

Stackelberg Equilibrium Seeking

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Game On! Seminar @ KTH



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Outline

1. Introduction


2. Induced Stackelberg Equilibrium


3. Stackelberg Equilibrium Learning & Seeking

4. Conclusion & Outlook

1. Introduction

This Talk

 Cianchi, Sanjab, **SG**, “Induced Stackelberg equilibrium seeking via iterative Tikhonov regularization”, arXiv, 2026

 Cianchi, Baghbadorani, Sanjab, **SG**, “Learning-based Stackelberg equilibrium seeking with application to demand-side energy management”, arXiv, 2026



Silvia Cianchi



Reza Rahimi Baghbadorani

Stackelberg Equilibrium Problem

- N **follower** agents, 1 **leader** agent
- Each follower $i \in \mathcal{J}$ has decision variable $\mathbf{x}_i \in \mathbb{R}^n$
- The leader has decision variable $\mathbf{y} \in \mathbb{R}^m$
- The followers play a (lower-level) Nash game: $\forall i \in \mathcal{J} : \min_{\mathbf{x}_i \in \mathcal{X}_i(\mathbf{x}_{-i})} J_i(\mathbf{x}_i, \mathbf{x}_{-i}; \mathbf{y})$
- v-GNEs of the followers: $\mathcal{E}(\mathbf{y}) := \text{SOL}(F(\cdot; \mathbf{y}), \Omega)$

Stackelberg Equilibrium Problem (+)

- Stackelberg game:

$$\begin{array}{ll} \min_{\mathbf{y} \in \mathcal{Y}} & J_0(\mathbf{y}, \mathbf{x}) \\ \text{s. t.} & \mathbf{x} \in \mathcal{E}(\mathbf{y}) \end{array}$$

- If the **followers'** reaction is unique, i.e. $\mathbf{x}^*(\mathbf{y}) := \{\mathcal{E}(\mathbf{y})\}$

then Stackelberg game = bilevel optimization problem: $\min_{\mathbf{y} \in \mathcal{Y}} J_0(\mathbf{y}, \mathbf{x}^*(\mathbf{y}))$

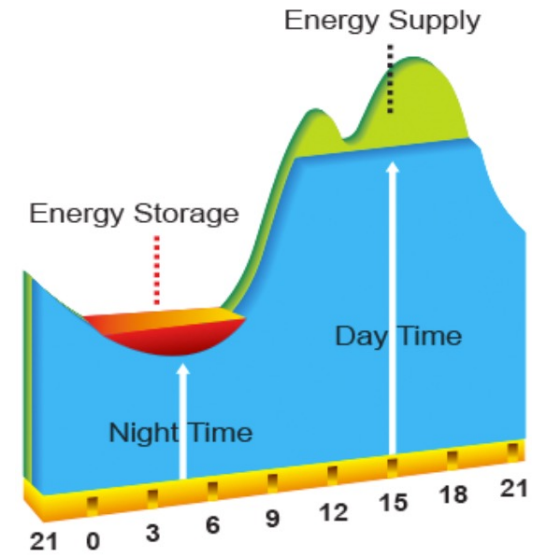
- **Global minima** are **Stackelberg equilibria**

due to nonconvexity, **stationary points** are “good enough”

Illustrative application in smart energy systems

Hierarchical demand side management

- DSO (leader):
$$\begin{cases} \max_{\mathbf{y}} & \text{revenue}(\mathbf{y}, \sum_{j \in \mathcal{J}} \mathbf{x}_j) \\ \text{s. t.} & \mathbf{x} \in \mathcal{E}(\mathbf{y}) \end{cases}$$
- Prosumers (followers):
$$\begin{cases} \min_{\mathbf{x}_i} & \text{discomfort}_i(\mathbf{x}_i) + \text{cost}_i(\mathbf{x}_i, \mathbf{y}) \\ \text{s. t.} & \mathbf{x}_i \in \{\text{limits}(\sum_{j \in \mathcal{J}} \mathbf{x}_j)\} \end{cases}$$




📄 Cianchi, Sanjab, **SG**, A two-part pricing mechanism for demand side management, CoDIT, 2025

2. Induced Stackelberg Equilibrium

Induced Stackelberg equilibrium: Setting & Definition

- Followers reaction **set-valued**: Stackelberg equilibrium well defined?
- **uniqueness** via strongly convex selection: $\mathbf{x}_\phi^*(\mathbf{y}) := \arg \min_{\mathbf{x} \in \mathcal{E}(\mathbf{y})} \phi(\mathbf{x})$
- **Induced Stackelberg equilibrium** = global minima of $\min_{\mathbf{y} \in \mathcal{Y}} J_0(\mathbf{y}, \mathbf{x}_\phi^*(\mathbf{y}))$
(due to nonconvexity, we seek a **stationary point**)

 Cianchi, Sanjab, **SG**, “Induced Stackelberg equilibrium seeking via Iterative Tikhonov regularization,” arXiv, 2026

Induced Stackelberg Equilibrium: Toy Example

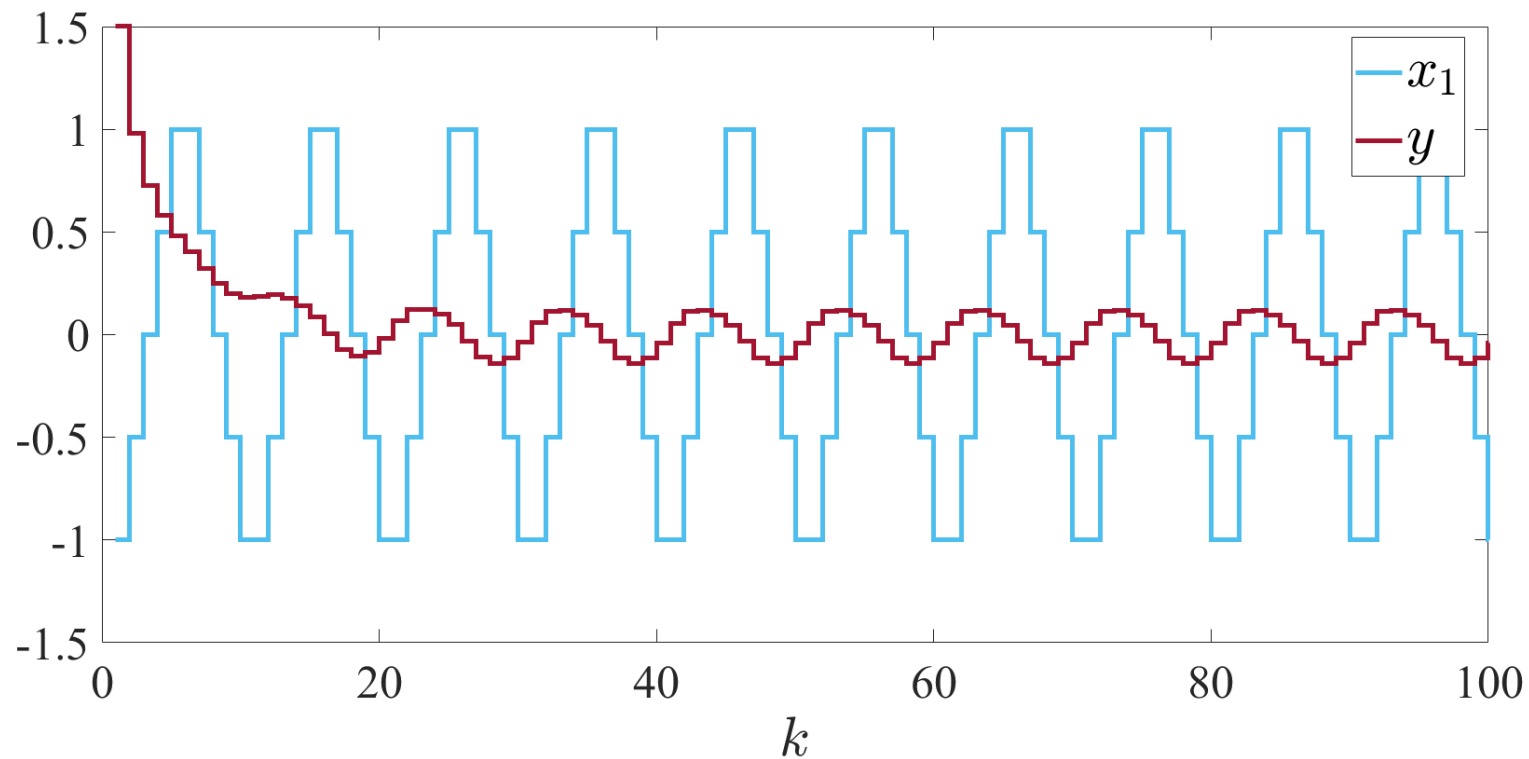
- **Low-level game:**
$$\begin{cases} \min_{x_1 \in \mathcal{X}_1} & J_1(x_1, x_2; y) := \frac{1}{2}(y + \epsilon)x_1^2 + x_1x_2 \\ \min_{x_2 \in \mathcal{X}_2} & J_2(x_2, x_1; y) := \frac{1}{2}x_2^2 + (y + \epsilon)x_1x_2 \end{cases}$$

- **Low-level v-GNEs:**
$$\mathcal{E}(y) = \{\mathbf{x} \in \text{int}(\mathcal{X}_1) \times \text{int}(\mathcal{X}_2) \mid x_2 = -(y + \epsilon)x_1\}$$

- **High-level optimization:**
$$\begin{cases} \min_y & J_0(y, \mathbf{x}) := y^2 + y(x_1 + x_2) \\ \text{s. t.} & \mathbf{x} \in \mathcal{E}(y) \end{cases}$$

Induced Stackelberg Equilibrium: Toy Example (+)

- Non-uniqueness of followers v-GNE may generate **persistent oscillations!**





Induced Stackelberg Equilibrium

- Unique selection of followers v-GNE via **iterative Tikhonov regularization**

- Followers: $\forall i \in \mathcal{J} : \min_{\mathbf{x}_i \in \mathcal{X}_i(\mathbf{x}_{-i})} J_i(\mathbf{x}_i, \mathbf{x}_{-i}; \mathbf{y}) + \beta\phi(\mathbf{x})$

- vanishing regularization: $(\mathbf{x}_\beta(\mathbf{y}))_{\beta \rightarrow 0}$

 Cianchi, Sanjab, **SG**, “Induced Stackelberg equilibrium seeking via iterative Tikhonov regularization,” arXiv, 2026

 Benenati, Ananduta, **SG**, “Optimal selection and tracking of generalized Nash equilibria in monotone games,” TAC, 2023


Induced Stackelberg Equilibrium Seeking

Algorithm 1 Zeroth-order induced SE seeking

Data: Time horizon K , Initial conditions $\mathbf{y}_0 \in \mathbb{R}^m$, Step sizes (η_k) , Perturbation radius (δ_k) , Regularization parameters (β_k)

- 1: **for** $k = 1$ to $K - 1$ **do**
 - 2: Sample $\mathbf{v}_k \sim \text{Unif}(\mathcal{S}(\mathbb{R}^T))$;
 - 3: Assign $\hat{\mathbf{y}}_k = \mathbf{y}_k + \mathbf{v}_k \delta_k$;
 - 4: Collect $\mathbf{x}_k = \mathbf{x}_{\beta_k}(\mathbf{y}_k)$;
 - 5: Collect $\hat{\mathbf{x}}_k = \mathbf{x}_{\beta_k}(\hat{\mathbf{y}}_k)$;
 - 6: Compute $\hat{\mathbf{g}}_k = \frac{m}{\delta_k} (J_0(\mathbf{y}_k, \mathbf{x}_k) - J_0(\hat{\mathbf{y}}_k, \hat{\mathbf{x}}_k)) \mathbf{v}_k$;
 - 7: Update $\mathbf{y}_{k+1} = \mathbf{y}_k - \eta_k \hat{\mathbf{g}}_k$;
 - 8: **end for**
-

Leader agent sets parameter of incentive and queries followers

 Cianchi, Sanjab, **SG**, “Induced Stackelberg equilibrium seeking via iterative Tikhonov regularization,” arXiv, 2026

 Maheshwari, Cheng, Sastry, Ratliff, Mazumdar, “Follower agnostic learning in Stackelberg games,” CDC 2024


Convergence Theorem

- Expected distance from stationary point decreases (Theorem 1)

Let $\eta_k = \bar{\eta}(k+1)^{-1/2}m^{-1}$, $\delta_k = \bar{\delta}(k+1)^{-1/4}m^{-1/2}$, such that $\bar{\eta} \leq m/2\tilde{\ell}$,
and $\beta_k = \bar{\beta}(k+1)^{-\alpha}$ with $\alpha > \frac{1}{2}$.

Then, the iterations $(\mathbf{y}_k)_{k \in [K]}$ of Algorithm 1 are such that

$$\frac{1}{\sum_{k=1}^K \eta_k} \sum_{k=1}^K \eta_k \mathbb{E} \left[\|\nabla J_0(\mathbf{y}_k, \mathbf{x}_\phi^*(\mathbf{y}_k))\|^2 \right] \leq \mathcal{U}(K)$$

 Cianchi, Sanjab, **SG**, "Induced Stackelberg equilibrium seeking via iterative Tikhonov regularization," arXiv, 2026


Induced Stackelberg Equilibrium: Application example


- Followers = users in daily P2P energy trading $\mathbf{x}_{i,h} = [p_{i,h}^g, p_{i,j}^{\text{mg}}, p_{i,j}^{\text{st}}, \{p_{(i,j),h}^{\text{tr}}\}_{j \in \mathcal{N}_i}, \theta_{i,h}]$

$$J_i(\mathbf{x}; \mathbf{y}) = \sum_{h=1}^{24} f_{i,h}^g(p_{i,h}^g) + f_{i,h}^{\text{tr}}(\{p_{(i,j),h}^{\text{tr}}\}_{j \in \mathcal{N}_i}; \mathbf{y}) + f_{i,h}^{\text{mg}}(p_{i,h}^{\text{mg}}, p_{-i,h}^{\text{mg}})$$

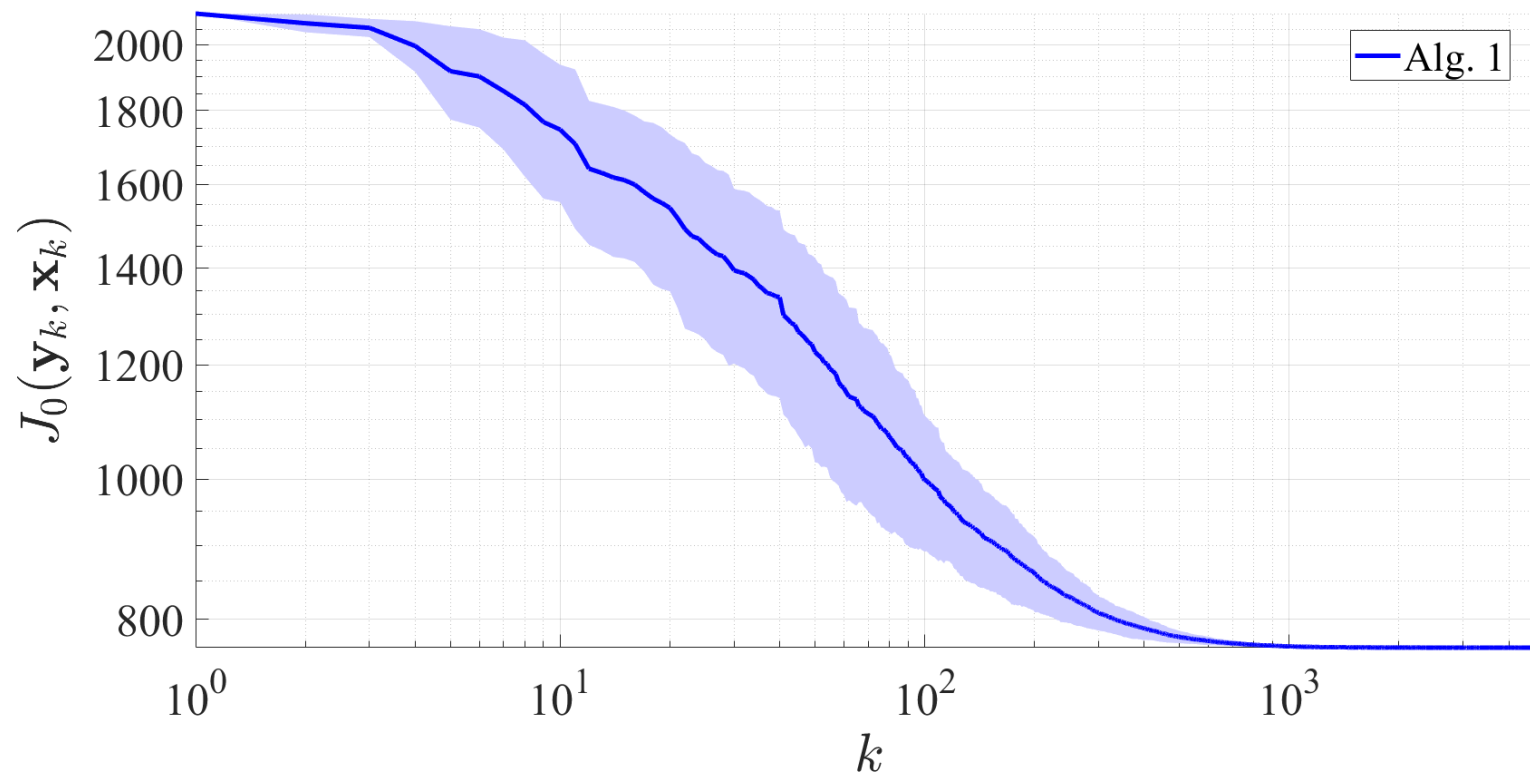
- Leader = community manager setting trading prices $J_0(\mathbf{y}, \mathbf{x}) = \sum_{i \in \mathcal{J}} J_i(\mathbf{x}, \mathbf{y}) + \lambda \|\mathbf{y} - \bar{\mathbf{y}}\|^2$
- Leader incentivizes users to reduce grid load/imbbalances & enhance renewable energy

$$\phi(\mathbf{x}) = \sum_{h=1}^{24} \|\mathbf{p}_h^g - \bar{\mathbf{p}}^g\|^2 + \|\mathbf{p}_h^{\text{mg}}\|^2 + \|\theta_h - \bar{\theta}\|^2 + \|\mathbf{p}_h^{\text{tr}}\|^2 + \|\mathbf{p}_h^{\text{st}}\|^2$$

 Cianchi, Sanjab, **SG**, “Induced Stackelberg equilibrium seeking via iterative Tikhonov regularization,” arXiv, 2026

 Belgioioso, Ananduta, **SG**, Ocampo-Martinez, “Operationally-safe peer-to-peer energy trading in distribution grids: A game-theoretic market-clearing mechanism,” IEEE TSG, 2022

Induced Stackelberg Equilibrium Seeking converges



3. Stackelberg Equilibrium Learning & Seeking

Linear-Quadratic Stackelberg Equilibrium Problem

- **Followers:** $\forall i : \begin{cases} \min_{\mathbf{x}_i \in \mathcal{X}_i} & J_i(\mathbf{x}_i; \mathbf{y}) := \|\mathbf{x}_i - \mathbf{r}_i\|^2 + (\mathbf{p} + \mathbf{y})^\top \Pi_i A_i \mathbf{x}_i, \\ \text{s. t.} & \sum_{i=1}^N A_i \mathbf{x}_i \leq \mathbf{b} \end{cases}$
- v-GNE set: $\mathcal{E}(\mathbf{y}) = \{\mathbf{x}^*(\mathbf{y})\}$ with $\mathbf{x}^*(\mathbf{y}) = \text{proj}_C(\Theta_A \mathbf{y} - \Theta_b)$
- **Leader:** $\begin{cases} \min_{\mathbf{y} \in \mathcal{Y}} & J_0(\mathbf{y}, \mathbf{x}) := -\mathbf{y}^\top \Lambda A \mathbf{x} + \mu(\mathbf{1}^\top \mathbf{y} - \bar{y})^2 + \lambda \|\mathbf{y}\|^2 \\ \text{s. t.} & \mathbf{x} \in \mathcal{E}(\mathbf{y}) \end{cases}$

 Cianchi, Baghbadorani, Sanjab, **SG**, "Learning-based Stackelberg equilibrium seeking with application to demand-side energy management," arXiv, 2026

Stackelberg Equilibrium Learning & Seeking

- Stackelberg game: $\min_{\mathbf{y} \in \mathcal{Y}} J_0(\mathbf{y}, \mathbf{x}^*(\mathbf{y}))$
- **Leader** interacts with followers via queries (zeroth order)
- **Leader** knows **parametric structure** of followers' reaction: $\mathbf{x}^*(\mathbf{y}; \Theta_A, \Theta_b) := \text{proj}_C(\Theta_A \mathbf{y} - \Theta_b)$

Learning-Based Stackelberg Equilibrium Seeking:

1. Zeroth-order algorithm with datase collection
2. Parameter estimation
3. Solution of the estimated Stackelberg game

Zeroth order Algorithm with Data Collection

1. Zeroth-order algorithm with data collection

Algorithm 2 Zeroth-order algorithm

Data: Number of iterations K , Initial condition $\mathbf{y}_0 \in \mathbb{R}^T$,

Step sizes $(\eta_k)_{k \in [K]}$, Perturbation radius $(\delta_k)_{k \in [K]}$

1: **for** $k = 1$ to $K - 1$ **do**

2: Sample $\mathbf{v}_k \sim \text{Unif}(\mathcal{S}(\mathbb{R}^T))$;

3: Assign $\tilde{\mathbf{y}}_k = \mathbf{y}_k + \mathbf{v}_k \delta_k$;

4: Collect $\mathbf{x}_k = \mathbf{x}^*(\mathbf{y}_k)$;

5: Collect $\tilde{\mathbf{x}}_k = \mathbf{x}^*(\tilde{\mathbf{y}}_k)$;

6: Compute $\hat{\mathbf{g}}_k = \frac{T}{\delta_k} (J_0(\mathbf{y}_k, \mathbf{x}_k) - J_0(\tilde{\mathbf{y}}_k, \tilde{\mathbf{x}}_k)) \mathbf{v}_k$;

7: Update $\mathbf{y}_{k+1} = \mathbf{y}_k - \eta_k \hat{\mathbf{g}}_k$;

8: **end for**


Dataset collection:
 $\mathcal{D} := \{(\mathbf{y}_k, \mathbf{x}_k)\}_k$

Convergence Theorem

- Expected distance depends on initial function value (Theorem 1)

Let $\eta_k = \bar{\eta}(k+1)^{-1/2}T^{-1}$, $\delta_k = \bar{\delta}(k+1)^{-1/4}T^{-1/2}$, such that $\bar{\eta} \leq T/2\tilde{\ell}$.
Then, the iterations $(\mathbf{y}_k)_{k \in [K]}$ of Algorithm 2 are such that

$$\frac{1}{\sum_{k=1}^K \eta_k} \sum_{k=1}^K \eta_k \mathbb{E} \left[\|\nabla J_0(\mathbf{y}_k)\|^2 \right] \leq \mathcal{U}(J_0(\mathbf{y}_0), K, \bar{\eta}, \bar{\delta}).$$

 Cianchi, Baghbadorani, Sanjab, **SG**, “Learning-based Stackelberg equilibrium seeking with application to demand-side energy management,” arXiv, 2026


Inverse Problem for Parameter Estimation

2. Parameter estimation (to improve next initial condition, hence convergence)

$$\begin{cases} \min_{\hat{\Theta}_A, \hat{\Theta}_b} & \frac{1}{2K} \sum_{k=1}^{2K} \left\| J_0(\mathbf{y}_k, \mathbf{x}_k) - J_0(\mathbf{y}_k, \mathbf{x}^*(\mathbf{y}_k; \hat{\Theta}_A, \hat{\Theta}_b)) \right\|^2 \\ \text{s.t.} & \mathbf{x}^*(\mathbf{y}_k; \hat{\Theta}_A, \hat{\Theta}_b) = \text{proj}_{\mathcal{C}}(\hat{\Theta}_A \mathbf{y}_k - \hat{\Theta}_b) \end{cases} \longrightarrow \mathbf{x}^*(\mathbf{y}; \hat{\Theta}_A, \hat{\Theta}_b)$$

(Theorem 2, informal):

For each data point $(\mathbf{y}_k, \mathbf{x}_k) \in \mathcal{D}$, there exists a region, $\mathcal{B}(\mathbf{y}_k, \rho)$, where the estimation $\mathbf{x}^*(\mathbf{y}; \hat{\Theta}_A, \hat{\Theta}_b)$ is sufficiently accurate.

 Cianchi, Baghbadorani, Sanjab, **SG**, "Learning-based Stackelberg equilibrium seeking with application to demand-side energy management," arXiv, 2026

Estimated Stackelberg Game solved by Leader agent

3. Solution of the estimated Stackelberg game

Leader minimizes $J_0 \left(\mathbf{y}; \mathbf{x}^* \left(\mathbf{y}; \hat{\Theta}_A, \hat{\Theta}_b \right) \right)$


Algorithm 3 Difference of Convex Programs

Data: Initial condition \mathbf{z}_0

- 1: **while** $t \leq t_{\max}$ **do**
- 2: Solve $\mathbf{z}_{t+1} \in \arg \min_{\mathbf{z} \in \mathcal{Z}} g(\mathbf{z}) - \langle \nabla p(\mathbf{z}_t), \mathbf{z} \rangle$
- 3: **end while**

Return: $\hat{\mathbf{y}} = \mathbf{y}_{t_{\max}}$

keep iterates in trust region!

 Tao, An, "Convex analysis approach to DC programming: theory, algorithms and applications," Acta Mathematica, 1997

Stackelberg Equilibrium Learning & Seeking (+)

Tradeoff between learning and seeking:

Long data collection means slow convergence (ZOM) but also accurate learning

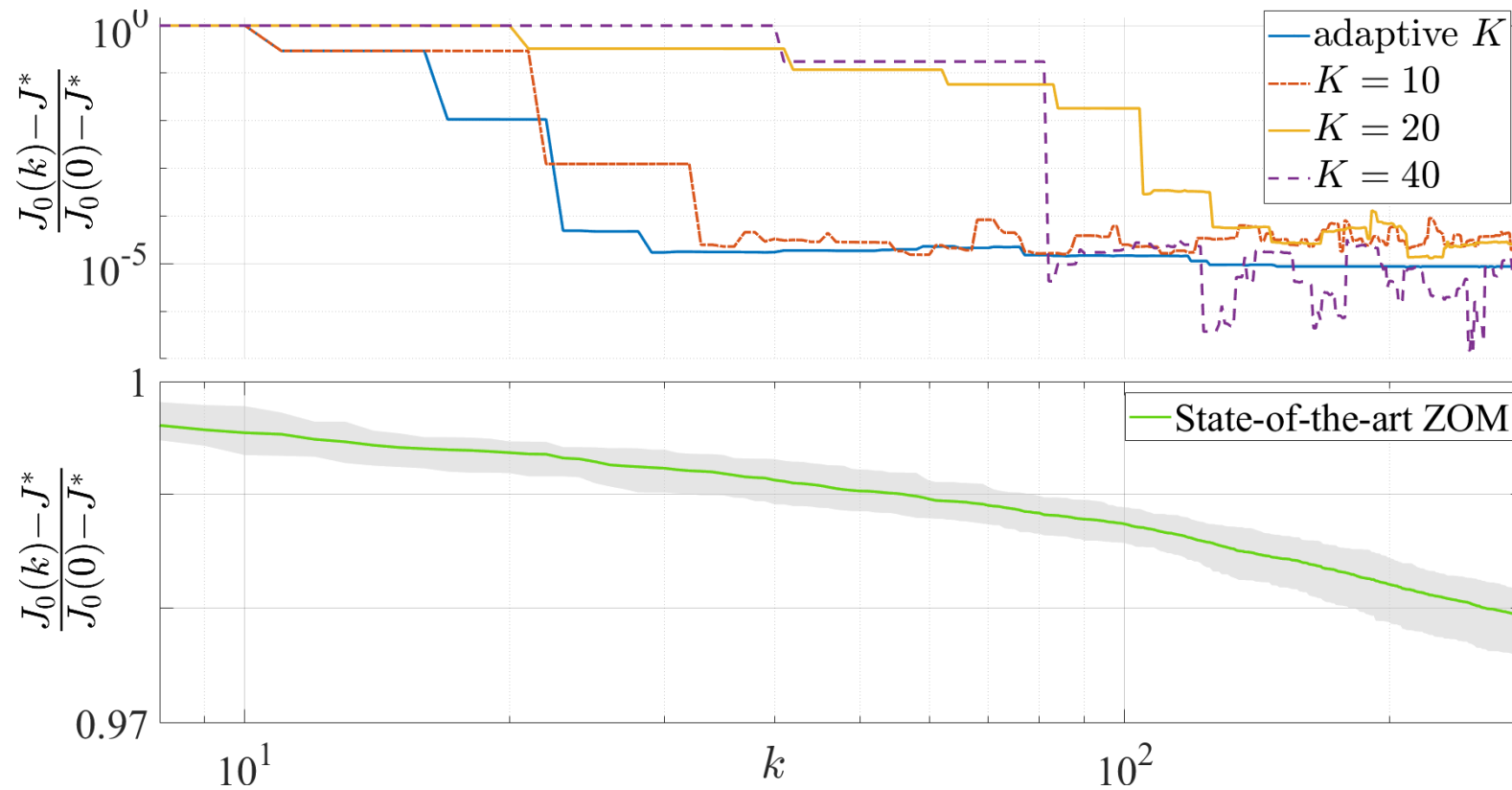
Adaptive K (Remark 1):

- Zeroth-order algorithm runs for K_1 iterations
- Next round of zeroth order algorithm: at least K_2 iterations, based on convergence rate

 Cianchi, Baghbadorani, Sanjab, **SG**, “Learning-based Stackelberg equilibrium seeking with application to demand-side energy management,” arXiv, 2026

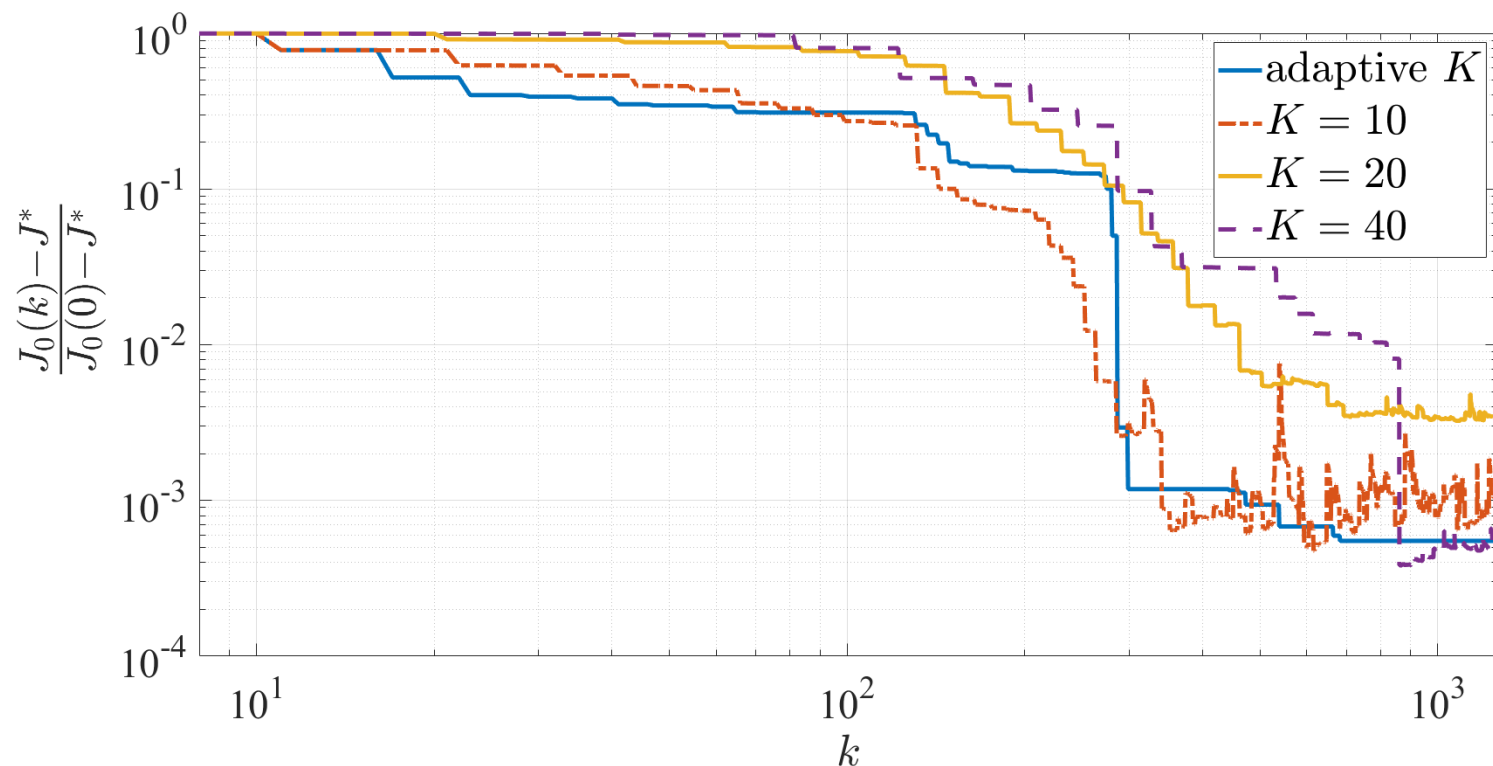
Learning & Seeking converges fast

- Known feasible set

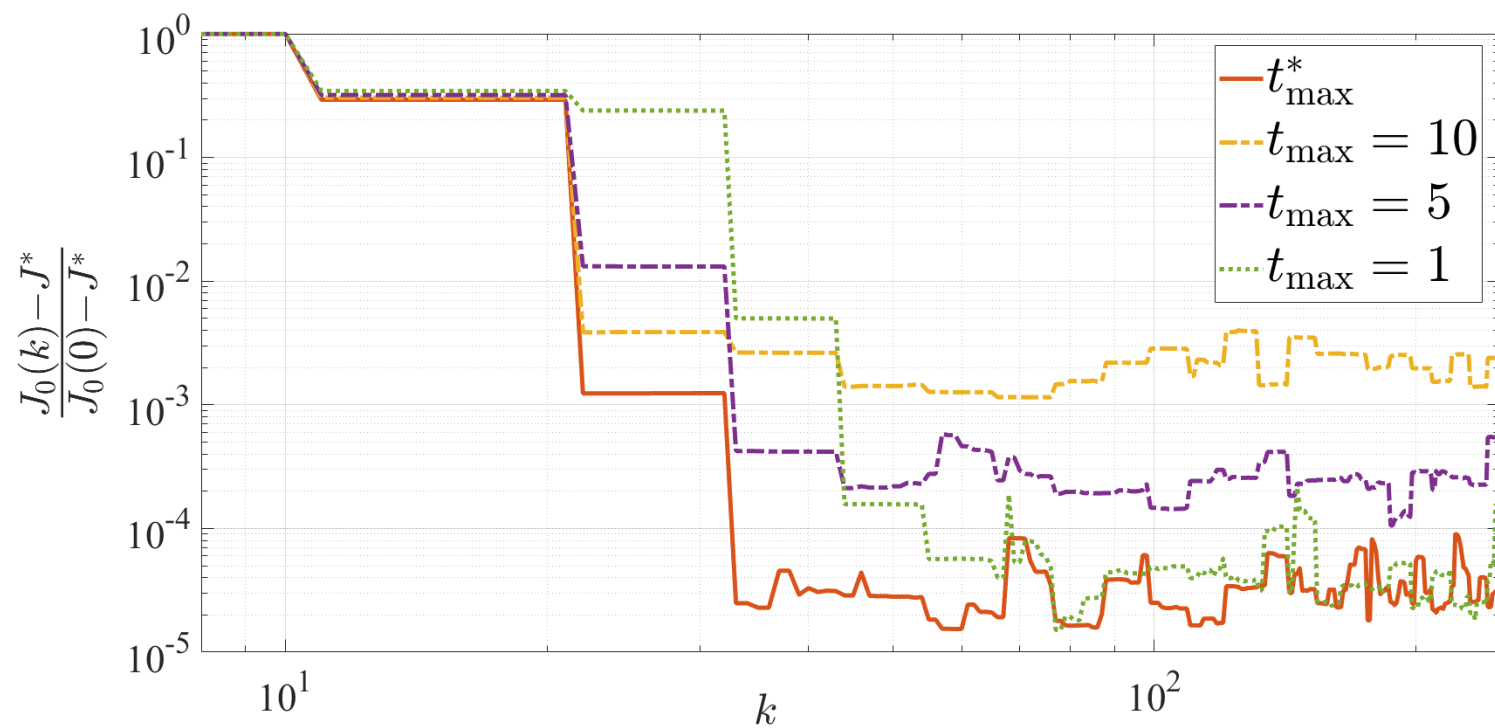


Effect of partially unknown feasible set

- Feasible set learned from collected data



Effect of unknown trust region



4. Conclusion & Outlook

Conclusion and Outlook

- Stackelberg games model hierarchical decision making, leading to **bilevel and nonconvex optimization problems**
- **Equilibrium selection via followers regularization** makes Stackelberg equilibrium problems well posed
- Zeroth order Stackelberg equilibrium seeking is slow; **Hybrid learning-and-seeking accelerates convergence significantly**
- For **non-quadratic Stackelberg games**, kernel-based learning sounds promising

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Thank you for your kind attention!