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Baseline Estimation and Scheduling for Demand Response

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***Abstract*— Demand Response (DR) programs serve to reduce the demand for electricity at times when the supply is scarce and expensive. Consumers or *agents* with flexible consumption profiles are recruited by an aggregator who manages the DR program. These agents are paid for reducing their energy consumption from contractually established baselines. Baselines are counter-factual consumption estimates against which load reductions are measured. Baseline consumption and the true cost of load reduction are consumer specific parameters and are unknown to the aggregator. The key components of any DR program are: (a) establishing a baseline against which demand reduction is measured, (b) designing the payment scheme for agents who reduce their consumption from this baseline, and (c) the selection scheme. We propose a self-reported baseline mechanism (SRBM) for the DR program. We show that truthful reporting of baseline and marginal utility is both incentive compatible and individually rational for every consumer under SRBM. We also give a a pod-sorting algorithm based DR scheduling for selecting consumers that is nearly optimal in terms of expected cost of DR provision.**

I. Introduction

The core problem in power systems operations is to maintain the fine balance of electricity supply and demand at all times. This must be done economically through markets while respecting resource and reliability constraints. Adeptly managing flexible demand is a far better alternative to increased reserve generation, since it is inexpensive, produces no emissions, and consumes no resources. At certain times such as mid-afternoons on hot summer days, the total demand for electricity surges. At these times or *events*, it is more cost-effective to reduce demand than to increase supply to maintain power balance.

Demand Response programs are designed to reduce electricity consumption during such events. In these programs, aggregators recruit residential or industrial customers who are willing to reduce their electricity consumption in exchange for financial rewards. The aggregator serves as an intermediary and represents these flexible consumers or *agents* to the local utility. The aggregator receives a payment from the utility for the ability to reduce demand at short notice, and, in-turn, pays the agents for their consumption reduction during DR events. The key difficulty is in measuring this reduction in consumption. While the actual consumption of agents is measured, their intended consumption or *baseline* is a counter-factual, i.e., the energy an agent would have consumed if they were not participating in the DR program.

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There are three key components of any DR program that need to be designed: (a) a *baseline* against which demand reduction is measured, (b) the *payment scheme* for agents who reduce their consumption from this baseline, and (c) the *scheduling scheme* in order to minimize the cost of DR. Commonly used baselines include historical averages of consumption on similar days (by the agent, or by a peer group of similar agents). These baseline estimation methods and their variations are prone to inaccuracies and participating agents have incentives to inflate to increase the payments [1], [2], [3], [4]. Inaccurate baselines can result in over-payment, compromising the cost-effectiveness of the DR program, or in under-payment, adversely affecting the ability to recruit participants into DR programs. Addressing these issues is essential to encourage and sustain wider use of DR programs. At the same time it is critical from the point of view of the aggregator that the DR programs can be implemented in a *cost efficient* way.

A. Our Contributions

We approach the baseline estimation and scheduling for DR as a *mechanism design* problem. The utility informs the aggregator of an upcoming DR event. The aggregator who manages the DR program is required to deliver a target load reduction in response. Our objective is to design an incentive mechanism that, (a) establishes the true baseline, (b) delivers the required load reduction reliably, and (c) achieves both (a) and (b) in a cost effective way. We propose a novel *self-reported* baseline mechanism (SRBM) to solve the problem. Under the proposed mechanism the agents are required to *self-report* their baselines which are forecasts of their intended future consumption, and their unit cost to reduce load or *marginal utilities* to an aggregator. In addition, we propose a *pod sorting* based randomized scheduling scheme for selecting or *calling* the consumers that is nearly optimal in the metric of expected cost of DR provision

We show that, under the proposed scheme, reporting the true baseline and marginal utility is a dominant strategy for each agent. Also, the aggregator can guarantee delivery of the required demand reduction target. In addition the pod sorting based scheduling scheme achieves this at nearly optimal cost.

B. Related Work

There is a substantial literature on baseline estimation methods. These can be broadly classified into (a) averaging,

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(b) regression, and (c) control group methods. Authors in [5] give a short description on these different baseline schemes.

Averaging methods determine baselines by averaging the consumption on past days that are similar (ex: in temperature or workday) to the event day. There are many variants such as (i) weighted averaging and (ii) using an adjustment factor to account for variations between the event day and prior similar days. A detailed comparison of different averaging methods is offered in [6] [7] [8]. Averaging methods are simple, but they suffer from (i) estimation biases that can be substantial [8] [9] and (ii) they require significant data access, especially for residential DR programs [10].

Regression methods fit a model to the historical data which is used to predict the baseline [11] [12]. They can potentially overcome biases incurred by averaging methods [10]. They often require considerable historical data for acceptable accuracy, and the models may be too simple to capture the complex behavior of individual agents.

Control group methods are found to be more accurate than averaging or regression methods [13] [14]. While they do not require large amount of historical data, they require metering infrastructure.This complicates and raises the costs of implementation, particularly for large numbers of recruited agents. Finally, [9] proposes a probabilistic method using Gaussian statistics to estimate baselines.

The methods discussed above only focus on baseline estimation and ignore the behavioral or gaming aspects of agents intentionally inflating their baselines. There are some exceptions, notably [15], [16], [17], [18], which models the strategic behavior consumers but either assumes knowledge of utility functions or true baselines. In [19] authors addresses the gaming aspect where consumers inflate their baseline to maiximize the payment. They characterize the optimal contract between DR aggregators and consumers. However they assume that true reduction can be observed at a later time, and the payment depends on this information. Our approach doesn't require this assumption. Instead we propose a joint design of baseline estimation and incentive design to address both problems together.

II. Problem Formulation

A. Aggregator Model

The aggregator recruits N agents into its DR program from a large candidate pool such that they deliver D KWh of demand reduction target during DR events over some contract window. Recruited agents are obligated to participate in m DR events contractually. The cost of recruitment is π^o per enrolled agent.

The aggregator's profit is the revenue from the utility, minus the payout to the agents and recruiting costs. It may also receive penalty revenue from agents, but we will show that this is not the case under our baseline mechanisms. The total expected cost faced for the aggregator is

$$J_{\text{agg}} = m\mathbb{E}[\psi] + \pi^o\mathbb{E}[N]$$

where ψ is the payout per DR event and N is the number of recruited agents. The aggregator's *expected cost of demand response* ϕ, i.e. the average cost per KWh of demand reduction is then

$$\phi = \frac{J_{\text{agg}}}{mD} = \underbrace{\frac{\mathbb{E}[\psi]}{D}}_{\text{payout per KWh}} + \underbrace{\frac{\pi^o\mathbb{E}[N]}{mD}}_{\text{recruitment cost}} \tag{1}$$

TABLE I
NOTATIONS

$\mathbb{E}[X]$	expected value of the random variable X
D	load reduction target
m	number of DR events agents must participate in
N	number of agents recruited by aggregator
u_k	utility of agent k
q_k	discretionary energy consumption of agent k
b_k	true baseline consumption of agent k
π_k	true marginal utility of agent k
$\pi_{\max}$	upper bound on marginal utilities
α_k	probability that agent k is selected
f_k	baseline report of agent k
μ_k	marginal utility report of agent k
π_k^r	reward/kWh awarded to agent k
π_k^p	penalty/kWh imposed on agent k
π^e	retail price of energy
π^o	recruitment cost per enrolled agent
$\mathbb{P}^i$	pod i
$\mathbb{S}^i$	pod core i
$\mathbb{H}^i$	pod header i
β^i	probability that pod i is selected for DR
ν^i	maximum reported marginal utility in pod i
ϕ	average cost of DR provision per KWh
ψ	payout to agents per DR event

B. Consumer Model

Let $u_k(q_k)$ be the utility of agent k derived by consuming q_k units of energy. We assume that the utility functions $u_k(\cdot)$ have the piece-wise linear form

$$u_k(q_k) = \begin{cases} \pi_k q_k & \text{if } q_k < b_k \\ \pi_k b_k & \text{if } q_k \geq b_k \end{cases} \tag{2}$$

Here b_k is the maximum possible consumption of agent k. Any additional consumption will not increase its utility. We call π_k the *true marginal utility* of agent k. We assume that π_ks are i.i.d and so are b_ks and that π_ks and b_ks are independent of each other. Let π^e be the retail price of electricity offered by the utility. The net utility $U_k(\cdot)$ of agent k is

$$U_k(q_k) = \begin{cases} \pi_k q_k - \pi^e q_k & \text{if } q_k < b_k \\ \pi_k b_k - \pi^e q_k & \text{if } q_k \geq b_k \end{cases}$$

We clearly require $\pi_k > \pi^e$, else agent k would not consume electricity. Equivalently, for every agent, the marginal utility derived from electricity consumption exceeds the retail electricity price.

The optimal consumption for agent k maximizes the net utility. This is b_k as is evident from Figure 1(b). We call b_k the *true baseline consumption* of agent k.

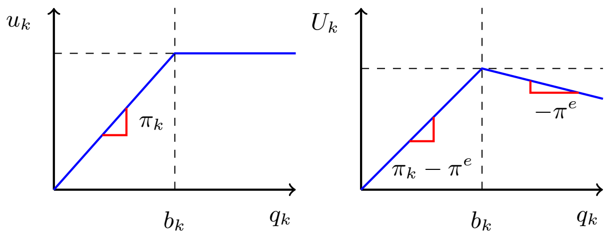

Fig. 1. (a) Utility, and (b) net utility of agent k

Remark 1: The agent utility functions are private information. The aggregator does not have knowledge of agent baselines and marginal utilities. We assume that the aggregator has knowledge of an upper bound on the agent marginal utilities, i.e. it knows $\pi_{\max}$ where

$$\pi_{\max} \geq \max_k \pi_k. \tag{3}$$

We note that $\pi_{\max}$ has the interpretation of the maximum price that the aggregator is *willing to pay* agents per KWh of demand reduction.

Remark 2: We assume that the agent parameters π_k and b_k are independent across the agents. This is reasonable because the true marginal utility and the true baseline of an agent are not dependent on the behavior of other agents. In addition π_k and b_k are also independent.

C. Mechanism Time-line

Below we outline the time-line of the mechanism as shown in Figure 2.

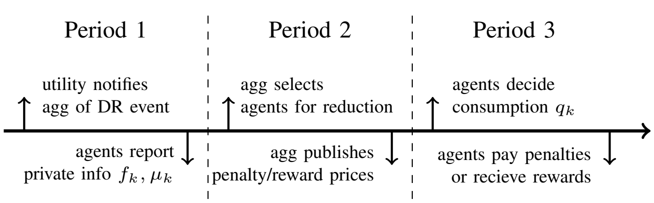

Fig. 2. Event Time-line

Period 0 (Common information): The aggregator recruits N agents into its DR program. Agents enroll based on the opportunity to receive financial rewards. The aggregator informs participating agents of (a) the selection scheme (b) the payment scheme.

Period 1 (Reporting): The utility notifies the aggregator of an anticipated DR event. In response the aggregator is obligated to deliver D KWh of demand reduction. All agents (indexed by k) report their baselines and marginal utilities, f_k and μ_k respectively, to the aggregator, which need not be truthful. The agents report (f_k, μ_k) strategically, i.e. they may opt to deliberately submit incorrect reports.

Period 2 (Selection): The aggregator selects a subset of agents to delivers the aggregate load reduction target D. The selection is based on the collective reports submitted by the agents. The aggregator calls the selected agents to reduce their consumption. The selection scheme has to address the tradeoff arising from the following two aspects (i) strategic manipulation of reports (ii) delivering the target at minimum cost. The aggregator computes and publishes reward prices π_k^r for agents who are called, and a penalty price π_k^p for agents who are not called.

Period 3 (Load reduction and payment): During the DR event, all agents decide on their actual consumption q_k. The consumption they decide depends on whether they are called or not. If agent k is called, it receives an *ex post* reward

$$R = \pi_k^r (f_k - q_k)^+. \tag{4}$$

If agent k is not called, it is assessed an *ex post* penalty

$$P = \pi_k^p (f_k - q_k)^+. \tag{5}$$

Called agents are rewarded for consumption reduction from their reported baselines, and agents that are not called are penalized for consumption shortfalls below their reported baselines.

D. The Agent's Problem

We assume that the agents are rational and non-cooperative. Each agent faces a two stage decision problem. In the first stage, it has to decide the value of its reports (f_k, μ_k). In the second stage, it has to decide on its actual energy consumption q_k during the DR event. This second stage decision depends on whether or not agent k is called for the DR event. Selected agents are rewarded for consumption reduction from their reported baselines, and agents that are not selected are penalized for consumption shortfalls below their reported baselines. Suppose agent k submits a baseline report f_k. If this agent is selected, its second stage cost function is

$$J_{\mathrm{s}}(q_k, f_k) = \pi^e q_k - u(q_k) - \pi_k^r (f_k - q_k)^+.$$

If the agent is not selected, its second stage cost function is

$$J_{\mathrm{ns}}(q_k, f_k) = \pi^e q_k - u(q_k) + \pi^p (f_k - q_k)^+.$$

Define the optimal consumptions

$$q_{\mathrm{s}}^* = \arg\min_{q_k} J_{\mathrm{s}}(q_k, f_k), \quad q_{\mathrm{ns}}^* = \arg\min_{q_k} J_{\mathrm{ns}}(q_k, f_k).$$

Note that these depend on the first stage decision f_k, i.e. the reported baselines. The first stage reports (f_k, μ_k) of agent k are such that it minimizes the overall cost of participation in the DR program. The overall cost of participation depends on the selection mechanism, and the the second stage costs J_{s} and J_{ns}.

III. Self-Reported Baseline Mechanism

The agents who are recruited, submit reports of their baseline f_k and marginal utility μ_k. This establishes the baseline of the consumer. As stated before the agents can be strategic in what they report. The key idea is to design the DR program so that agents *reveal their true baselines and marginal utilities*. This avoids inaccurate baselines and allows the aggregator to deliver the DR target at minimal cost. SRBM is given in Algorithm 1 below.

Algorithm 1 Self-Reported Baseline Mechanism (SRBM)

1) Receive aggregate load reduction target D from utility
2) Receive reports f_k and μ_k from all consumers
3) Sort agents into M pods $\mathbb{P}^1, \mathbb{P}^2 ..., \mathbb{P}^M$
4) Select $\mathbb{P}^i$ with probability β^i
5) Call the agents in the pod core $\mathbb{S}^i$ of $\mathbb{P}^i$
6) Observe consumption q_k of every agent k
7) Reward the called consumers based on the reported reduction, as given by (4)
8) Impose penalty for deviation from the reported baseline, as given by (5)

The algorithm in terms of the time line in Fig. 2 entails the following steps.

Period 1 (Reporting): In this stage each agent report its baseline and its marginal utility f_k and μ_k. These may not be their true values.

Period 2 (Selection): The selction is a randomized scheduling scheme which entails the following steps: (a) agents are sorted in the increasing order of their reported marginal utility μ_k, (b) these agents are then arranged into pods, $\mathbb{P}^1, \mathbb{P}^2, ..., \mathbb{P}^M$, where each pod is a subset of agents that can deliver the required demand target under SRBM, (c) aggregator selects pod i with a certain probability β^i, (d) a subset of agents in the selected pod (pod core) are called for the DR event. Details of the selection scheme are discussed in Section IV.

Period 3 (Load reduction and payment): After the DR event the agents who were called are paid a reward R according to (4). The agents who are not called gets a penalty P according to (5) if their consumption deviates from their reported baseline. However this requires the specification of the reward price π_k^r and penalty price π_k^p.

Let $\mathbb{S}_{-k}$ be the set of agents who *would have been called* if agent k was not participating in the DR program. Define the reward price for agent k to be

$$\pi_k^r = \max\{\mu_j\} - \pi^e \ , \ j \in \mathbb{S}_{-k}. \tag{6}$$

We stress that the reward price π_k^r depends on the target D, and is agent-specific. Agents who are not selected face a penalty price π^p for consumption deficits $(f_k - q_k)^+$ below their reported baselines. The penalty price π_k^p for agent k is chosen to satisfy $\pi^p \geq \pi^e$. It is best to select the smallest penalty price, i.e. $\pi_k^p = \pi^e, \forall k$, so as not to discourage agents from participating. For a detailed discussion of the self-reported baseline mechanism we direct the reader to [20]. We summarize the properties of SRBM in the theorem below.

Remark 3: Under SRBM, **agents are not privy to the randomized sheduling scheme**. Each agent is provided limited information about the mechanism that is sufficient to establish their selection and reward mechanism. We refer the reader to [20] for a detailed discussion.

Theorem 1: SRBM has the following properties:
(a) truthful reporting of baselines and marginal utilities is a dominant strategy
(b) called agents consume $q_s^* = 0$, providing the maximal reduction in their discretionary consumption
(c) agents that are not called consume $q_{ns}^* = b_k$
(d) the aggregator receives no penalty revenue
(e) the load reduction target D is met by each pod

Proof is omitted to due to page limit. Detailed analysis and proof are given in [20].

Remark 4: We have assumed that agent utility functions (and resulting true baseline consumption b_k) are deterministic. However, b_k depends on (exogenous) random parameters such as temperature and occupancy. For example, A more realistic model would accommodate dependence on exogenous random processes such as temperature and occupancy. This might result, for example, in a baseline consumption of the form $b_k = \bar{b}_k + a_k|\theta - \theta_0|$. Here, θ is the realized temperature during the DR event, and θ_0 is the predicted temperature. In this case, agents can be required to report their best-effort forecast $\bar{b}_k$ of their baseline consumption along with the temperature sensitivity a_k. Historical consumption data can be used to assist agents in making these reports. The SRBM mechanism can be easily extended to incorporate these more complex reporting scenarios. The most general scenarios with uncertain utility functions that explicitly depend on exogenous random processes θ is challenging and is an ongoing work.

IV. Randomized Scheduling Scheme

In this section we discuss the selection/scheduling scheme, *pod sorting algorithm*, that constitutes the SRBM. The basic idea is to arrange the agents in the increasing order of marginal utility and selects the agents with lowest marginal utility. However this is done in a randomized way in order to elicit the true reporting from the agents and to minimize expected cost of DR provision. The algorithm is given below.

Pod Sorting Algorithm

1 Sort agents in the increasing order of reported marginal utilities
2 Set pod index $i = 1$. Set $n = 1$
3 Place $k^*(i)$ agents indexed from n to $n + k^*(i) - 1$ in pod core $\mathbb{S}^i$ where $k^*(i)$ is the smallest number such that $\displaystyle\sum_{j=n}^{n+k^*(i)-1} f_j \geq D$. Increment $n \leftarrow n + k^*(i)$
4 Place $k^*(i+1)$ agents indexed from n to $n+k^*(i+1)-1$ in pod header $\mathbb{H}^i$ where $k^*(i+1)$ is the smallest number such that $\displaystyle\sum_{j=n}^{n+k^*(i+1)-1} f_j \geq D$.
Increment $n \leftarrow n + k^*(i+1)$
5 Define the pod $\mathbb{P}^i = \mathbb{S}^i \cup \mathbb{H}^i$. Define the pod selection probability $\beta^i = \min \beta_k^i, \ k \in \mathbb{S}^i$. Increment $i \leftarrow i + 1$
6 Define $\mathbb{S}^i = \mathbb{H}^{i-1}$.
7 If $\sum_i \beta^i < 1$, go to step 4. Else stop.

Based on the submitted reports, the agents are arranged in the increasing order of μ_k and sorted into M pods,

$\mathbb{P}^1, \cdots, \mathbb{P}^M$. A pod contains a subset of recruited agents that can deliver the demand reduction target D under SRBM.

Suppose there are n_i agents in pod $\mathbb{P}^i$, arranged in such a way that $\mu_k \leq \mu_{k+1}, k = 1, \ldots, n_i - 1$. These agents in pod $\mathbb{P}^i$ are divided into the pod core $\mathbb{S}^i$ and pod header $\mathbb{H}^i$ such that $\mathbb{P}^i = \mathbb{S}^i \cup \mathbb{H}^i$. More precisely, the first k^* agents form the pod core $\mathbb{S}^i$ where

$$\sum_{k=1}^{k^*} f_k \geq D, \quad \sum_{k=1}^{k^*-1} f_k < D. \tag{7}$$

In order to compute the reward prices π_k^r, the pod header must also contain sufficiently many agents. More precisely, we require that if any agent in the core $\mathbb{S}^i$ is removed, we can still find sufficiently many agents in the same pod $\mathbb{P}^i$ to determine $\mathbb{S}_{-k}^i$ and in turn π_k^r. This can be ensured by defining pod header $\mathbb{H}^i$ as the set of the next k^{**} agents such that

$$\sum_{k=k^*+1}^{k^{**}} f_k \geq D, \quad \sum_{k=k^*+1}^{k^{**}-1} f_k < D. \tag{8}$$

The pod $\mathbb{P}^i$ is defined as $\mathbb{P}^i = \mathbb{S}^i \cup \mathbb{H}^i$.

Equivalently, k^* is the smallest index such that the first k^* agents from pod $\mathbb{P}^i$ in the sorted list of marginal utilities can deliver the target D. If pod $\mathbb{P}^i$ is selected in response to a DR event, agents in its core $\mathbb{S}^i$ are *called on* to provide their demand reduction. The remaining agents form the pod header $\mathbb{H}^i$. Since agents in the header of a pod are not called, they can serve as the core of another pod. In this way we reduce the number of agents to be recruited.

The key idea in our pod selection algorithm is to organize agents into pods so that pods with large rewards are selected with low probability. This reduces the expected payout to agents. The maximum reward price paid to agents in pod $\mathbb{P}^i$ is bounded by

$$\pi_k^r \leq \nu^i - \pi^e, \text{ where } \nu^i = \max_{k \in \mathbb{P}^i} \pi_k.$$

Also, pod $\mathbb{P}^i$ is selected with probability $\beta^i = \pi^e/\nu^i$. As a result, pods with larger reward prices are selected with lower probability, reducing the expected cost of DR provision. Agents with high marginal utility are called on less frequently, reducing the expected dis-utility. Pod sorting is illustrated in Fig. 3.

Remark 5: As discussed above, the design of the pod sorting based randomized scheduling scheme is such that it is optimal in terms of expected cost of DR provision. For lack of space we do not include a discussion here and we direct the reader to [20] for a more detailed discussion.

V. Conclusion

In this paper, we have addressed the baseline estimation problem that is central to demand response programs. We proposed a mechanism where agents participating in a DR program self-report their baselines and marginal utilities. Under this self reported baseline mechanism (SRBM), agents reveal their true baselines and marginal utilities. We also

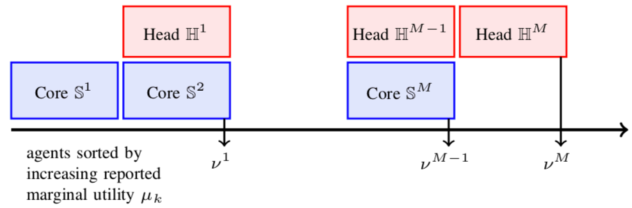

Fig. 3. Pod Sorting

proposed a pod-sorting algorithm based DR scheduling for selecting consumers that is nearly optimal in terms of expected cost of DR provision.

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