Adequate Feedback-based Customer Incentives in Automated Demand Response

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ABSTRACT

Most often, incentives involved in Automated Demand Response (ADR) contracts are statically defined and assume full customer rationality, thus hindering sustained customer enrollment to them of customers with other characteristics (e.g. altruism). In this paper, we derive appropriate incentives for ADR contracts, so that non-fully rational customers are compensated even when information for consumer utilities is not available. In case such information is hidden, we assume that customers provide feedback on their satisfaction from direct endowments, albeit sustaining energy-consumption reduction. We mathematically model the customer and the utility company's problems for the aforementioned cases of full and hidden information and solve them algebraically or in a distributed manner. Based on numerical evaluation and simulation experiments, we showcase the validity of our analytical framework in realistic scenarios and that, for the case of hidden information, customer feedback is adequate for calculating incentives that lead to successful DR campaigns.

CCS CONCEPTS

• **Information systems** → *Information systems applications*; • **Applied computing** → *Economics*; • **Hardware** → Smart grid;

KEYWORDS

altruism, behavioral economics, ADR contracts, uncertainty, demand side management

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1 INTRODUCTION

Demand Response (DR) programs for curtailing energy consumption in critical times for the operation of the energy grid are becoming popular. Automated DR (ADR) automates the response process of the customer to the DR signals by means of electric controls installed at the customer premises. Enrolling to ADR is usually linked to a contract that predefines a financial reward for the customer for the energy saved. The endowment in ADR contracts aims to compensate for any user utility losses due to lower energy consumption regardless the underlying reasons for these losses. ADR rebates are defined mostly statically and based either on the costs of ADR equipment [7] or the cost per unit of energy at peak times (similarly to Critical Peak Rebate tariffs).

This contractual form of financial endowment should not be based solely on the market value of the energy saved. First, the utility loss for the customer in the time periods that energy is curtailed may not be linked to the market value of that energy, but may include other aspects, such as activity associated to a need, personal comfort, etc. In such a case, endowment may fall short as means for customer engagement to the ADR program. Second, the amount of energy-consumption reduction and the associated customer endowment of an ADR program do not take into account customer satisfaction. As a result, an unsatisfied customer may not renew her ADR contract after it expires.

In this paper, we investigate flexible ADR incentives that can ensure the desired level of wide customer acceptance. Moreover, we consider that customers are not solely driven by financial motives, but also by a number of behavioral factors, such as *altruism*. As argued in [4], altruistic values can complement or even dominate the narrow self-interest presumed by a standard rational choice theory of decision making. We mathematically model the problem of finding minimum ADR incentives that are satisfactory at least for a certain percentage of customers, when customers exhibit various degrees of altruism. We solve this problem algebraically for the case that user utilities are fully known to the utility company. In case of hidden information, customer feedback on the acceptance of ADR incentives is employed; a feedback-based distributed iterative algorithm is developed for finding minimum ADR incentives. We derive a mathematical formula, so that each customer that exhibits a certain degree of altruism can estimate a missing term (related to the well-being of others) involved in her individual utility loss from energy-consumption reduction by employing the aggregate feedback of others. Based on numerical evaluation and simulation experiments, we showcase certain important tradeoffs and the effectiveness of our distributed algorithms for finding low satisfactory ADR incentives in few iterations.

There is some prior work related to the design of optimal incentives for DR programs based on implicit feedback on customer acceptance [1, 2, 5]. In [1], an aggregator is assumed to iteratively post incentives to users for load scheduling and users state whether

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they would like to participate or not and how. In the same direction, in [5], whenever a DR signal is emitted, users are compensated in proportion to their reported energy-consumption reduction, if accurate. In [2], the authors calculate the required energy load change for customers, the corresponding adequate incentive value and the best timing to implement DR, in order to maximize customer acceptance. However, to the best of our knowledge, our approach is the first one that explores the utilization of explicit customer feedback for approximating hidden information on user utilities to design ADR contracts that are acceptable by the desired proportion of customers.

The remainder of this paper is organized as follows: In Section 2, we present our system model. In Section 3, we define the DR designer's problem to offer minimum ADR incentives that satisfy a desired proportion of customers in the cases of full and hidden information on user utilities. In Section 4, we assess our approach based on numerical evaluation and simulation experiments. Finally, in Section 5, we discuss our key findings and outline some future work.

2 SYSTEM MODEL

We consider a district of residential buildings served by a utility company. The utility company offers ADR contracts to the residents of the district. Denote $\mathcal{N}$ the set of residential houses that enroll into the ADR programs. According to the ADR contract, the utility company curtails the total energy consumption of the house of a customer in specific periods by a specific amount. A customer i enjoys net benefit U_i (i.e., user satisfaction minus energy cost) from consuming baseline energy q_i^0 and an energy-consumption reduction ΔQ_i in specific time periods according to an ADR contract results to a net benefit loss $\Delta U_i = -\eta_i U_i$. Note that ΔQ_i may be calculated as a fraction of q_i^0 or as a necessary energy curtailment, so as to bring energy load under a certain threshold [6]. In return, the customer i receives an endowment b_i by the utility company. Throughout the paper, whenever the endowment is the same for all customers, it is denoted as b, otherwise as b_i.

Moreover, we consider that the user utility function of the consumer does not solely depend on her total energy consumption, but additionally on other socio-demographic or psychological factors, such as *altruism* [4]. We consider altruism as an intrinsic motivation factor and derive our model from the one of Charness and Rabin (2002) [3] without *inequity aversion.* (An individual is inequity averse if, in addition to her material self-interest, her utility increases for more equitable allocation of material payoffs.) Our user utility model that incorporates altruism is given by:

$$u_i = (1-\gamma_i)U_i + \gamma_i \overline{U}_{-i}\,, \tag{1}$$

where $\gamma_i \in [0,1]$ is the degree of altruism of customer i and $\overline{U}_{-i}$ is the mean net benefit from consuming energy for all N customers except for i. Note that a customer i with $\gamma_i = 0$ is considered fully selfish, while with $\gamma_i = 1$ is considered completely "disinterested" in her own net benefit from consuming energy in the sense that she cares only for the net benefits of others from energy consumption. Henceforth, for easiness in the calculations and without loss of generality we assume the net benefit U_i of customer i from her baseline energy consumption to be *normalized* by the maximum net benefit $\hat{U}$ from consuming energy of all customers, i.e., $U_i \in [0,1]$. Then, the endowment b is also normalized by the maximum utility of all customers, e.g., $b = 0.3$ means that the endowment equals the 30% of the maximum utility value.

Overall, the user utility difference for customer i due to the ADR contract is given by:

$$\Delta u_i = -(1-\gamma_i)\eta_i U_i + \gamma_i \overline{\Delta U}_{-i} + b\,, \tag{2}$$

Note that since U_i is normalized and u_i is in $[0,1]$, b is also normalized by the maximum net benefit of all customers. Most importantly, note that the aforementioned formulation allows for any individual energy-consumption reduction to be applied to customers, whether uniform or not.

We define that when the endowment covers the loss of a customer, then the customer is considered to be *satisfied* by the ADR contract; otherwise, the customer is *unsatisfied*. More formally, we define that customer i is satisfied, when $\Delta u_i \geq 0$ and unsatisfied otherwise. The fraction α of satisfied customers is given by:

$$\alpha \triangleq \frac{\sum_{i\in\mathcal{N}} \mathbb{1}(\Delta u_i \geq 0)}{N}\,, \tag{3}$$

where $\mathbb{1}(\cdot)$ is the indicator function that equals 1 when its argument is true and it is 0 otherwise.

3 DR DESIGNER'S PROBLEM

The DR designer needs to construct ADR contracts appropriately, so as customers to (a) enroll in them in the first place, (b) extend/renew their ADR contracts. The former can be achieved if the reduction in the customer benefit due to the lower energy consumption, as specified in the ADR contract, is *expected* by the customer to be compensated for by the associated endowment. The latter necessitates that the *materialization* of the ADR contract is indeed satisfactory for the customer. Obviously, an indefinitely high endowment would achieve both aforementioned goals, but that would be prohibitively costly. There is a *trade-off* among the value loss for the customer due to the energy-consumption reduction as defined in her contract, the associated endowment to the customer and the customer satisfaction by the ADR contract. Within this trade-off, the objective of the DR designer is to minimize the total endowment cost for a lower-bound $\underline{\eta}$ in the net benefit loss due to energy-consumption reduction of each customer and a lower-bound $\underline{\alpha}$ in customer satisfaction, i.e.,

$$\begin{aligned} &\textbf{Minimize: } \sum_{i\in\mathcal{N}} b_i \\ &\textbf{such that: } \alpha \geq \underline{\alpha} \ \wedge \ \eta_i \geq \underline{\eta}\,, \forall\, i \in \mathcal{N}\,. \end{aligned} \tag{4}$$

Below, we analytically establish the aforementioned trade-off. We first consider the case of full information regarding user utilities and, subsequently, we analyze the case where user utilities are hidden for the DR designer.

3.1 Full Information

In this subsection, we assume that the normalized benefit from energy consumption U_i and the level of altruism γ_i are known to the DR designer for each customer i. We now derive a relationship among the various parameters of the system. Adding down (2) for all customers and then dividing by N, while taking for large N that

$\overline{\Delta U}_{-i} = \overline{\Delta U}$, $\forall i \in \mathcal{N}$, we derive:

$$\frac{\sum_{i=1}^{N} \Delta u_i}{N} = -\frac{\sum_{i=1}^{N} (1-\gamma_i)\eta_i U_i}{N} + \overline{\Delta U}\frac{\sum_{i=1}^{N} \gamma_i}{N} + b \tag{5}$$

Then, by employing

$$\bar{\gamma} = \frac{\sum_{i=1}^{N} \gamma_i}{N}\ , \tag{6}$$

$$\overline{\Delta u} = \frac{\sum_{i=1}^{N} \Delta u_i}{N} \tag{7}$$

in equation (5), we get

$$\overline{\Delta u} = -\frac{\sum_{i=1}^{N} (1-\gamma_i)\eta_i U_i}{N} + \overline{\Delta U}\bar{\gamma} + b\ . \tag{8}$$

Note that, by definition, $\overline{\Delta U}$ is given by:

$$\overline{\Delta U} = -\frac{\sum_{i=1}^{N} \eta_i U_i}{N} \tag{9}$$

Equation (8) expresses the various trade-offs among the parameters of the system.

Note that for $\gamma_i = 0$ and $\eta_i = \eta\ \forall i \in \mathcal{N}$, equation (8) becomes as follows:

$$\begin{aligned} \overline{\Delta u} &= -\eta \frac{\sum_{i=1}^{N} U_i}{N} + b \Leftrightarrow \\ \overline{\Delta u} &= -\eta \bar{U} + b \end{aligned} \tag{10}$$

Therefore, for a society of rational customers where b compensates customers for their mean value loss due to their decreased energy consumption, the mean overall utility difference is given by (10).

Problem (4) can be solved by sorting all consumers with respect to Δu in a descending order for b=0 and then solve the equation $\Delta u_k(b) = 0$ to find b, with $k = \lceil \alpha \cdot N \rceil$. This is the value of b that leads to α% customers having $\Delta u \geq 0$.

3.2 Hidden Information

Assume now that U_i and γ_i are private information known only to customer i; hence, Δu_i is also private. However, we assume each customer i *honestly* provides *binary feedback* on her respective satisfaction Δu_i. Customer feedback is provided on an anonymized manner (e.g., through an e-ballot). Specifically, assuming she is sincere, customer i provides feedback $v_i = 1$ when $\Delta u_i \geq 0$ and $v_i = 0$ when $\Delta u_i < 0$. Then, the following is true:

$$\frac{\sum_{i=0}^{N} v_i}{N} = \alpha\ , \tag{11}$$

where α is the fraction of customers that are satisfied with the direct incentive b.

Consider a distributed algorithm where, at each round t, the DR designer sets a b_t and each customer i responds to it with feedback $v_{i,t+1}$ that result to a mean satisfaction level α_{t+1} for the received incentives at the next round of the game. The feedback $v_{i,t+1}$ of customer i at round $t+1$ is determined by the sign of:

$$\Delta u_{i,t+1} = -(1-\gamma_i)\eta_i U_i + \gamma_i \overline{\Delta U}_{-i,t} + b_t \tag{12}$$

We need to calculate $\overline{\Delta U}_{-i,t}$ at round t. Note that there holds $-1 \leq -U_i \leq 0$. Since $\gamma_i, \eta_i \in [0,1]$, it follows that

$$-1 \leq \Delta U_i \leq 0 \Rightarrow -1 \leq \overline{\Delta U} \leq 0 \tag{13}$$

Observe from (9) that $\overline{\Delta U}_{-i} \approx \overline{\Delta U}$ for large N. Also, from (11), (13), $\overline{\Delta U}$ and $\alpha - 1$ have the same target set, while it can be reasonably assumed that the mean net benefit from energy consumption $\overline{\Delta U}_t$ at round t varies approximately as the reported average customer satisfaction α_t at round t. Therefore, we can assume the following approximation for any round t:

$$\overline{\Delta U}_t \approx \alpha_t - 1 \tag{14}$$

Then, employing (14) in (12), we have that for each customer i at round $t+1$ the following is true:

$$\Delta u_{i,t+1} = -(1-\gamma_i)\eta_i U_i + \gamma_i(\alpha_t - 1) + b_t \tag{15}$$

Customer i provides her satisfaction feedback at round $t+1$ according to the sign of (15). Equation (15) is very *important*, because it shows how customer i can estimate her individual utility difference from energy-consumption reduction by employing the aggregate feedback announced at round t for estimating $\overline{\Delta U}$, for which no other information is available.

For solving problem (4), the DR designer needs to update b_t at each round t, so as to find incentives that achieve minimum desirable customer satisfaction. Employing gradient ascent, the DR designer selects b_{t+1} for the round $t+1$ as follows:

$$b_{t+1} = \begin{cases} \max\{b_t + \Delta\alpha \cdot \kappa, 0\}\ , & \text{when } \Delta\alpha \neq 0 \\ b_t + \kappa, & \text{when } \Delta\alpha = 0 \end{cases} \tag{16}$$

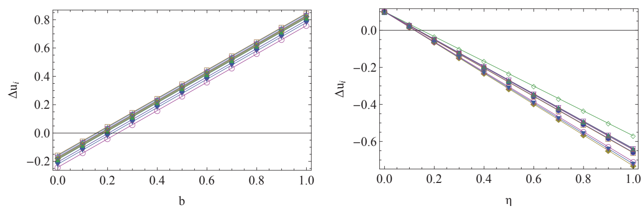
where $\Delta\alpha = \alpha_{t+1} - \alpha_t$ and $0 < \kappa << 1$ the step size of the gradient ascent algorithm.

If we reached minimum desired customer satisfaction, i.e., $\alpha_t \geq \underline{\alpha}$, then stop iterations.

4 EVALUATION

We consider a system of N=1000 customers. We take simple distributions of the system parameters to enhance the clarity of our findings. The degree of altruism γ_i for customer i follows Uniform in $[0,1]$, while the fraction η_i of her net benefit loss due to energy-consumption reduction is assumed to be uniformly distributed in $[0.1, 0.3]$, unless otherwise specified. Note that this net benefit loss per customer may arise due to different individual consumption reductions. The net benefit of customer i for her nominal energy consumption is assumed to follow Normal distribution with mean 0.8 and standard deviation 0.1, i.e., $U_i \sim N(0.8, 0.1)$ truncated to $[0,1]$.

We first assume that the utility company has full information on the user utility functions of its customers. Thus, the utility company can calculate the acceptability ratio α for any endowment for a specific energy-consumption reduction. We explore the trade-offs between the overall utility difference functions (equation (2)) of the various customers, the endowment b and the energy-consumption reduction η. The overall utility differences of 10 random customers with respect to the endowment b are depicted in Figure 1a. As shown therein, an endowment around 0.2 is needed to render customers indifferent for their energy-consumption reduction. Also, Figure 1b depicts the overall utility difference functions of 10 random customers with respect to the fraction η of net benefit loss due to energy-consumption reduction for endowment $b = 0.1$. Apparently, this endowment can only keep customers satisfied for



(a) (b)

Figure 1: Full Info: Overal utility difference functions with respect to (a) endowment b and (b) energy-consumption reduction fraction η when b=0.1.

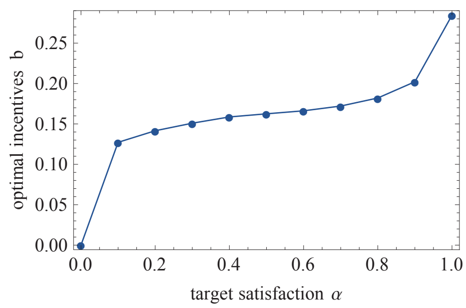
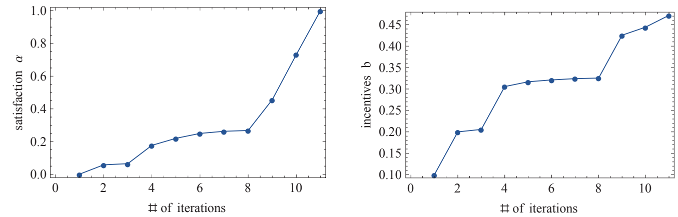


Figure 2: Full Info: Minimum endowment b that achieves targeted customer satisfaction when $\eta_i \sim U[0.1, 0.3]$.

net benefit loss from energy-consumption reduction smaller than roughly 15%.

We solve problem (4) and find the minimum b for each targeted customer satisfaction α for this community of customers. As shown in Figure 2, when full information is available, all customers can be satisfied for $b = 0.3$. This was actually expected, since the maximum reduction fraction of net benefit from energy consumption was assumed to be 0.3.

We now assume that the utility company does not know the user utility functions of customers (i.e., hidden info) and that customers provide feedback on their satisfaction for the endowment provided to each of them in an iterative manner according to (16) with κ=0.1. Solving problem (4) for target customer satisfaction 90%, the reported customer satisfaction per iteration is depicted in Figure 3a, based on the corresponding customer endowment per iteration, depicted in Figure 3b. Evidently from Figure 3b, the approach in (16) converges very fast to the minimum value of endowment b that achieves target customer satisfaction. Comparing Figure 3a and Figure 3b with Figure 2, we observe that hidden information increases the minimum endowment cost for the utility company. Figure 4 depicts the minimum endowment cost for different fractions of net benefit losses from energy-consumption reduction applied uniformly to all customers. As it can be seen therein, hidden information is costly; yet, the extra cost of incentives b due to hidden information (as estimated by our distributed algorithm) can be kept actually low (i.e., mostly around 0.2).



(a) (b)

Figure 3: Hidden info: For achieving target customer satisfaction $\geq$ 90%, (a) the reported customer satisfaction per iteration and (b) the minimum endowment per iteration.

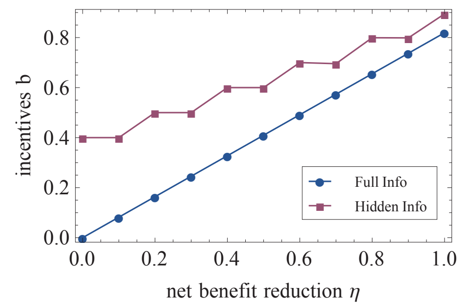


Figure 4: Optimal endowment b with respect to the consumption-reduction fraction imposed to all customers, in order to achieve 90% customer satisfaction in the full-info and the hidden-info cases.

5 CONCLUSIONS

In this paper, we studied the calculation of minimum ADR endowments that are satisfactory for a specific percentage of consumers that may exhibit a certain degree of altruism or not. Most importantly, we dealt with the case of hidden information on user-utility function and proposed a distributed algorithm to calculate ADR contracts with minimum satisfactory endowments based on customer feedback. Our evaluation results have shown the effectiveness of our distributed algorithm for the calculation of appropriate ADR incentives, in the cases of either full or hidden info on user utilities.

Overall, a serious concern on designing appropriate ADR contracts is reducing uncertainty regarding customer acceptance. The applicability of our approach in practical cases of ADR has no serious limitations. No knowledge regarding user-utility functions is necessary to find satisfactory endowments for different energy-consumption reductions applied to the various customers.

However, customer feedback has been assumed to be truthful in this paper. The investigation of the case of strategic lying and its alleviation constitute an interesting direction for future work. Finally, note that, our formulation is generic-enough to accommodate different user utility models. The consideration of additional behavioral factors in the design of appropriate ADR contracts is left for future work too.

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