payment of the operator is decreasing in \( f \) and the net utility of the user is increasing in \( r \). Thus, convergence of best-response iterations cannot be achieved (see Remark 2).
2) Stackelberg Leader-Follower Game: We consider now that the operator acts as leader in the market. This gives rise to an one-shot Stackelberg game, with the consumer acting as follower. The operator first offers the reward and the consumer responds by declaring the fine she is willing to pay in case of non-conformance. The game is solved by backward induction. The operator considers a priori the best-response of the consumer in terms of fine (i.e. the fine that maximizes the consumer net utility) for a given \( r \). Then, the operator picks the value of reward that minimizes its expected payment, predicting the anticipated response of consumer. The latter observes this reward, and in equilibrium she picks the fine as a response. The operator solves the following problem:

\[
\min_{r \geq 0} L_{op}(r, F_u(r)) \\
\text{s.t. } U(r, F_u(r)) \geq v - p, \text{ and } L_{op}(r, F_u(r)) \leq (C - p)d. \tag{6}
\]

Again the equilibrium outcome of the game, \((r^*, f^*)\) with \( f^* = F_u(r^*) \) represents the terms of the curtailment contract between the operator and the consumer.

3) Stackelberg Leader-Follower Game In An Incomplete Information Setting: Then, we consider that the operator has incomplete information on consumer valuation and we adapt the mechanism described above. We assume that the operator is informed that consumer valuation follows the Bernoulli distribution, \( v \sim \text{bern}(v^1, v^2, g) \), which is incorporated into user expected net benefit and operator expected payment.

\[
\bar{U}(r, f) = U(r, f; v^1)g + U(r, f; v^2)(1 - g). \tag{7}
\]

\[
L_{op}(r, f) = L_{op}(r, f; v^1)g + L_{op}(r, f; v^2)(1 - g). \tag{8}
\]

The operator picks the value of reward that minimizes its expected payment, predicting the best response of the user, \( F(r) = \arg \max_j \bar{U}(r, f) \) and solves a problem as in (6).

However, when the operator announces \( r^* \), the consumer computes her best response strategy under her actual valuation for the unit of load, i.e. \( F(r^*) = \arg \max_j \bar{U}(r^*, f) \). When the consumer responds with \( f^* = F(r^*) \), the operator realizes which her actual valuation is, and finally can compute his expected payment according to (4).

B. N consumers and an operator

We now assume that \( N \) consumers offer to perform load reduction, but only one will be selected. We also assume that the operator knows the valuations of users and that they are truthful in declaring them. We study two market mechanisms: (i) \( N \) separate leader-follower Stackelberg games between the operator and each user. In this case, users ignore the existence of other users. (ii) A Stackelberg game model where the operator announces a reward, and users respond, each one with a different fine, while being in competition among each other for being selected. While the first model above seems more natural and more easily implementable by the operator, the second one leads to substantial performance improvement for the operator due to the incurred competition.

1) \( N \) separate Stackelberg games: Here, the users act in isolation from each other in that they do not take into account the incurred competition or simply they are not aware of it. The operator runs a separate one-shot Stackelberg game with each one of them. The operator announces a different reward \( r_i \) to each user \( i \) through predicting her anticipated best-response, \( F_u(r_i) \). That is, for each user \( j \), the operator solves problem (6) with \( r_j \) as variable. Then, the operator selects the user \( j \) so that its expected payment is minimized, i.e. it selects user \( i^* = \arg \min_j L_{op}(r^*_j, F_u(r^*_j)) \), where \( f^*_j = F_u(r^*_j) \) and \((r^*_j, f^*_j)\) is the consumer-operator \( j \) Stackelberg equilibrium.

2) One Leader-N-Follower Stackelberg game with uniform reward: In this one-shot Stackelberg game the operator acts as leader and announces a reward which is identical for all users (followers). Given this reward, users interact and compete among themselves in a game-theoretic fashion by making offers of fines to the operator. Assume that for a given \( r \), \( f^*(r) = (f^*_1(r), \ldots, f^*_N(r)) \) is the NEP of this game-theoretic interaction of users. The operator selects user \( j^* \) whose response \( f^*_j(r) \) minimizes operator expected net payment subject to (5).

Sub-game among consumers. The best-response strategy of each consumer is as follows; for a given \( r \), each consumer computes the fine to declare so as to maximize her net utility subject to being selected for curtailment, i.e. subject to being ranked first by the operator in terms of incurred expected net payment for the operator. The sub-game evolves in rounds. At each round \( n \), consumer \( i \) sees the fines announced by other consumers and solves the optimization problem:

\[
\max_{f_i > 0} U_i(r, f_i) \\
\text{s.t. } L_{op}(r, f_i) \leq \min_{j \neq i} L_{op}(r, f_j^{(n-1)}), \text{ and } U_i(r, f_i) \geq v_i - p. \tag{9}
\]

Due to monotonicity of the operator net payment (see Remark 2), the selected user \( j^* \) will be the one that proposes the largest fine at the NEP, i.e. \( j^* = \arg \max_j f^*_j(r) \). The operator computes the NEP of the subgame above, it identifies user \( j^* \) and then it selects the value of reward \( r \) that minimizes its expected payment. The computation of \( r \) could be made with numerical methods such as dichotomous search.

IV. Model Extension I: Multiple Load Units To Be Curtained

We consider a specific time instance in which the operator wishes to curtail \( K \) units of load, but each of the \( N \) consumers may curtail one unit of load. Thus, the operator needs to select \( K \) users for load curtailment, where \( K \) is the set of selected consumers and \( K \subseteq N \). The expected net benefit of consumer \( i \) if selected for curtailment is given by equation (2). Let \( r = (r_1, \ldots, r_N) \) and \( f = (f_1, \ldots, f_N) \) be the reward and fine vectors respectively for all consumers, with \( r_i \) and \( f_i \) referring to consumer \( i \) for curtailment of one unit of load. The operator expected net payment for that unit of load is given by equation (4), and the operator total expected net payment is, \( L_{total}(r, f) = \sum_{i \in K} L_{op}(r_i, f_i) \).

We consider: (i) \( N \) separate Stackelberg games with different rewards for users, (ii) \( N \) separate Stackelberg games with
uniform reward across consumers and, (iii) an one-leader-\(N\)-follower Stackelberg game with uniform reward.

A. 1-to-1 separate Stackelberg games with different rewards

This is an extension of the mechanism of subsection III-B1; the operator now needs to select \(K\) consumers instead of one for load curtailment. Consumers are not aware of competition. The operator runs \(N\) separate one-to-one Stackelberg games with each user \(i\). For the Stackelberg game with each user \(i\), it computes the Stackelberg equilibrium \((r^*_i, f^*_i)\). Then, it ranks users in increasing order according to incurred \(L_{op}(r^*_i, f^*_i)\). Finally, it selects the top-\(K\) ones from the ranked list above.

B. 1-to-1 separate Stackelberg games with uniform reward

As a special case of the mechanism above, the operator announces the same reward \(r\) to all users. The latter are still not aware of the competition. Recall that for a fixed reward \(r\), the operator expected net payment is decreasing in the fine. Also, the lower the consumer valuation is, the higher the is fine that the user is willing to pay if she fails to curtail the load (Remark 2). The operator takes the properties above into account and selects a priori the users with the \(K\) lowest valuations (we denote this set as \(\mathcal{K}\)), i.e. the ones that minimize its total net expected payment. Then, it runs \(K\) separate Stackelberg games with each one of them. The operator considers a priori the best response of each consumer \(i\) in terms of fine for a given \(r\), \(f^*_i = \min_{j \in \mathcal{K}} f_j\) \(\forall i \in \mathcal{K}\) and in equilibrium it picks the value of reward that minimizes its total expected net payment. The operator solves the following optimization problem,

\[
\min_{r} L_{total}(r, f^*)
\]

s.t. \(L_{total}(r, f^*) \leq (C - p)d\), \(U_i(r, f^*_i) \geq v_i - p\), \(\forall i \in \mathcal{K}\).

The first constraint is operator’s participation constraint for \(K\) units of load curtailment and the second is user’s participation constraint for each user \(i\) selected for load curtailment.

C. 1-to-\(N\) Stackelberg game with uniform reward

This is an extension of the mechanism in section III-B2. The operator announces a reward which is the same for all consumers and selects \(K\) consumers for load curtailment. Given a reward, consumers interact in a game theoretic fashion and compete by making offers of the fine they can afford to the operator. The operator computes a priori the NEP \(f^* = (f^*_1(r), … , f^*_N(r))\) of the subgame among consumers and finds the value of reward and the set of consumers that minimize its total expected net payment.

Sub-game among consumers. For a given announced \(r\), each user computes a fine to declare so as to maximize her expected net benefit subject to being selected for load curtailment, i.e. subject to offering a fine that is high enough so that she is ranked among the top \(K\) consumers willing to pay the highest fines in case of failure. Let us denote with \(\mathcal{F}_K\) the set of the top-\(K\) fines. The sub-game among consumers evolves in rounds. At each round \(n\), consumer \(i\) sees the fines announced by others and solves the following optimization problem

\[
\max_{f_i} U_i(r, f_i), \text{s.t. } f_i > \min_{j \in \mathcal{F}_K} f_j, U_i(r, f_i) \geq v_i - p.
\]

Sub-game Nash Equilibrium. From the participation constraint of each consumer \(i\) we extract the maximum value of fine she is willing to pay for given \(r\), \(F_i^{\max}(r)\). The latter combined with \(F_u(r)\), defines the feasible negotiation region of each consumer \(i\) for a given \(r\), \((U_i(r), F_i^{\max}(r))\).

- If \(F_i^{\max}(r) \leq \min_{j \in \mathcal{F}_K} f_j\), then \(f^*_i(r) = F_i^{\max}(r)\) and consumer \(i\) is not selected for load curtailment, \(i \notin \mathcal{K}\).
- If \(F_u(r) < \min_{j \in \mathcal{F}_K} f_j \leq F_i^{\max}(r)\), then \(f^*_i(r) = \min_{j \in \mathcal{F}_K} f_j + \varepsilon\) and consumer \(i\) is selected for load curtailment, \(i \in \mathcal{K}\). Here \(\varepsilon\) is a very small number.
- If \(F_u(r) > \min_{j \in \mathcal{F}_K} f_j\), then \(f^*_i(r) = F_u(r)\) and consumer \(i\) is selected for load curtailment, \(i \in \mathcal{K}\).

Note that when the user selection process is completed, the operator makes a contract separately with each one of the selected users for one unit of load curtailment. The terms of the contract between the operator and each user are defined by the equilibrium outcomes of the aforementioned mechanisms.

V. Model Extension II: Consumers With Different Curtailment Capabilities

In this section, we extend the previous models by assuming that each consumer \(i\) is willing to curtail \(k_i \geq 1\) units of load, while the operator still wishes to curtail \(K\) units of load. Now, the problem for the operator is twofold: (i) select the subset of consumers for possible load curtailment and (ii) decide on the portion of load to curtail from each one of them. These choices are made by the operator based on the mechanisms described in the sequel. The solution is computed before the specific time slot when curtailment is to be applied. Then, at that time slot the operator will ask each selected user to perform the computed load curtailment. The mechanisms proceed by selecting for each unit of load the user to curtail it. The reason we adhere to this class of policies is that the behavior of the user in terms of conformance probability depends naturally on the amount of curtailed load.

Valuation vector: Each consumer \(i\) that is willing to curtail up to \(k_i\) units of load is characterized by a valuation vector \(v_i = [v^1_i, … , v^{k_i}_i]\). The entry \(v^j_i\) is the user \(i\) valuation for the \(j\)-th unit of load to curtail, provided that she has already agreed to curtail \((j - 1)\) units and \(v^j_i\) is non-decreasing in \(j\).

Conformance probability: For each consumer \(i\), we define \(s^j_i(r^1_i, f^1_i)\) to be the probability that consumer \(i\) curtails her \(j\)-th unit of load, as a function of the reward \(r^1_i\) and fine \(f^1_i\) she agrees upon for that unit of load. We also define \(S^j_i(r^1, f^1)\) to be the probability of curtail the \(j\)-th unit of load, provided that she has already agreed to curtail \((j - 1)\) units of load. Thus, consumer \(i\) will curtail the first unit of load with probability \(S^1_i(r^1, f^1) = s^1_i(r^1_i, f^1_i)\), that depends on the provisioned incentives for that unit of load. Clearly, she will be eligible for possible curtailment of a second unit of load if she has been selected (and thus agreed) to curtail her first unit of load. If consumer \(i\) is selected for the curtailment of a second unit of load, she will conform to that with probability \(S^2_i(r^2_i, f^2_i) = s^2_i(r^2_i, f^2_i)\), where \(s^2_i = s^1_i(r^1_i, f^1_i)\) is the value of conformance probability of the first unit of load for the computed reward and fine. In a similar fashion, she may be selected to curtail her \(j\)-th unit of load provided that she has

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been selected for curtailing all previous \((j-1)\) units. Thus, the conformance probability for the \(j\)-th unit of load depends both on the incentives for the curtailment of the \(j\)-th unit of load and the probability that she will curtail all previous \((j-1)\) units, and thus it is \(S_i^j(r_i^j, f_i^j) = (\prod_{k=1}^{j-1} s_i^k)(r_i^j, f_i^j)\), where \(s_i^k = S_i^k(r_i^k, f_i^k)\). The expected net benefit of consumer \(i\) for the curtailment of its \(j\)-th unit of load \(U_i^j(\cdot)\) is,

\[
U_i^j(r_i^j, f_i^j) = r_i^j S_i^j(r_i^j, f_i^j) + (v_i^j - f_i^j - p)(1 - S_i^j(r_i^j, f_i^j)).
\]

For simplicity and without loss of generality, instead of \(L_{op}(\cdot)\), we work with the operator expected profit from the curtailment of one unit of load. Then, the operator expected profit if user \(i\) is selected to curtail its \(j\)-th unit of load is,

\[
P_{op}(r_i^j, f_i^j) = (C - p - r_i^j S_i^j) - (C - p - f_i^j)(1 - S_i^j).
\]

Load Curtailment Allocation Mechanism (LCAM): Next, we propose two mechanisms to allocate the desired amount of load curtailment among consumers. The mechanism evolves in \(K\) rounds. At each round, the operator launches a call for expression of interest for curtailing one unit of load and each interested consumer proposes. The operator interacts with them in a Stackelberg-game-like fashion and recruits one consumer for curtailment, namely the one that minimizes its expected net payment. Before the selection at round \(k\) takes place, suppose that each user \(i\) has already been selected in the previous rounds for the curtailment of \(j \geq 0\) units of her load. Then, user \(i\) will participate at round \(k\) with valuation \(v_i^k\) and conformance probability \(S_i^{j+1}\). We study two versions of the mechanism in terms of operator-consumer interaction:

1) LCAM–I: At each round, the operator runs separate 1-1 Stackelberg games with different rewards, with each consumer \(i\) in the spirit of the mechanism described in III-B.1 above. Then, it chooses for load curtailment the one that minimizes its expected payment, namely user \(i^* = \arg \min_i L_{op}(r_{i(1,j)}, f_{i(1,j)})\), where \((r_{i(1,j)}, f_{i(1,j)})\) is the resulting Stackelberg equilibrium point of the game between the operator and each user \(i\) and \(j\) is the unit of load to be curtailed by selected user \(i^*\). The equilibrium of the Stackelberg game between the operator and the selected user \(i^*\), \((r_{i^*(1,j)}, f_{i^*(1,j)})\), sets the contractual obligations between the operator and selected user \(i^*\) for the curtailment of her \(j\)-th unit of load.

2) LCAM–II: The operator runs an one-shot one leader-follower Stackelberg game, with all users participating in the round as in III-B.2. Note that in this version, the optimal uniform reward \(r^*\) is computed at each round, and then users interact in a subgame fashion to decide on the fines \(f^*\). The NER \((r^*, f^*)\) of the game sets the reward paid by the operator to selected user \(i^*\), if she successfully curtails her \(j\)-th unit of load and the fine paid by her to the operator if she fails.

Note that consumer may have a motive to stay off for one or more rounds and wait until the consumers with the lowest valuations are selected. Then, she will participate in a less competitive environment, i.e. game in which the consumers with the higher valuations offer lower fines, and if selected it is possible to obtain a larger benefit. To avoid this, we assume a mandatory participation rule according to which the consumer is obliged to participate in every round until she has no other units of load she is willing to curtail.

Example. Consider a toy Nega-watt market in which the operator wishes to curtail \(K = 2\) units of load and \(N = 2\) users participate in the market with curtailment capabilities \(k_1 = 1\) and \(k_2 = 2\) respectively.

Round 1: Each user offers her first unit of load. The valuation of each user, i.e. \(v_1^1\) and \(v_2^1\), enters in the respective conformance probability as function of incentives. Suppose that user 2 minimizes operator expected payment and thus she is selected for curtailment. The equilibrium of the Stackelberg game at round 1 is \((r_{i(1,1)}^*, f_{i(1,1)}^*)\). User 2 will receive \(r_{i(2,1)}^*\), if she curtails the unit of load otherwise she will pay \(f_{i(2,1)}^*\).

Round 2: User 2 that was selected in round 1, offers to curtail her second unit of load and participate with valuation \(v_2^2\), while user 1 will offer her first with \(v_1^1\). These valuations are entered in the conformance probabilities of consumers. Suppose that the winner of round 2 is again user 2 and that the equilibrium is \((r_{i(2,2)}^*, f_{i(2,2)}^*)\). Then, the incentives for the curtailment of her second unit of load are \(r_{i(2,2)}^*\) and \(f_{i(2,2)}^*\).

Our mechanism can be employed repetitively as part of the day-ahead energy market. The operator chooses to employ the mechanism e.g. when some imbalance in supply and demand is expected to arise and rewards consumers that are selected and eventually curtail the pre-specified amount of load.

VI. NUMERICAL EVALUATION

In order to evaluate the performance of the mechanisms we conduct numerical investigation. We consider meaningful cases where wholesale prices exceed retail ones. We assume that the operator buys energy from the wholesale market at price \(C = \$1000/MWh\), and resells it to users at fixed price \(p = \$100/MWh\). Without loss of generality, instead of \(I_{op}(\cdot)\), we work with the operator expected profit, \(P_{op}(r, f) = (C - p - r s(r, f) - (C - p - f)(1 - s(r, f))\). To compare the net benefit among users with different valuations, we subtract quantity \(v_i - p\) from user expected net benefit and work with the following expression \(U = U - (v_i - p)\geq 0\). The unit of load curtailment is 1MWh and \(r\), \(f\) and \(v\) are measured in $/MWh. Throughout this section, units are omitted for brevity.

A. Curtailment of one unit of load

1) One user and the operator: First, we study the case of one user interacting with the operator. In Table I we compare the Stackelberg game and bilateral negotiation cases. The former results in higher expected utility for the user and higher expected profit for the operator. Also, at Stackelberg game equilibrium, we observe a higher user conformance probability, i.e. the conformance probability is about 5% larger for \(v = 100\) and 15% larger for \(v = 150\). This is because at the bilateral negotiation, the entities compete and limit each other in their myopic best-response strategies, thus both are led to a less efficient outcome. In the Stackelberg-game, the operator predicts the strategy of the user, it perceives the importance of appropriate incentives and offers a relatively high reward, which leads the game to a more beneficial equilibrium outcome for both entities.

Then, we study the leader-follower Stackelberg game under incomplete information. The operator is informed that user...
valuation follows the $v \sim \text{ber}(200, 380, g)$ while her actual valuation is $v = 200$. Figure 1a, depicts the values of the reward and fine as function of the Bernoulli probability $g$. For lower values of $g$, i.e. when the operator likely overestimates user valuation, announces higher rewards. If the operator has more accurate information, i.e. for higher values of $g$, the reward decreases. Thus, as shown in Figure 1b the operator expected profit increases with $g$. The user, on the other hand, reaches higher values of expected net benefit for lower values of $g$. In such cases, the fact that the operator has inaccurate information (particularly he overestimates consumer valuation) and thus announces higher rewards, is beneficial for the user. Of course, for $g = 1$, we obtain the same outcomes as in the corresponding full-information case.

2) $N$ users and the operator: We consider that $N = 20$ users offer to reduce the load, with valuations $v_i \in [150, 400]$. We ran $N$ separate 1-to-1 Stackelberg games and found that user $j^* = \arg \min_i v_i$, i.e. with valuation 150, maximizes operator expected profit and thus she is selected for curtailment. Also, this is the user with the highest conformance probability. The outcome at equilibrium gives: $r_j^* = 135.04$, $f_j^* = 87.517$, $s_j^* = 0.8769$, $P_{op}^* = 681.5$ and $U_j^* = 113.8$.

Table II presents the results of 1-to-N Stackelberg game. The selected user is $j^* = \arg \min_i v_i$. Here we wish to see the impact user competition on the outcomes of the game. We fix the user with the smallest valuation, $v_j = 150$ and vary the second smallest valuation in the set of users. As the competition among users becomes more intense (i.e. the second smallest valuation gets closer to $v_j = 150$), the operator expected profit increases. If the competition is lighter, (i.e. $v_j = 150$, and $v_i \geq 270$ for consumers $i \neq j$), the rest of the consumers cannot effectively compete with the one with the smallest valuation. Thus, the mechanism essentially becomes similar to an 1-to-1 Stackelberg game between the operator and the user with the smallest valuation. The comparison of the two mechanisms reveals that a higher competition among users is more preferable for the operator, since it forces them to respond with increasing fines. Note that in the case of intense competition (i.e. $v_j = 150$, and $v_i \geq 200$) the selected user responds with an extremely high fine that can be argued to be unacceptable while the reward may be unconscionably high for the operator too. In the Stackelberg game the operator predicts its outcome so, he could interfere in advance by setting a fixed reward, smaller than the one he would announce, in order to restrict the fine offered by the consumer.

**B. Curtailment of multiple units of load**

We assume a Nega-Watt market in which the operator wishes to curtail $K = 10$ units of load in a specific time instance. The $N = 16$ users that participate in the market offer to curtail one unit of load each with valuations $v_i \in [100, 700]$.

In Figs. 2a, 3a and 4a we depict the values of reward and fine as function of selected consumer valuation at the end of each Stackelberg game-like interaction of section IV, while in figures 2b, 3b and 4b we plot user expected net benefit and operator expected profit. Note that in all plots, from total $N = 16$, the users that are selected for load curtailment are the ones with the 10 lowest valuations ($v_1^* = 100, \ldots, v_{10}^* = 460$), i.e. the most possible ones to achieve the curtailment which proves the selection mechanisms work efficiently.

Fig. 2a shows that, given the uniform reward offered by the operator, users with higher valuations respond with lower fines, as expected. Figure 3a shows that the equilibrium of the subgame among consumers gives equal fines for all users and equal to the highest losing fine offer (see IV-C). In figure 4a we observe that both the reward and the fine increase as user valuation increases, as expected. However, the reward needs to be increased by the operator with a much higher rate (slope) than the fine by the user. As user valuation increases, the consumer is less confident about curtailing the load and is thus more reluctant to increase substantially her fine offer.

Figs. 2b and 3b show that Stackelberg games with uniform reward lead to significantly higher expected benefits for selected users with low valuations, than 1-to-1 Stackelberg games with different rewards (Fig. 4b). This is because the operator is less flexible when it offers a uniform reward. In order to achieve the 10 units of load curtailment, the operator

---

Table I: Comparison between the Bilateral negotiation and the operator-consumer Stackelberg game.

<table>
<thead>
<tr>
<th>$v_i$</th>
<th>100</th>
<th>150</th>
<th>100</th>
<th>150</th>
</tr>
</thead>
<tbody>
<tr>
<td>$r_i$</td>
<td>380</td>
<td>77.5</td>
<td>77.5</td>
<td>135.04</td>
</tr>
<tr>
<td>$f_i$</td>
<td>73.7</td>
<td>81.174</td>
<td>73.7</td>
<td>135.04</td>
</tr>
<tr>
<td>$P_{op}^*$</td>
<td>341.4</td>
<td>341.4</td>
<td>341.4</td>
<td>341.4</td>
</tr>
<tr>
<td>$U_j^*$</td>
<td>73.7</td>
<td>73.7</td>
<td>73.7</td>
<td>73.7</td>
</tr>
</tbody>
</table>

Table II: Operator-N consumers Stackelberg game.

<table>
<thead>
<tr>
<th>$v_i$</th>
<th>100</th>
<th>150</th>
<th>100</th>
<th>150</th>
</tr>
</thead>
<tbody>
<tr>
<td>$r_i$</td>
<td>58.69</td>
<td>77.71</td>
<td>91.72</td>
<td>135.04</td>
</tr>
<tr>
<td>$f_i$</td>
<td>47.8</td>
<td>19.30</td>
<td>81.174</td>
<td>135.04</td>
</tr>
<tr>
<td>$P_{op}^*$</td>
<td>104.76</td>
<td>104.76</td>
<td>104.76</td>
<td>104.76</td>
</tr>
<tr>
<td>$U_j^*$</td>
<td>87.517</td>
<td>87.517</td>
<td>87.517</td>
<td>87.517</td>
</tr>
</tbody>
</table>

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Fig. 1: Leader-Follower Stackelberg game in incomplete information setting.
needs to sufficiently motivate consumers with high valuations. Thus, it announces a relatively high reward. Then, consumers with lower valuation receive a much higher reward than the one in a Stackelberg game with different rewards (Fig. 2a, 3a and 4a). So, the Stackelberg games with uniform reward lead to lower operator expected profits compared to 1-to-1 Stackelberg games with different rewards (Fig. 4b).

In Fig. 5 we plot the conformance probability at the end of all Stackelberg game-like interactions of section IV, as function of selected user valuation. The most efficient mechanism in terms of conformance probability, i.e. the one that leads to higher conformance probability for the selected users on average, is the 1-to-N Stackelberg game with uniform reward. This can be justified by: (i) the uniform reward where consumers with lower valuation receive a much higher reward and (ii) the existence of competition, that forces consumers to respond with substantially higher fines.

C. Consumers with different curtailment capabilities


In Fig. 6 we present the load curtailment allocation among selected users at the end of the mechanism introduced when separate 1-to-1 Stackelberg games (LCAM–I) and one leader–many followers Stackelberg game is employed at each round (LCAM–II) respectively. In LCAM–I load curtailment varies between 2 and 4 units per user and in LCAM–II between 1 and 6 units per user. Hence, the amounts of curtailed load per user are more balanced in LCAM–I. Competition among users (LCAM–II) forces them to respond with increasing fines and this leads to substantially higher conformance probabilities per unit of load (vary between 0.928 and 0.991). Recall that the conformance probability of each additional unit depends both on the incentives and the probability that she will curtail all previous units. The latter in LCAM–II is $> 0.92$ and does not affect substantially the outcome. Thus, the allocation pattern in LCAM–II mainly depends on load unit valuation, i.e. load units with lower valuations are preferable.

On the contrary, LCAM–I leads to lower conformance probabilities (they vary between 0.396 and 0.896). In fact, the conformance probability of each additional load unit offered by a user decreases substantially, as the number of units agreed to be curtailed increases. Thus, the curtailment allocation pattern in LCAM–I depends both on user’s valuation for the unit of load and on how many units she has already agreed to curtail, i.e. units of low valuation and small amount of previously agreed curtailment are preferable. Finally, total operator expected profit in LCAM–I ($P_{total} = 7739$), is substantially lower than total operator expected profit in LCAM–II ($P_{total} = 10864$). As is expected, competition favors the operator.

VII. Conclusion

In this paper we study and design dynamic contracts for load curtailment between the operator and users. Contrary to existing static contract scenario that are determined only by the operator, our work sets the stage for a novel class of contracts that emerge out of the dynamic interaction of the operator and the user (and/or the interaction among users) in the form of a game. The contract terms emerge naturally as equilibrium points of the interactions. The novelty in our setup stems from the arising uncertainty due to users’ possible non-engagement to load reduction which gives rise to two-branch incentive mechanisms that include both rewards and fines.
The main findings for the base case of one unit of load curtailment are: (i) both the user and the operator are better off in Stackelberg equilibrium than in bilateral negotiation, (ii) as a result, N-parallel Stackelberg games is better for both entities than N-parallel negotiations (in both cases users are not aware of the competition), (iii) when competition is announced to users the operator is better off in Stackelberg game with N-followers than in N-parallel Stackelberg games. For the extension to multiple units of curtailed load per user, we see that: (i) Stackelberg games with uniform reward are in favor of users with low valuations, (ii) the operator is better off in N-parallel Stackelberg games with different rewards and (iii) the most efficient mechanism in terms of conformance probability is the Stackelberg game with N followers. Finally, the curtailment allocation mechanism with the operator running N separate Stackelberg games at each round leads to a more balanced allocation among users than the mechanism with the 1-to-N interaction.

In this work we have not considered shifting of loads as a response to DR (instead of curtailment). Taking shifting into account requires to include an additional option in the decision-making of the user, and possibly a different reward and fine. This extension constitutes a direction for future work.

REFERENCES


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