Personalized Feedback-based Customer Incentives in Automated Demand Response

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Introduction

Introduction

- Demand Response (DR) programs for curtailing energy consumption in critical times for the grid are becoming common

- Automated DR (ADR) automates the response process of the customer to the DR signals by means of electric controls installed at the customer premises

- ADR rebates are defined mostly statically and based on
  - either the costs of ADR equipment or the cost per unit of energy at peak times

- Two problems with that:
  - First, the utility loss for the customer due to curtailed energy may include other aspects, such as actual needs, sensitivity to personal-comfort loss, etc.
    - Endowment may fall short for engagement

  - Second, ADR programs currently do not take into account the customer satisfaction from the provided endowment for load curtailment
    - Unsatisfied customers may not renew contracts

Our Objectives

1) Find ADR endowments that satisfy customers for a specific load curtailment
   - For non-purely rational customers
   - Even when user utility functions are not known

2) Keep incentive cost as low as possible or within a specific budget
   - Trade-off between load curtailment, incentive cost and customer satisfaction

System Model

System Model

- A customer i enjoys net benefit U_i (i.e., user satisfaction minus energy cost) from consuming baseline energy $q^0{}_{\mathrm{i}}$

- An energy-consumption reduction ΔQ_i in specific time periods according to an ADR contract results to a net-benefit loss $\Delta U_i = -\eta_i U_i$
  - Different per customer i

- In return, the customer i receives an endowment b_i by the utility company

User Utility Model

- Generic user utility model: $u_i = g(U_i, U_{-i})$

  NB of others

  net benefit (NB) from power consumption of customer i

- User utility difference:
  - $\Delta u_i = \hat{g}(\Delta U_i, \Delta U_{-i}) + b_i$

- Specific instance of user utility model: *altruism*
  - $u_\mathrm{i} = (1 - \gamma_i)\, U_i + \gamma_i\, U_{-i}$
  - $\gamma_i \in [0, 1]$ is the degree of altruism

- Then: $\Delta u_i = -(1 - \gamma_i)\eta_i U_i + \gamma_i \Delta U_{-i} + b_i$

DR Designer’s Problem

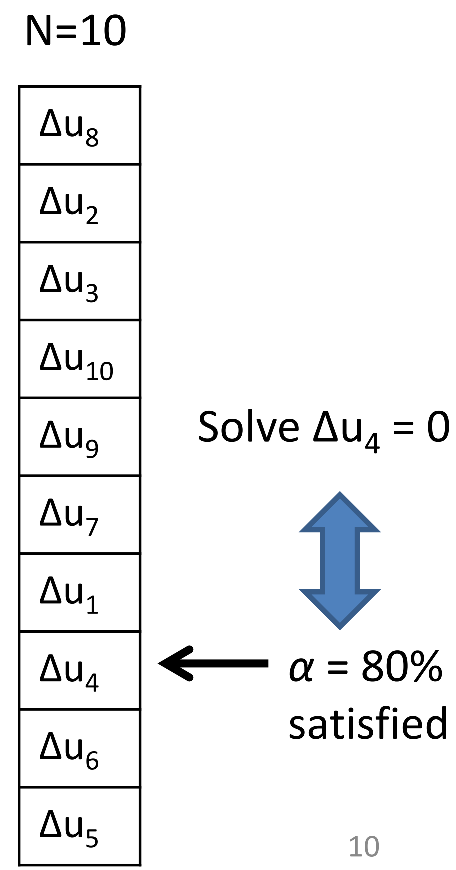
Optimization goals

I. Maximize customer satisfaction α for a specific net benefit reduction η_i due to load curtailment for each customer i within a budget limit B for endowments

II. Minimize total endowment cost for a lower-bound η in the net-benefit loss due to load curtailment of each customer and for a lower-bound α in customer satisfaction

Full-info solutions: Uniform Endowment

- Full-information on user utilities
- Observe that customer satisfaction ratio α is monotonic in the uniform endowment b
- Problem (I) can be solved by sorting all consumers with respect to Δu_i of each customer i after using maximum endowment $b = B/N$ and count how many of them are positive
- Problem (II) can be solved by sorting all consumers with respect to Δu in a descending order for b=0 and then solve the equation $\Delta u = 0$ at position k to find b, with $k = \alpha \cdot N$. This is the value of b that makes α% customers having $\Delta u \geq 0$



Full-info solutions: Personalized Endowment

- Full-information on user utilities

- If personalized incentive b_i per customer i is employed, then problem (I) is again solved as described above, while problem (II) is solved as follows:
  - For each customer i, calculate the personalized incentive that renders $\Delta u_i = 0$
  - Sort the list of customers based on their personalized incentive in ascending order
  - The minimum total incentive required for satisfying $\alpha \cdot 100\%$ customers is given by summing the top-(αN) personalized endowments

Hidden Info → Customer Feedback

- Customers provide feedback on satisfaction
  - In a ballot

  - Personalized

  - It can also be strategic!

Distributed Algorithm

- At each round t, the DR designer sets a b_t and each customer i responds to it with feedback $v_{i,t+1}$, which collectively result to a mean satisfaction level α_{t+1} for the received incentive at the next round
- The feedback $v_{i,t+1}$ of customer i at round t + 1 is determined by the sign of:

$$\Delta u_{i,t+1} = \hat{g}(\Delta U_i, \widetilde{\Delta U}_{-i,t}) + b_t$$

- Employing gradient ascent, the DR designer selects b_{t+1} for the round t+1 as follows:

$$b_{t+1} = \begin{cases} \max\{b_t + \Delta\alpha \cdot \kappa, 0\} \\ b_t + \kappa, \end{cases}$$

Stopping Criteria

- Problem (I):If $\Delta\alpha/\alpha_t < \Delta b/b_t$ or $b_t \geq B$, then stop iterations
- Problem(II): if $\alpha_t \geq \underline{\alpha}$, then stop iterations

Estimating $\widetilde{\Delta U}_{-i,t}$

- Assuming $$\frac{\sum_{i=1}^{N}(1-\gamma_i)\eta_i U_i}{N} \approx (1-\bar{\gamma})\overline{\Delta U}$$
- We obtain $$\overline{\Delta u}_{t+1} = \overline{\Delta U}_t + b_t$$
- Observe that $\overline{\Delta u}_{t+1}$ and $\eta_{max}(a_{t+1}-1)+b_t$ have the same output sets and move similarly according to $\Delta u_{i,t+1}$ values
- Then, <u>approximate that</u> $\overline{\Delta u}_{t+1} = \eta_{max}(a_{t+1}-1) + b_t$
- It follows that $$\boxed{\overline{\Delta U}_t \approx \eta_{max}(a_{t+1}-1)}$$

Strategic Feedback

- However, customers have incentive to lie on their satisfaction
- **DR mitigation policy**:
  - The DR designer b sets an upper bound on the budget B for endowments that is unknown to the customers
  - If b_t becomes infeasible, then no endowment is provided (load curtailment is still sustained)
- Then, user utility difference function for customer i becomes

$$\Delta u_{i,t+1} = -(1-\gamma_i)\eta_i U_i + \gamma_i \underbrace{\overline{\Delta U}_{-i,t}}_{\eta_{max}(a_{t+1}-1)} + Pr[b_t < B | \underbrace{z_i \ lies}_{\text{\# of times that customer lied}}] b_t$$

Customer Targeting

Customer Targeting

- Recall that same energy consumption reduction ΔQ results to a different net benefit loss fraction η_i for each customer *i*
  - According to internal individual function $h_i(\Delta Q_i)$ of each customer *i*
- Then, customer utility difference is given by

$$\Delta u_i = -(1-\gamma_i)h_i(\Delta Q_i)U_i + \gamma_i \overline{\Delta U}_{-1} + b_i(\Delta Q_i)$$

- Assume discrete levels of consumption reduction in

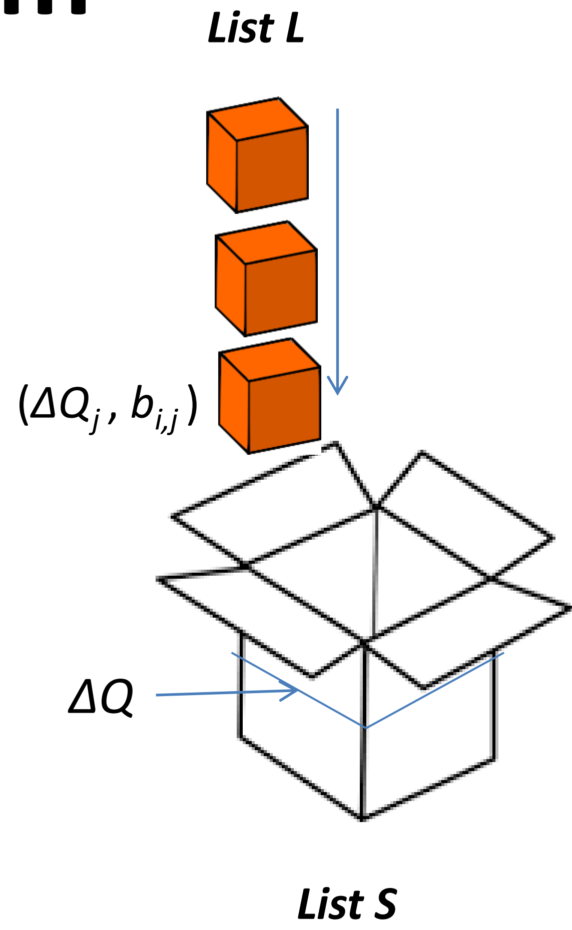
$$H = \left\{\frac{1}{\mathrm{N}}\Delta Q, \frac{2}{\mathrm{N}}\Delta Q, \dots, \theta_{max}\, \Delta Q\right\}$$

Finding Endowments for Targeting

- Problem: For each $\Delta Q_j \epsilon H$, find $b_{i,j}$
- **Full info:** Simply solve $\Delta U_i(b) \geq 0$ for each customer *i*
- **Hidden info**, yet customer feedback individually observable or not :
  - Assume each ΔQ_j a uniform reduction for all customers and employ the distributed algorithm for determining either personalized or uniform $b_{i,j}$ for each customer *i*
  - Entails approximation due to altruism

Targeting Algorithm

- Given (ΔQ_j KWh, $b_{i,j}$ €) pairs in list L
- Sort them based on $\Delta Q_j/b_{i,j}$ in decreasing order
- Add pairs from list L into a list S until next item exceeds desired total ΔQ
- Then, if desired total ΔQ has been reached in S, you are done
- Otherwise, from remaining items in L find the one that completes exactly ΔQ, if exists, and add to S; if not, add to S the cheapest item, so that desired ΔQ is overfilled



It can find optimal solution!

"When it is possible our targeting algorithm to fill the bag with exactly ΔQ, it finds an optimal *solution."*

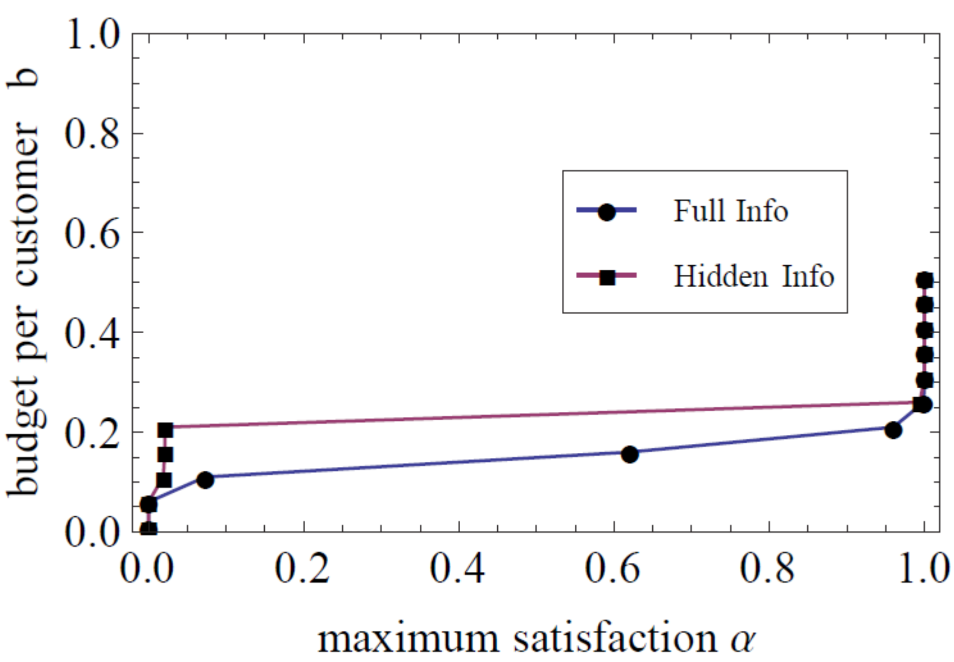
- *Sketch of Proof:*
  - By contradiction: trying to replace one of the items in bag *S*, as selected by the algorithm so that *ΔQ* load is curtailed, with one or multiple other ones results in higher total incentive cost

Evaluation

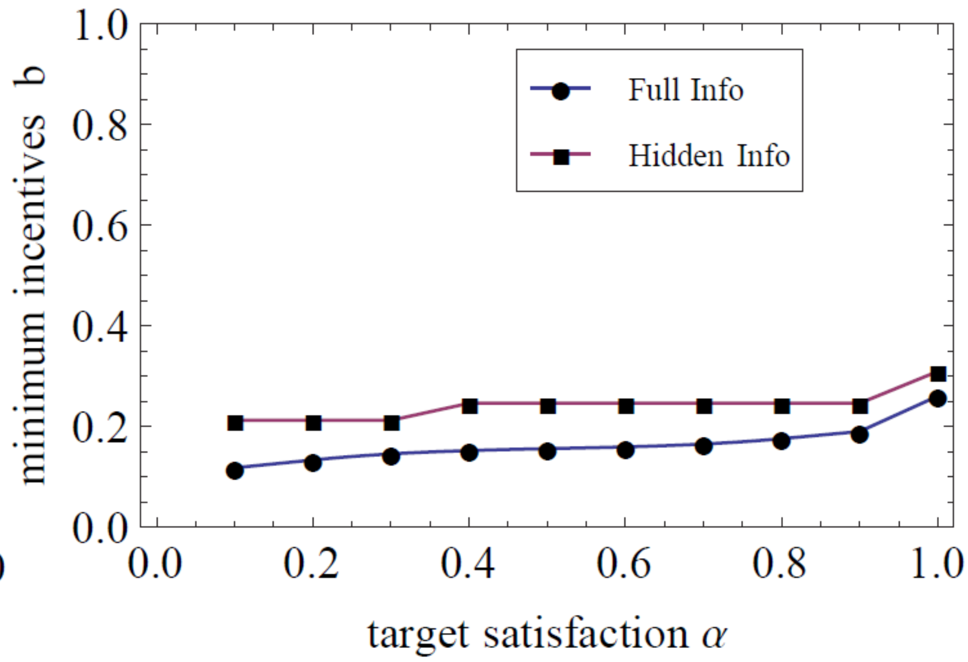
Evaluation Setup

- N = 1000 customers
- Altruism for customer *i:* γ_i ~ U(0, 1)
- Net benefit loss of customer *i*: η_i ~ U(0.1, 0.3), unless otherwise specified
- The DR designer is assumed to have guessed semi-correctly η_{max} = 0.5
- Satisfaction of customer *i* for her nominal energy consumption: $U_i \sim N(0.8, 0.1)$
- U_i assumed normalized by maximum net benefit, so is b
- Nominal consumption q^0_i is 1 for all customers

Uniform Load Reduction: Anonymous Feedback



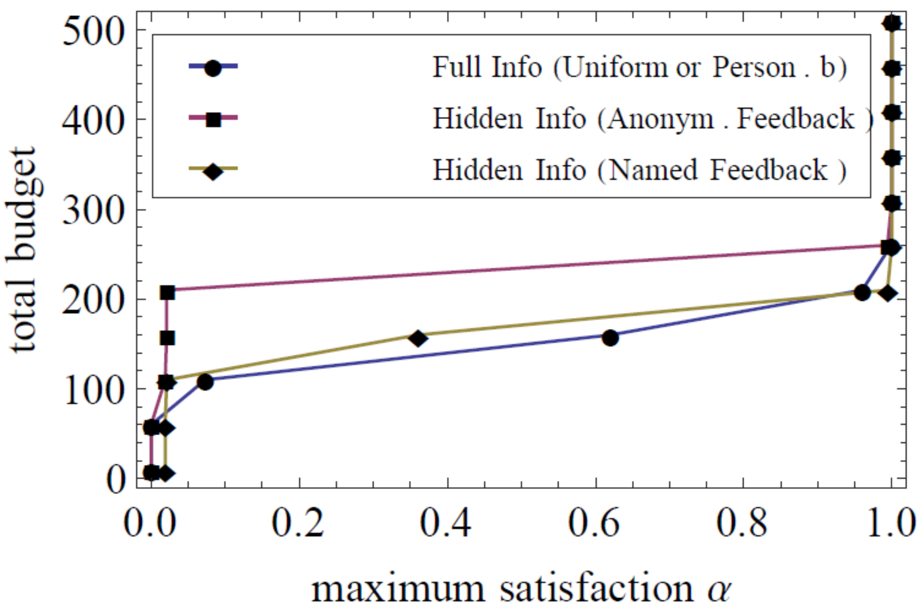
Objective (I)



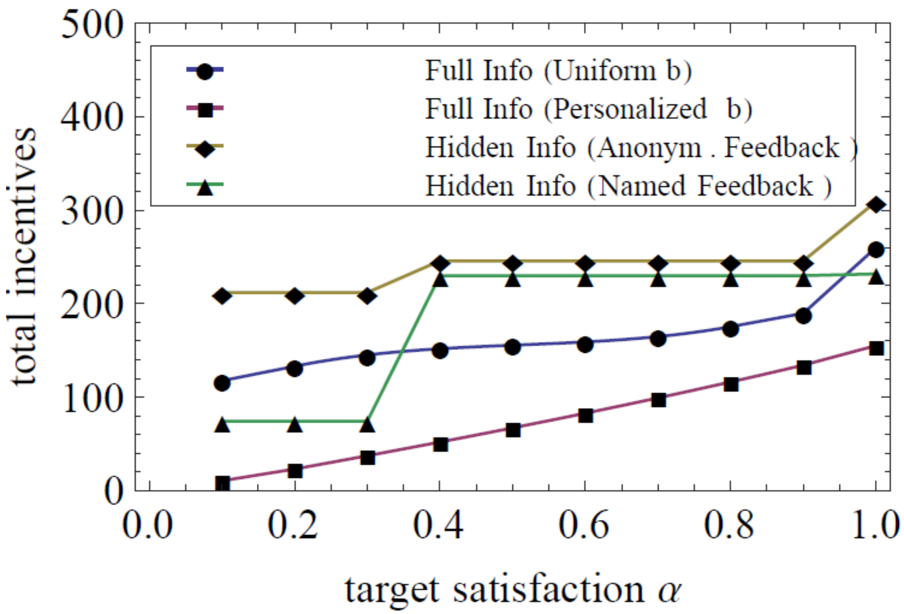
Objective (II)

- In case of hidden info, the distributed algorithm finds uniform endowment close to those of the full-info case
- Thus, approximation of $\widetilde{\Delta U}_{-i,t}$ is <u>good enough</u>

Uniform Load Reduction: Named Feedback



Objective (I)

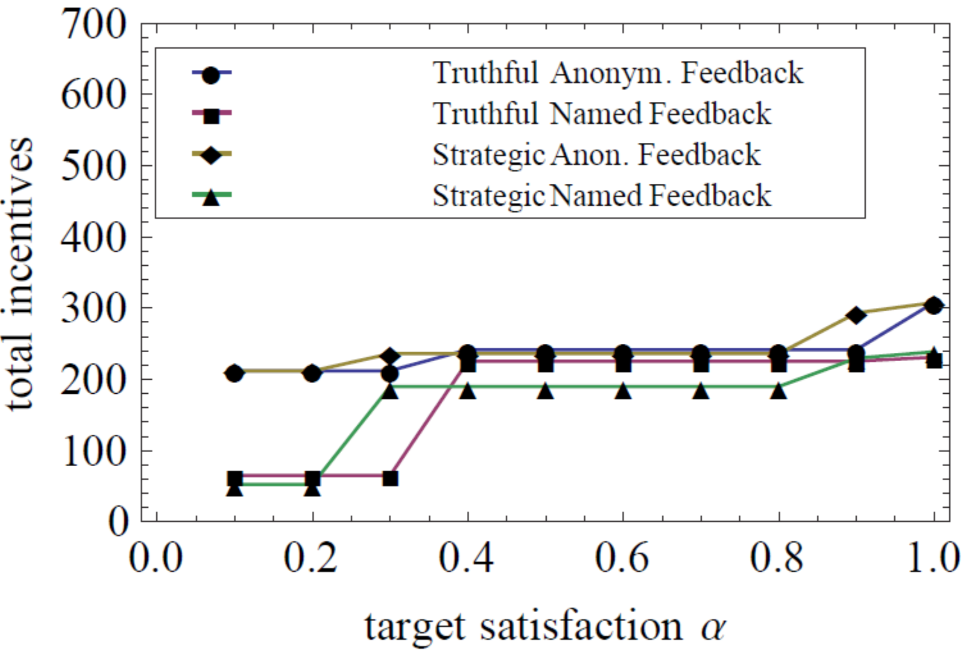


Objective (II)

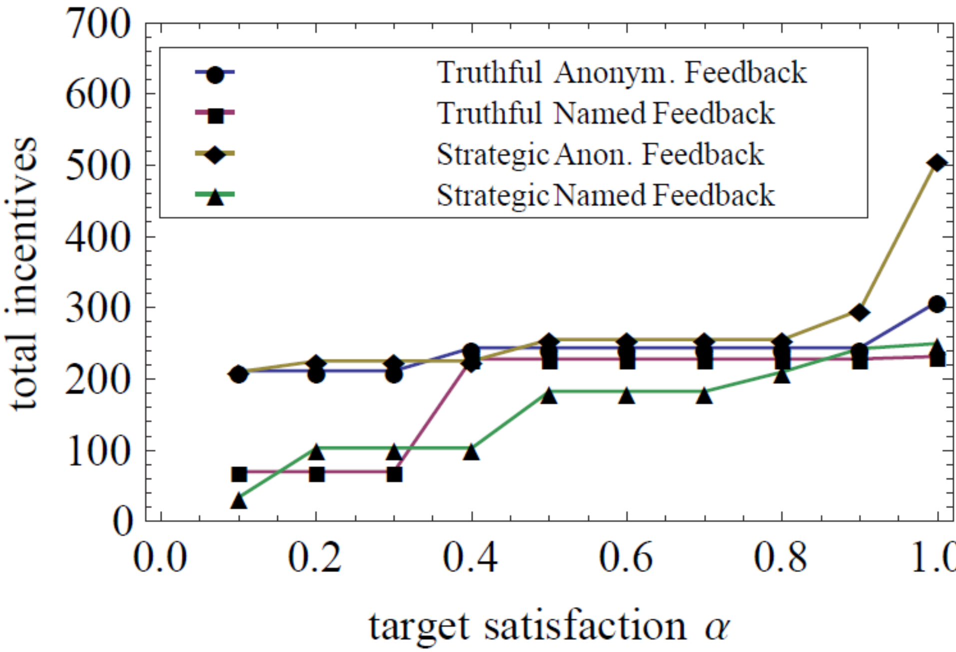
Named feedback almost reveals hidden info for objective (I), while it moderately improves endowment cost for objective (II)

Strategic Lying

20% liars

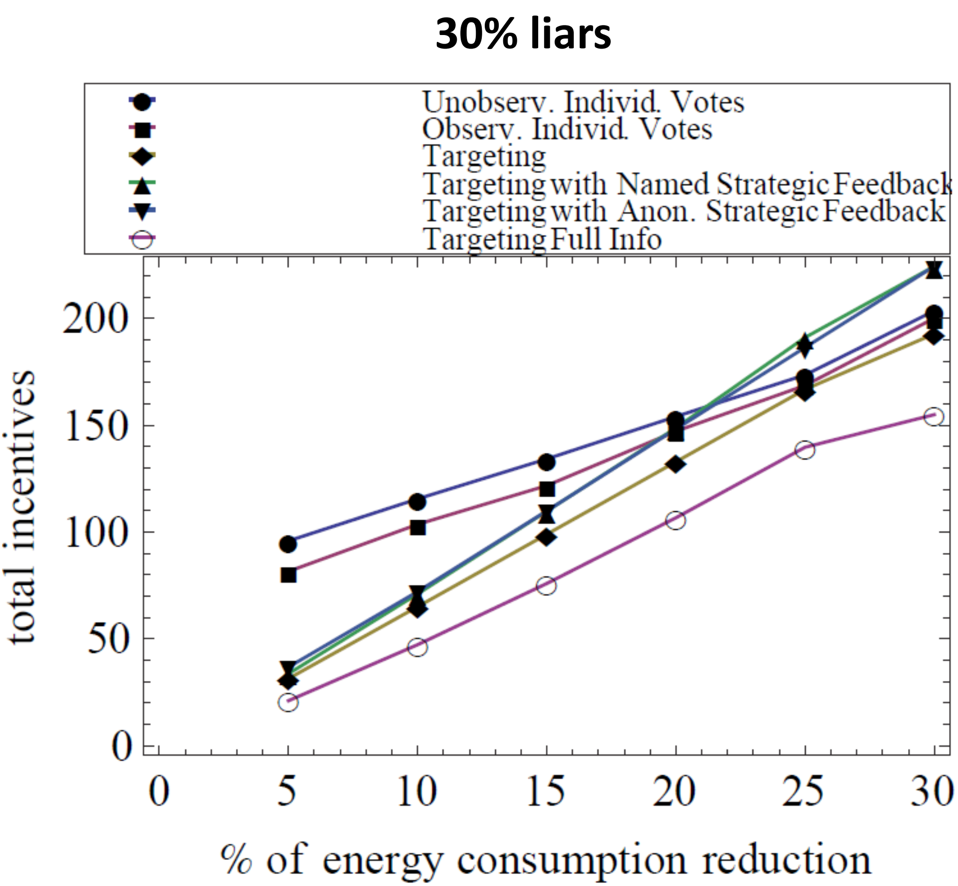


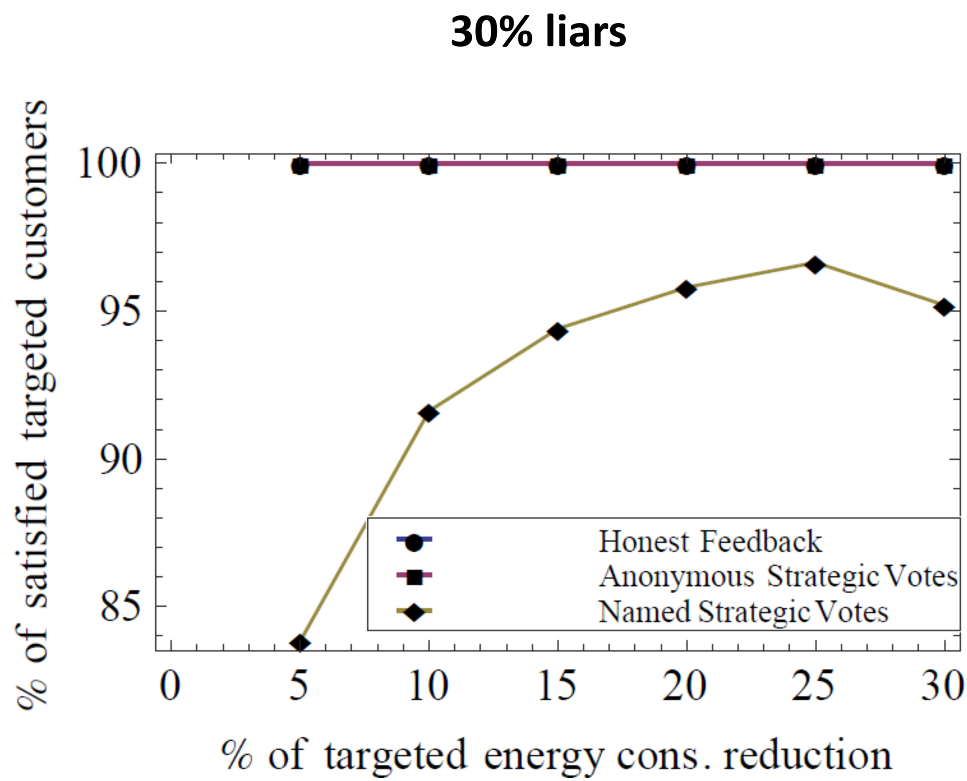
50% liars



- Strategic lying is successfully mitigated

Targeting





- **Targeting lowers significantly endowment costs in case of hidden info for low fractions of load curtailment**
- **Not affected significantly by strategic lying**
- **Targeted customers are kept satisfied, even in presence of lying!**

Conclusions

Conclusions

- We proposed algorithms for calculating satisfactory ADR endowments for uniform or personalized energy-load reduction for non-rational customers in the cases of both full and hidden info on user utilities
  - In case of hidden info on user utilities, we employed anonymous and named feedback on customer satisfaction, which may be strategic or not
- Our evaluation has shown the effectiveness of the various algorithms for all cases
  - even in the presence of high fractions of strategic liars among customers
- Customer targeting is preferable for low (<20%) desired energy consumption reductions, even for hidden information on user utility functions and even in the presence of 30% strategic liars
- Our formulation and approach are generic-enough to consider different user utility functions
- As a future work, we plan to consider different behavioral factors in the user utility

Thank you for your attention

Any questions?

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http://stecon.cs.aueb.gr/research/energy-environment/

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Support Slides

Estimating $\widetilde{\Delta U}_{-i,t}$

- It holds $-1 \le -U_i \le 0$
- Since $\eta_i \in [0, 1]$, it follows that

$$-\eta_i \le \Delta U_i \le 0 \text{ and } -\eta_{max} \le \Delta U \le 0,$$

- Therefore and since $\gamma_i \in [0, 1]$, it is true that

$$b_t - \eta_{max} \le \Delta u_{i,t+1} \le b_t, \ \forall i \in N$$

- Recall that $\overline{\Delta U}_{-i} = -\frac{\sum_{\substack{j=1 \\ j \neq i}}^{N} \eta_j U_j}{N}$
- Adding down utility differences and dividing by N, we have

$$\overline{\Delta u}_{t+1} = -\frac{\sum_{i=1}^{N} (1-\gamma_i)\eta_i U_i}{N} + \bar{\gamma}\overline{\Delta U}_t$$