Gaming on Coincident Peak Shaving: Equilibrium and Strategic Behavior

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Motivation

Coincident peak (CP) charge - charge the customer based on their demand at the system peak time, e.g., 4CP program in Texas [1]:

Charge the highest hour in each month between Jun. – Sep., and count in the next year's electricity bill.

Research gap - CP time realizes posterior and depends on all customers' strategies [2] $\rightarrow$ current work focuses on predicting CP time and misses the interaction between customers [3, 4] $\rightarrow$ motivates a game formulation.

Research question

1 Whether the game-based framework workable for the CP shaving problem?

2 How do gaming consumers' strategic behavior causes anarchy compared to the centralized method

Model and formulation

Two-agent two-periods CP shaving model

Agent *i* - *game*   CP charge at time 1   CP charge at time 2

$$\max_{x_i} f_i(x_i, x_{-i}) = -\pi(X_{i,1}+x_i)I(S_1(x)-S_2(x)) - \pi(X_{i,2}-x_i)I(S_2(x)-S_1(x)) - \alpha_i x_i^2,$$

System peak time determination   Shifting penalty

$$I(x) = \begin{cases} 1 & x \geq 0 \\ 0 & x < 0 \end{cases},$$

$$S_1(x) = X_{i,1} + X_{-i,1} + x_i + x_{-i} = S_{1,0} + x_i + x_{-i},$$

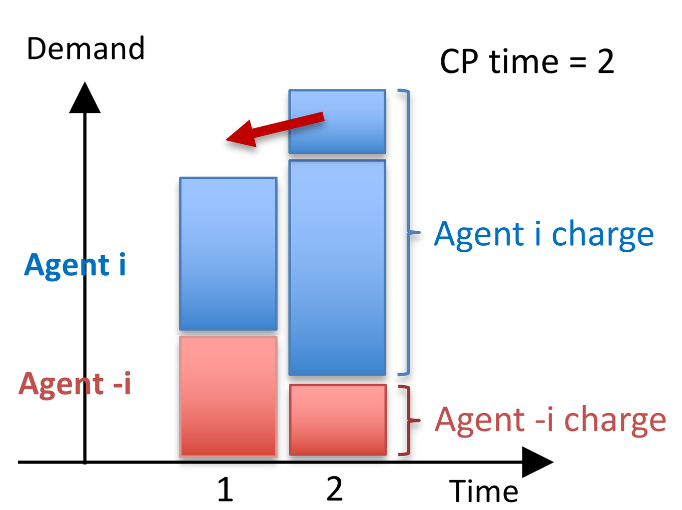
$$S_2(x) = X_{i,2} + X_{-i,2} - x_i - x_{-i} = S_{2,0} - x_i - x_{-i},$$

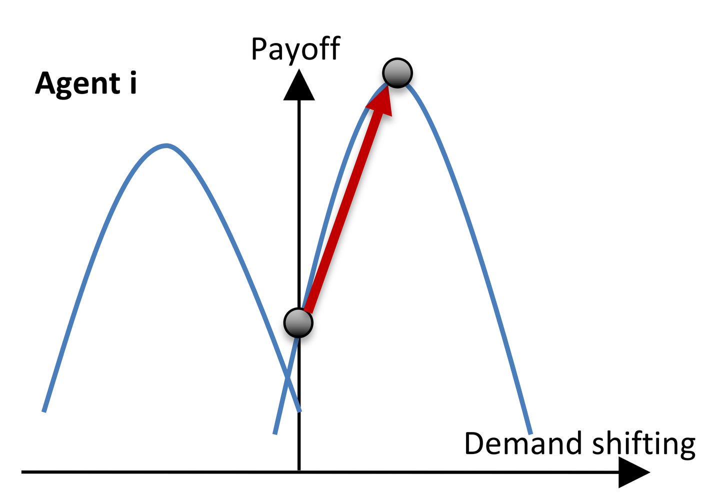
$$x_i \in \mathcal{X}_i = \mathbb{R}, x_{-i} \in \mathcal{X}_{-i} = \mathbb{R}$$

- *X* – baseline demand,
- *x* – shifting strategy
- S – system demand
- α – shifting penalty parameters

Centralized $$x^* \in \arg\max_{x_i, x_{-i}} -f_i(x_i, x_{-i}) - f_{-i}(x_i, x_{-i})$$

Agent i's strategy - $\min\{$critical point $r_i = \pi/2\alpha_i$, balance point $b_i = (X_{i,2} - X_{i,1})/2\}$





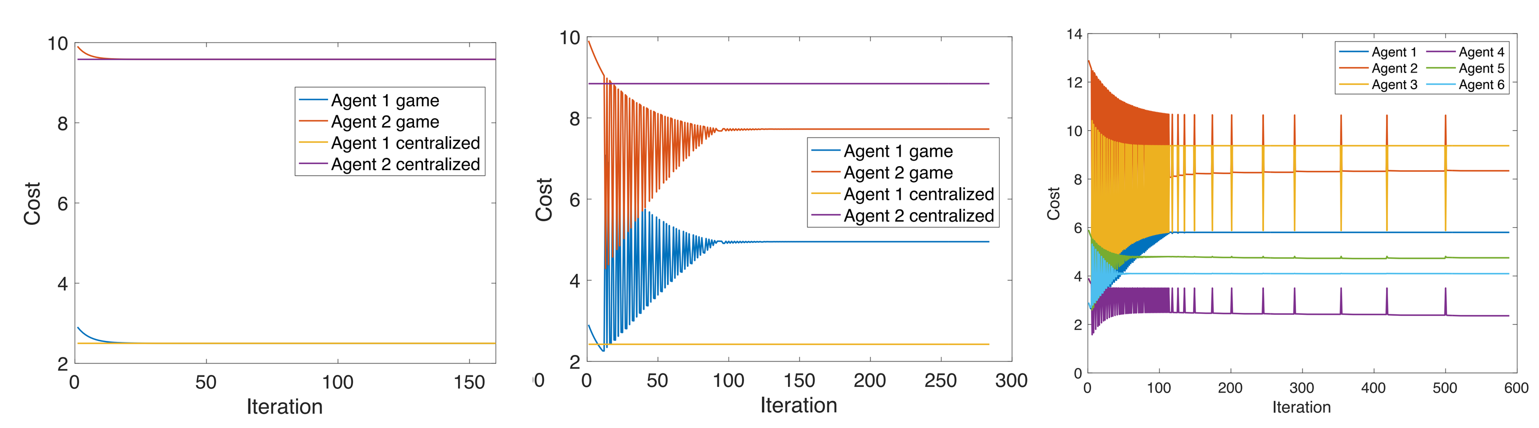
Q1: NE exist, unique, stable, and reachable

Theorem –Nash equilibrium (NE) (informal)

The CP game could be concave, quasiconcave/discontinuous, and non-concave/discontinuous, and under the two-agent two-period setting, all types of CP games have unique pure-strategy NE.

Theorem – stability and convergence (informal)

- The CP game system is global uniform asymptotically stable if all customers' baseline demand is positive (Denoting system dynamics following the gradient of each agent's payoff function)
- Gradient-based algorithms can converge with an updating rule from the finite difference approximation to the system dynamics (learning rate chosen from backtracking line search)



(a) Two-agent concave game.   (b) Two-agent quasiconcave game.   (c) Multi-agent non-concave game

Figure 1. Convergence performance.

Extending to multi-agent two-period settings, everything still holds except non-concave game NE is not unique, but **CP time agent** (whose baseline peak demand is in the system baseline CP time) and **non-CP time agent** still balances system demand.

Takeaway - Although the game type is variant, the game framework is workable as the equilibrium exists, unique, stable, and reachable.

Q2: Peak shaving and anarchy

Theorem – peak shaving effectiveness (informal)

In all conditions (two-agent, multi-agent, all types of game), the peak shaving effectiveness of the game model is always the same as centralized model.

Takeaway - It is helpful for utilities/operators to apply the game model because they care more about peak shaving.

Theorem – price of anarchy (PoA) with agent equity (informal)

In two-agent settings, PoA (*P*) increases with inequity among agents, measured by the marginal shifting cost. $\frac{\partial P}{\partial[(\alpha_i x_i^* - \alpha_{-i} x_{-i}^*)^2]} > 0$

Theorem – PoA with game type (informal)

Under two-agent settings, fixed system conditions (system demand, CP charge price)

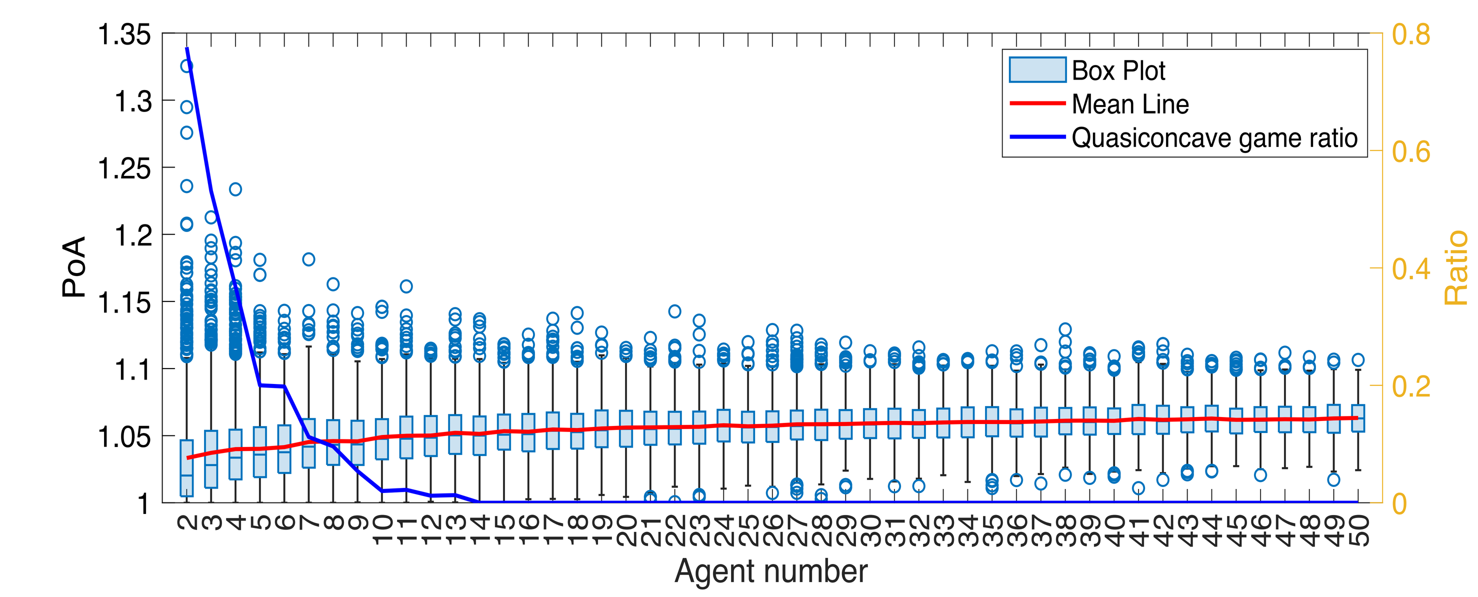
Agent flexibility reduce – $\alpha, X_{i,1}, X_{i,2}$

$$P(\text{Quasiconcave game}) \geq P(\text{Non-concave game}) \geq P(\text{Concave game}) = 1$$

Takeaway - (1) CP shaving mechanisms can consider effectiveness and fairness together – balance agents' marginal shifting cost; (2) Greater agent flexibility amplifies system inefficiency, reflected by the CP game type change; (3) Concave CP game equivalent to the centralized model.

Remark – game type with agent number

With agent numbers increasing, games are more likely to be non-concave games.



Takeaway - (1) PoA of a small system is more sensitive to the agents' flexibility (game type); (2) PoA of a large system is stable and can diminish flexible agent's influence; (3) Better to have large systems regarding flexible agents, and small systems for inflexible agents.

References

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[4] Z. Liu, A. Wierman, Y. Chen, B. Razon, and N. Chen, "Data center demand response: Avoiding the coincident peak via workload shifting and local generation," in *Proceedings of the ACM SIGMETRICS*, 2013, pp. 341–342.

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