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Dissecting demand response mechanisms: The role of consumption forecasts and personalized offers

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ABSTRACT

Demand-Response (DR) programs, whereby users of an electricity network are encouraged by economic incentives to re-arrange their consumption in order to reduce production costs, are envisioned to be a key feature of the smart grid paradigm. Several recent works proposed DR mechanisms and used analytical models to derive optimal incentives. Most of these works, however, rely on a macroscopic description of the population that does not model individual choices of users.

In this paper, we conduct a detailed analysis of those models and we argue that the macroscopic descriptions hide important assumptions that can jeopardize the mechanisms' implementation (such as the ability to make personalized offers and to perfectly estimate the demand that is moved from a timeslot to another). Then, we start from a microscopic description that explicitly models each user's decision. We introduce four DR mechanisms with various assumptions on the provider's capabilities. Contrarily to previous studies, we find that the optimization problems that result from our mechanisms are complex and can be solved numerically only through a heuristic. We present numerical simulations that compare the different mechanisms and their sensitivity to forecast errors. At a high level, our results show that the performance of DR mechanisms under reasonable assumptions on the provider's capabilities are significantly lower than those suggested by previous studies, but that the gap reduces when the population's flexibility increases.

1. Introduction

Demand Response (DR hereinafter) programs are envisioned to be a key feature of the Smart Grid paradigm [1]. By means of economic incentives (discounts or penalties), DR schemes encourage users to rearrange their consumption in response to the network state, thus mitigating the grid overload and driving wholesale prices down.

Several analytical models are available in the literature, which describe and quantify the effects of DR mechanisms. Whatever their specifics are, these schemes need to model how users react to the incentives. Ideally the models should capture the most realistic features of a practical DR mechanism while maintaining tractability.

Among these contributions, the authors of [2] study how an energy provider should select time-dependent discounts to minimize its production costs. They assume that the percentage of users who shift their consumption from slot i to slot j is a decreasing function of the temporal distance between slots i and j and a concave and increasing function of the discount offered in slot j (R_j), *independent* from discounts in other slots. The paper claims that, under these assumptions along with the requirement of piecewise linearity of energy production costs, the problem of finding the set of discounts that minimize the provider's cost is convex and therefore simple to solve. Under similar modeling assumptions, however, we find that the optimization problem can be non-convex even in such a simple scenario (see Section 4). The same user's model as in [2] is adopted also in [3], where the optimization problem is extended in order to account for battery storages and distributed renewable sources available into a specific microgrid. Authors of [4] propose a day ahead pricing scheme which maximizes the provider's profitability and capacity utilization. Users are assumed to reschedule their consumption by comparing the utility v_i they get by scheduling a task in each timeslot i; therefore they allocate their consumption proportionally to these utilities,

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i.e., they consume a fraction $\frac{v_i}{\sum_{j=1}^{T} v_j}$ of their total energy demand in timeslot i. The resulting optimization problem is non convex but some relaxation techniques are introduced, which allow one to calculate a solution within a reasonable amount of time. In [5], a more realistic model is proposed where each user first calculates the welfare (defined as utility minus time-dependent cost) she gets from consuming electricity in each of the possible timeslots, and then allocates all the consumption to the slot returning the largest welfare. As we show below (see Section 4.4) this model can lead to a much more complex optimization problem than the one presented in [5]. Finally, the authors of [6] propose a full-fledged game theoretical model, but their results hold only if users experience a large number of interactions without any change in the system.

We claim that these studies rely on too strong assumptions, which jeopardize their usability for practical purposes. Interestingly, we observe that the assumptions are sometimes hidden in the macroscopic models the papers start from. In particular in this paper we focus on [2] and show that its model requires personalized offers and a very precise forecast of the baseline consumption of each user. The implementation of these features may require potentially significant costs in terms of communication, measurement and computation infrastructure. Besides highlighting these implicit requirements in the analytical framework in [2] (and then also in [3]), we explore their potentials considering four DR mechanisms with different levels of complexity:

1. the *base* mechanism corresponds to an optimization problem similar to the one considered in [2], it requires personalized offers and individual consumption forecasts; the energy production cost is optimized over the discount values, each of which is offered to a given fraction of the population,
2. the *optimized* mechanism takes full advantage of personalized offers and consumption forecasts by minimizing the cost over both the discount values and the population fractions to which the discounts are offered,
3. the *robust* mechanism relies on personalized offers, but does not need individual consumption forecasts,
4. finally the *broadcast* mechanism (analogous to that in [5]) needs neither of the two features.

Interestingly, contrarily to prior studies, we find that the cost-minimization problems resulting from our DR mechanisms are not convex (even for the base mechanism). Nevertheless, simple heuristics can identify (potential) minima in a reasonable amount of time in realistic scenarios. Then, our numerical results show that the simpler robust and broadcast mechanisms achieve significantly lower cost reductions than the optimized mechanism, which is difficult to implement, but that the gap reduces when the population's flexibility increases.

The paper is organized as follows. In Section 2 we discuss how the macroscopic models considered in [2–4] hide some implicit assumptions about the user rationality or about the interactions between the provider and the user. We define our microscopic model in Section 3 and then describe different DR mechanisms and their corresponding optimization problems in Section 4. We evaluate their performance numerically in a realistic scenario in Section 5. Finally in Section 6 we discuss how our models can be tuned and which other psychological and social insights should be taken into account to explain users' decisions.

2. Pitfalls when starting from macroscopic models

In this section, we describe in more detail the macroscopic models proposed in the literature for day-ahead price optimization. Consider a finite time horizon discretized in a set $\mathcal{T}$ of N timeslots and a large population $\mathcal{S}$ of users. The baseline aggregate energy consumption in slot j is denoted by E_j^0.

The energy provider charges a flat rate B, but it can offer discount rates to incentivize the users to move some of their consumption so as to reduce the energy production cost. Due to consumption shifts, the actual aggregate consumption in time slot j is E_j^1. Observe that a usual assumption in the literature (including the papers mentioned above) is that the introduction of a DR scheme neither reduces nor increases users' demand; it merely rearranges users' consumption in a more cost effective way, so that

$$\sum_{j=1}^{N} E_j^0 = \sum_{j=1}^{N} E_j^1. \tag{1}$$

We denote the amount of consumption shifted from slot j to slot $i \neq j$ as $E_{j\to i}$, and the amount of consumption the users refuse to shift away from j as $E_{j\to j}$. Then we have

$$E_i^1 = E_i^0 + \sum_{z=1}^{N} E_{z\to i} - \sum_{k=1}^{N} E_{i\to k}.$$

We now start to further detail the model considering some specific assumptions made in previous works. In [2] and [3], the electricity provider offers an energy price discount $R_i \geq 0$ in each slot i. The users are assumed to react to these incentives by shifting a fraction of their baseline consumption from slot j to slot i ($|j-i|$ slots away) according to the following formula:

$$E_{j\to i} = E_j^0 S_j(R_i, |j-i|). \tag{2}$$

$S_j(R_i, |j-i|)$ is called the aggregate sensitivity function and is increasing in the discount R_i and decreasing in the temporal shift $|j-i|$, in order to take into account the user discomfort.

The provider selects the vector of discounts $\mathbf{R}$ in order to minimize its total cost, equal to the sum of the electricity generation costs and the loss of revenues due to the discounts. In particular the optimization problem considered in [2] is the following:

$$\min_{\mathbf{R}} \sum_i \sum_{j\neq i} R_i E_{j\to i} + \sum_i c_i\left(E_i^1\right) \tag{3}$$

$$\text{s.t. } 0 \leq R_i \leq B \quad \forall i = 1, \ldots, N, \tag{4}$$

where $c_i(\cdot)$ is the cost of electricity production in slot i. Eq. (4) guarantees that discounts $\mathbf{R}$ are non negative and smaller than the flat rate B, so that the money stream goes toward the provider.

As it often happens, the devil is hidden in the details, and in this case in Eqs. (2) and (3). Our first remark is that the cost of lost revenues $\sum_i \sum_{j\neq i} R_i E_{j\to i}$ in Eq. (3) implicitly assumes the possibility to reward only the consumption actually shifted from j to i, i.e., $E_{j\to i}$, but this quantity cannot be directly measured. The actual consumption E_i^1 can be measured, and then $E_{j\to i}$ can be quantified provided that we have good estimates of the sensitivity function $S_j(R_i, |j-i|)$ and of the baseline consumption E_i^0. Let us assume for a moment that $S_j(R_i, |j-i|)$ is known from historical data and that the aggregate baseline consumption may be predicted with a reasonably high level of accuracy on a large set of users. Then it seems possible to solve the macroscopic problem in Eqs. (3) and (4), but we need to consider also what should happen at the microscopic scale. While the estimates for the aggregate baseline consumption can be adequately precise, finally the billing is done at the user's granularity and each user expects to receive the price discount corresponding to the energy consumption she actually moved. If the energy bill's reduction does not correspond to her forecast, the user is likely to opt out of the program (in particular if she has experienced underpayments) or to reduce her efforts and