Energy Efficiency via Incentive Design and Utility Learning*

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ABSTRACT

Utility companies have many motivations for modifying energy consumption patterns of consumers such as revenue decoupling and demand response programs. We model the utility company–consumer interaction as a principal–agent problem and present an iterative algorithm for designing incentives while estimating the consumer's utility function.

General Terms

Theory

Keywords

game theory; incentive design; utility learning; energy disaggregation

1. INTRODUCTION

Utility companies have many motivations for changing energy consumption patterns of users. Many regions are beginning to implement revenue decoupling policies, whereby utility companies are economically motivated to decrease energy consumption [3]. Additionally, the cost of producing energy depends on many variables, and being able to control demand via demand response programs can help alleviate the costs of inaccurate load forecasting [7].

In brief, the problem of behavior modification in energy consumption can be understood as follows. Utility companies provide incentives to energy consumers, who seek to

maximize their own utility by selecting energy consumption patterns. Figure 1 depicts the abstract view of the behavior modification problem. The design of incentives can be
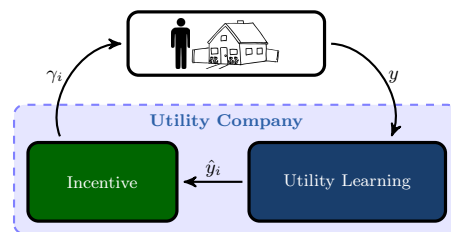

Figure 1: Behavior modification via incentives abstractly is a *control* and *estimation* problem.

thought of as a control problem for utility companies. Further, consumers do not report any measure of their satisfaction directly to the utility companies. Thus, it must be estimated. In this abstract, we formulate the problem of designing incentives for behavior modification given utility companies do not know consumers' utility functions and must learn them iteratively by issuing incentives in order to gather information about how consumers respond. We propose an algorithm for iteratively solving the incentive design and utility learning problem.

2. INCENTIVE DESIGN PROBLEM

A principal-agent problem occurs when the principal interacts with the agent to perform a task, but the agent is not incentivized to act in the principal's best interests [5]. This conflict is often the result of asymmetric information between the principal and the agent or a disconnect between their goals and objectives. We cast the utility–consumer interaction model in the framework of a principal–agent model in which the utility company is the principal and the consumer is the agent [9]. Both the principal and the agent wish to maximize their pay–off determined by the functions $J_p(v, y)$ and $J_a(v, y)$ respectively. The principal's decision is denoted v; the agent's decision, y; and the incentive, $\gamma : y \mapsto v$ where $\gamma \in \Gamma$ and Γ is the set of admissible controls from Y to $\mathbb{R}$. Let v and y take values in $V \subset \mathbb{R}^{n_p}$ and $Y \subset \mathbb{R}^{n_a}$, respectively; $J_p : \mathbb{R}^{n_p} \times \mathbb{R}^{n_a} \to \mathbb{R}$; $J_a : \mathbb{R}^{n_p} \times \mathbb{R}^{n_a} \to \mathbb{R}$. The incentive problem can be stated as follows. Determine the desired actions

$$(v^d, y^d) = \arg \max_{v \in \mathcal{I}_v, y \in \mathcal{I}_y} J_p(v, y) \qquad (1)$$

where $\mathcal{I}_v$ and $\mathcal{I}_y$ are constraints on v and y respectively. Then, solve the following problem:

PROBLEM 1. *Find* $\gamma : Y \to V$, $\gamma \in \Gamma$ *such that*

$$\arg\max_{y \in \mathcal{I}_y} J_a(\gamma(y), y) = y^d \qquad (2)$$

$$\gamma(y^d) = v^d \qquad (3)$$

where Γ *is the set of admissible incentive mechanisms.*

3. ALGORITHM

The principal's true utility is assumed to be given by

$$J_p(v, y) = g(y) - v \qquad (4)$$

where v is the value of the incentive paid to the agent and $g(\cdot)$ is a function of the consumer's energy usage y over a billing period and may represent an objective derived from *revenue decoupling* or *demand response* programs [3, 7].

The agent's true utility is assumed to be

$$J_a(\gamma(y), y) = -py + \gamma(y) + f(y) \qquad (5)$$

where p is the fixed price of energy known to both the agent and the principal and $\gamma : Y \to \mathbb{R}$ is the incentive mechanism. The principal does not know the agent's satisfaction function $f(\cdot)$, and hence, must estimate it as he solves the incentive design problem. We will use the notation $\hat{f}$ for the estimate of the satisfaction and $\hat{J}_p$ and $\hat{J}_a$ for the player's cost functions using the estimate of f.

We propose an algorithm for solving the incentive design problem iteratively. We assume that the agent's satisfaction function is parameterized using the following finite–dimensional, affine parameterization

$$f = \sum_{i=1}^{N} \alpha_i f_i \qquad (6)$$

where f_i are basis functions, $\alpha = (\alpha_1, \cdots, \alpha_N) \in \mathcal{A}$. We can interpret $\mathcal{A}$ as the prior information we have about the agent's satisfaction function f.

The proposed algorithm is as follows. Find (v^d, y^d) by solving the problem formulated in (4). Suppose we are given $\gamma^{(0)}$. Then, at iteration k, we execute the following steps:

1. Estimate $\hat{f}^{(k)}$ using $\{y^{(\ell)}, \gamma^{(\ell)}\}_{\ell=0}^{k}$.

2. Determine $\gamma^{(k+1)}$ by solving Problem 1 replacing J_a with $\hat{J}_a^{(k)} = -py + \gamma^{(k+1)}(y) + \hat{f}^{(k)}(y)$.

3. Issue $\gamma^{(k+1)}$ and observe the agent's response $y^{(k+1)}$. If $y^{(k+1)} = y^d$, stop. Otherwise, $k \leftarrow k + 1$ and return to step 1.

4. DISCUSSION

Preliminary results on discussed algorithm are presented in [9]. We are able to show that if the satisfaction function is the sum of polynomial basis functions up to a finite order and under some mild assumptions on the linear dependence of the incentives, then after a finite number of iterations we know the satisfaction function exactly and at the next iteration we can design an incentive to induce the desired behavior.

We are currently working on using tools from non–linear programming such as constraint qualification and second–order optimality conditions including Kharush-Kuhn-Tucker

conditions to solve the estimation problem when we allow for the agent to play an *approximately optimal* strategy at each iteration [4]. In addition, we are developing an experimental platform in which we deploy sensors to 12 homes and design incentives to induce energy efficient behavior.

Another interesting direction for future work is device–level feedback. Studies have shown that providing device–level feedback on power consumption patterns to consumers can modify behavior and improve energy efficiency [6, 8]. However, the current infrastructure only has sensors to measure the aggregated power consumption signal for a household. Additionally, deploying plug–level sensors would require entering households to install these devices. A low cost alternative to the deployment of a large number of sensors is *non–intrusive load monitoring* (or *energy disaggregation*) which refers to recovering the power consumption signals of individual devices from the aggregate power consumption signal [1]. Returning to Figure 1, we remark that the estimation problem is extended to include energy disaggregation so that utility companies may design device–level incentives. Again, preliminary results are reported in [9]. With an ε–error bound disaggregation algorithm in place [1], we are able to design incentives to induce a consumption pattern that is approximately the desired behavior. We are currently using fundamental limits on energy disaggregation algorithms [2] to derive rigorous bounds on the behavior modification and utility learning problem.

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