



# CONTROL AND OPTIMIZATION IN SMART-GRIDS

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## Course topics

- Session 1: Introduction to Power systems
  - Context and motivation
  - Power flow analysis
  - Economic dispatch
- Session 2: Renewable sources
  - Stochastic models of variable sources
  - Dispatching random sources
- Session 3: Energy dispatch
  - Risk-limiting dispatch
  - Matlab session





## Course topics

#### Session 4: Incentive-based demand response

- Modeling demand
- Peak time rebates
- Contract design for demand response

#### • Session 5: Flexible loads

- Modeling flexibility
- Load dispatch
- Case study: Electric vehicles
- Session 6: Micro-grids
  - Lean energy concept
  - Joint generation and load dispatch





# Incentive-based Demand Response

Joint-work with J. Vuelvas (PUJ), K. Poolla and P. Varaiya (UC-Berkeley)



# Demand Side Management



- > New paradigm in grid operation
- Active consumers are responsible of grid balance
- ➤ICT-based



#### **PRO-SUMER**





## Demand Side Management





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## Demand Side Management





Categories of Demand Side Managment (DSM) (Gellings, 1985).



# Incentive-Based Demand Response



- Participating agents are paid for diminishing their energy consumption
- ➢There are three key components of an incentive-based DR program:
  - 1) A baseline
  - 2) A payment scheme
  - 3) Terms and conditions (such as penalties)

#### ➤Examples:

- 1) Peak Time Rebates
- 2) Interruptible Capacity Program
- 3) Emergency DR



# Incentive-Based Demand Response



**BASELINE:** an estimation of the power consumption that would have been consumed by demand in the absence of DR

- ➢It is often based on the average historical consumption of a consumer or a customer group on days that are similar to the forthcoming DR event.
- ➤A counter-factual model is developed to estimate the customer baseline.



# Incentive-Based Demand Response

Peak Time Rebate (PTR):

➢Incentive=(Reduction) x (Reward/KWh)

Reduction= (Baseline)-(Measured consumption)







# Incentive-based Demand REsponse

Peak Time Rebate (PTR) analysis:

- >How will users behave under this contract?
- >How will uncertainty in energy requirements affect behavior?
- Does PTR guarantee a peak shaving effect?



#### User model





- Utility function: represents the welfare or satisfaction of a consumer from consuming a certain amount of energy.
- Risk-averse user: Concave utility function.
- Utility saturates after a threshold energy level.

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#### User model



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#### Parameters:

- $\gamma_i$ : energy preference (marginal utility)
  - p: energy price
  - $b_i$ : baseline

Variable:  $q_i$ : actual consumption

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#### **User model**



User faces uncertainty in energy requirements:

 $G(q_t; \theta_t) = G(q_t - \theta_t)$ 

With  $\theta$  a random variable with support:



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- Energy cost:  $\pi(q_t) = pq_t$
- User payoff:  $U_t(q_t, \theta_t) = G(q_t \theta_t) \pi(q_t)$
- Rational behavior without DR:

$$q_t^* = \max_{q_t \in [0, q_{max}]} U_t(q_t, \theta_t) = G(q_t - \theta_t) - \pi(q_t)$$

•  $q_{max}$  is the maximum allowable consumption (technical limit)





• Estimate baseline:

$$b(q_{t-1}, ..., q_{t-n})$$

• Load reduction:

$$b - q_t = \Delta_t (b(q_{t-1}, ..., q_{t-n}), q_t)$$

• Rebate:

$$\pi_2 (b, q_t) = \begin{cases} p_2 (\Delta_t (b(q_{t-1}) = p_2(b(q_{t-1}) - q_t) & q_t < b \\ 0 & q_t \ge b \end{cases}$$





➤The payoff of a user enrolled in PRT is:

$$U_t(q_t, \theta_t, b(q_{t-1}, \dots, q_{t-n})) = G(q_t - \theta_t) - \pi(q_t) + r\pi_2(b(q_{t-1}, \dots, q_{t-n}), q_t)$$

How would a strategic agent behave to maximize his payoff?

 $\max_{\substack{q_t,\ldots,q_{t-n}\in[0,q_{max}]}} E\left[U_{t-n}\left(q_{t-n},\theta_{t-n}\right)+\ldots+\right]$ 

$$+ ... + U_{t-1} (q_{t-1}, \theta_{t-1}) + U_t (q_t, \theta_t, b(q_{t-1}, ..., q_{t-n}))]$$





Stochastic programming algorithmSolved backwards in time

- 1.  $\max_{q_t \in [0, q_{max}]} U_t(q_t, \theta_t, b(\cdot))$
- 2.  $\max_{q_{t-1} \in [0, q_{max}]} U_{t-1}(q_{t-1}, \theta_{t-1}) + E[U_t(q_t^o, \theta_t, b(\cdot))]$
- n.  $\max_{q_{t-n} \in [0, q_{max}]} U_{t-n}(q_{t-n}, \theta_{t-n}) + E\left[U_{t-(n-1)}(q_{t-n}^{o}, \theta_{t-n}) + \dots + U_{t-1}(q_{t-1}^{o}, \theta_{t-1}) + U_{t}(q_{t}^{o}, \theta_{t}, b(\cdot))\right]$





Two periods problem:

At time t-1, the SO (or aggregator) "measures" the baseline as consumed energy:

$$b(q_{t-1}) = q_{t-1}$$

At time t, if called for a DR event, consumer decides how much energy to reduce with respect to the baseline, in exchange for an economic incentive.





• The consumer faces the problem:

 $\max_{q_t,q_{t-1}\in[0,q_{max}]} E\left[U_{t-1}\left(q_{t-1},\theta_{t-1}\right) + U_t\left(q_t,\theta_t,b(q_{t-1})\right)\right]$ 

• It is solved backwards in time:

First:

Then:

$$\boldsymbol{q_t^o}\left(\boldsymbol{q_{t-1}}; \boldsymbol{\theta_t}\right) = \operatorname{argmax}_{q_t \in [0, q_{max}]} U_t\left(q_t, \theta_t, b(q_{t-1})\right)$$

$$\boldsymbol{q_{t-1}^{o}}(\boldsymbol{\theta_{t-1}}) = \operatorname{argmax}_{q_{t-1} \in [0, q_{max}]} U_{t-1}(q_{t-1}, \boldsymbol{\theta_{t-1}}) + E\left[U_t\left(\boldsymbol{q_t^{o}}, \boldsymbol{\theta_t}, b(q_{t-1})\right)\right]$$





#### Theorem

The optimal consumption  $q_t^o$  of a user participating in a PTR program (i.e. the solution of the first-stage stochastic programming), given  $G(\cdot)$  and  $U_t(\cdot)$  is:

$$q_t^o = \begin{cases} q_t^* & r = 1 \text{ and } q_{t-1} - \overline{q} + \frac{p_2}{2\gamma} < \theta_t \le \overline{\theta} \text{ (strategy } A) \\ q_t^* - \frac{p_2}{\gamma} & r = 1 \text{ and } \frac{p_2}{\gamma} - \overline{q} < \theta_t \le q_{t-1} - \overline{q} + \frac{p_2}{2\gamma} \text{ (strategy } B) \\ 0 & r = 1 \text{ and } \underline{\theta} \le \theta_t \le \frac{p_2}{\gamma} - \overline{q} \text{ (strategy } C) \\ q_t^* & r = 0 \text{ (strategy } D) \end{cases}$$

 $q_t^*(\theta_t) = \overline{q} + \theta_t$ 





#### Theorem

Given  $\underline{\theta} > \frac{p_2}{\gamma} - \overline{q}$  (case 1) and  $\overline{q} + \frac{p}{\gamma} > \overline{q} + \overline{\theta} - \frac{p_2}{2\gamma}$ , then the optimal solution:

$$E\left[q_{t-1}^{o}(\theta_{t-1})\right] = \begin{cases} \overline{q} - \frac{p_2}{2\gamma} + \frac{2p_2\overline{\theta}}{2\overline{\theta}\gamma - p_2} & 0 \le p_2 < \frac{2}{3}\overline{\theta}\gamma \\ \overline{q} + \frac{p_2}{\gamma} & \frac{2}{3}\overline{\theta}\gamma \le p_2 < p \\ q_{max} & p \le p_2 < \gamma \left(\underline{\theta} + \overline{q}\right) \end{cases}$$





#### Theorem

Given  $\underline{\theta} \leq \frac{p_2}{\gamma} - \overline{q} < \overline{\theta}$  (case 2) and  $\overline{q} + \frac{p}{\gamma} > \overline{q} + \overline{\theta} - \frac{p_2}{2\gamma}$ , then the optimal solution:

$$E\left[q_{t-1}^{o}(\theta_{t-1})\right] = \begin{cases} \overline{q} - \frac{p_2}{2\gamma} + \frac{2p_2\overline{\theta}}{2\overline{\theta}\gamma - p_2} & \gamma\left(\underline{\theta} + \overline{q}\right) \le p_2 < \frac{2}{3}\overline{\theta}\gamma \\ \overline{q} + \frac{p_2}{\gamma} & \frac{2}{3}\overline{\theta}\gamma \le p_2 < p \\ q_{max} & p < p_2 \le \gamma\left(\overline{\theta} + \overline{q}\right) \end{cases}$$





# Theorem Given $\frac{p_2}{\gamma} - \overline{q} \ge \overline{\theta}$ (case 3) and $\overline{q} + \frac{p}{\gamma} > \overline{q} + \overline{\theta} - \frac{p_2}{2\gamma}$ , then $q_{t-1}^o$ is: $E\left[q_{t-1}^o\right] = \begin{cases} \overline{q} + \frac{p_2}{\gamma} & \gamma\left(\overline{\theta} + \overline{q}\right) \le p_2 p \end{cases}$





- The retail price is p = 0.26\$/kWh (based on peak summer rate in 10/1/16 by Pacific Gas and Electric Company in San Francisco, California).
- Deterministic baseline  $\overline{q} = 8kWh$  and the curvature  $\gamma = 0.05$ .
- Randomness  $\theta_t$  for each period has been created as a uniform random variable with zero mean and with simetric support.
- A Monte Carlo simulation is performed with 10000 realizations of  $\theta_t$  for each value of  $q_{t-1}$ .







<i>p</i> <sub>2</sub>	Profit	$q_{t-1}^o$	$q_t^o$	$q_{t-1}^o + q_t^o$
0	3.2	8	8	16
0.15	3.65	11	5	16
0.26	4.55	20	2.79	22.79
0.45	8.13	20	0	20







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27





# Incentive-based Demand Response

Conclusions:

For a two periods model results we show that:

- A strategic user overconsumes energy at the baseline settling period
- ➢For an incentive lower than energy price, users shift consumption to the baseline settling period

➢ For an incentive higher than energy price, the best consumer strategy is to overconsume as much energy as possible at the baseline settling period.



## NOVEL DR CONTRACT



- PTR exhibits gaming issues
- It's more profitable to over-consume at *t*-1 than to reduce to maximize benefits
- Gaming opportunities reduce with uncertainty
- New approach: User declared baseline + Uncertainty in service activation
- <u>Contract slides</u>



## Future directions



#### **Research questions:**

Consumer model: Up to now users are modeled as rational agents that maximize benefits. Rising concerns from behavioral economics.

*Reference point: users don't evaluate net Budget but gains and loses w.r.t. status quo.* 

Asymmetric value effect: high value for loses – Low value for gains.

Deformed weight for low or high probability events.

Consumer bandwidth: Incentive-based DR can be employed in real time markets or just day (hours) ahead markets? Is a user capable of following commands every xx seconds?





# Toward a Consumer-Centric Grid: A Behavioral Perspective

In addition to modern grid hardware, software, and network-control technologies, active consumer participation is seen as an integral part of the emerging smart grid. To address the challenges that this creates, this paper explores the potential of prospect theory, a Nobel-Prize-winning theory, as a decision-making framework that can help understand how risk and uncertainty can impact the decisions of smart grid consumers.

By WALID SAAD, Senior Member IEEE, ARNOLD L. GLASS, NARAYAN B. MANDAYAM, Fellow IEEE, AND H. VINCENT POOR, Fellow IEEE

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63

IEEE TRANSACTIONS ON SMART GRID, VOL. 6, NO. 1, JANUARY 2015

## Prospect Theoretic Analysis of Energy Exchange Among Microgrids

Liang Xiao, Senior Member, IEEE, Narayan B. Mandayam, Fellow, IEEE, and H. Vincent Poor, Fellow, IEEE





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Perspectives

Making 'Smart Meters' smarter? Insights from a behavioural economics pilot field experiment in Copenhagen, Denmark

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#### Renewable and Sustainable Energy Reviews

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Understanding household energy use, decision making and behaviour in Guinea-Conakry by applying behavioural economics



N'Famory Camara<sup>a,\*</sup>, Deyi Xu<sup>c</sup>, Emmanuel Binyet<sup>b</sup>

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Energy Strategy Reviews 15 (2017) 57-71



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# Actors behaving badly: Exploring the modelling of non-optimal behaviour in energy transitions

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