Distributed Optimization and Learning for Aggregative Management of Energy Communities

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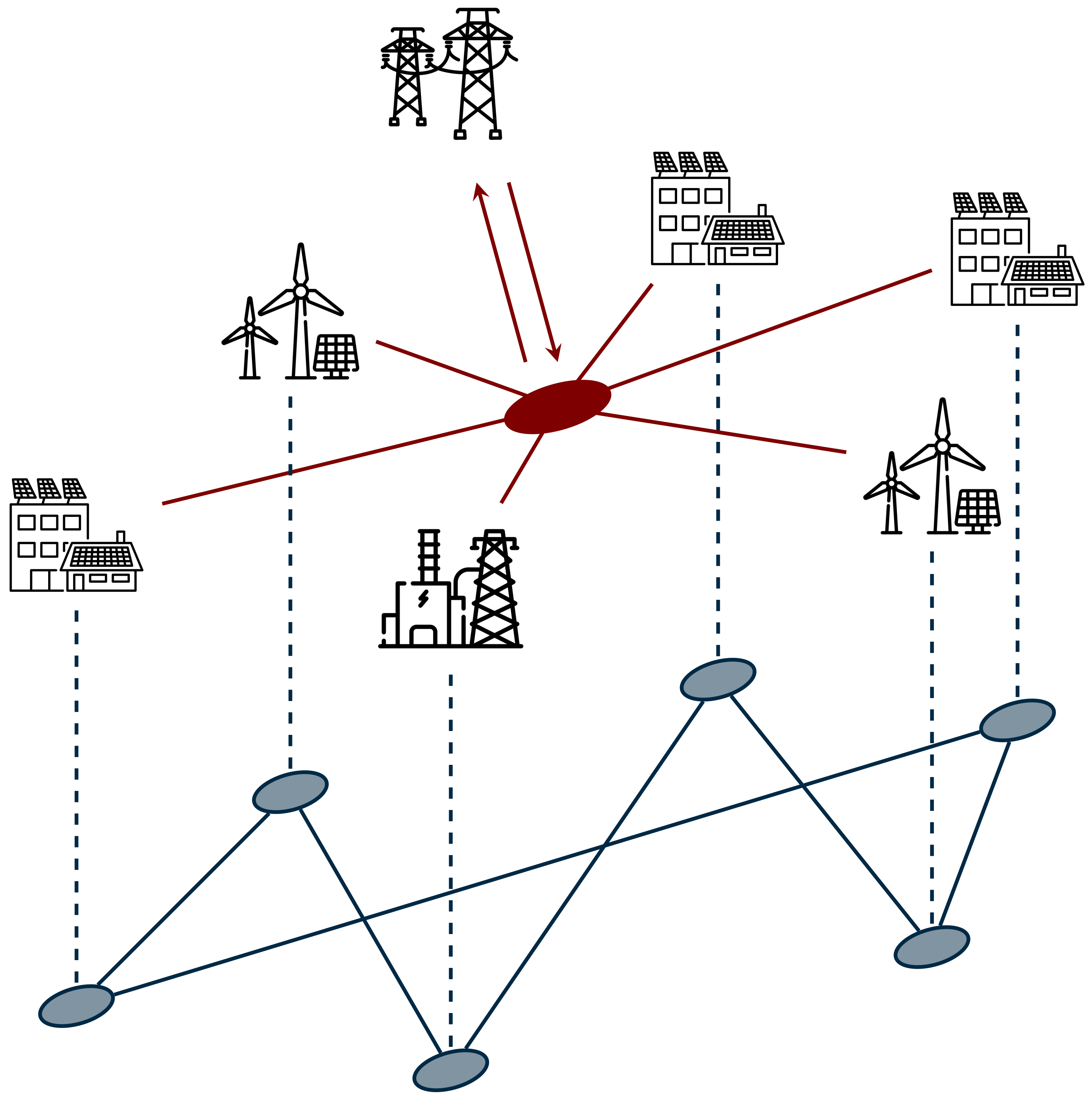
Distributed Algorithm for Coordination in Energy Communities

N interconnected units capable of

- Generating, consuming, and storing energy
- Exchanging energy and information



Energy exchange: (fully connected)

Units trade energy with everyone and the main grid

Information exchange: (graph-based)

Units communicate only with their neighbors

Goal: Leverage distributed optimization to enable cooperation among units, achieving a global objective

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Energy Community Setup

Setup

N agents divided among *buyers* and *sellers*

Buyers: Can't satisfy their energy demand

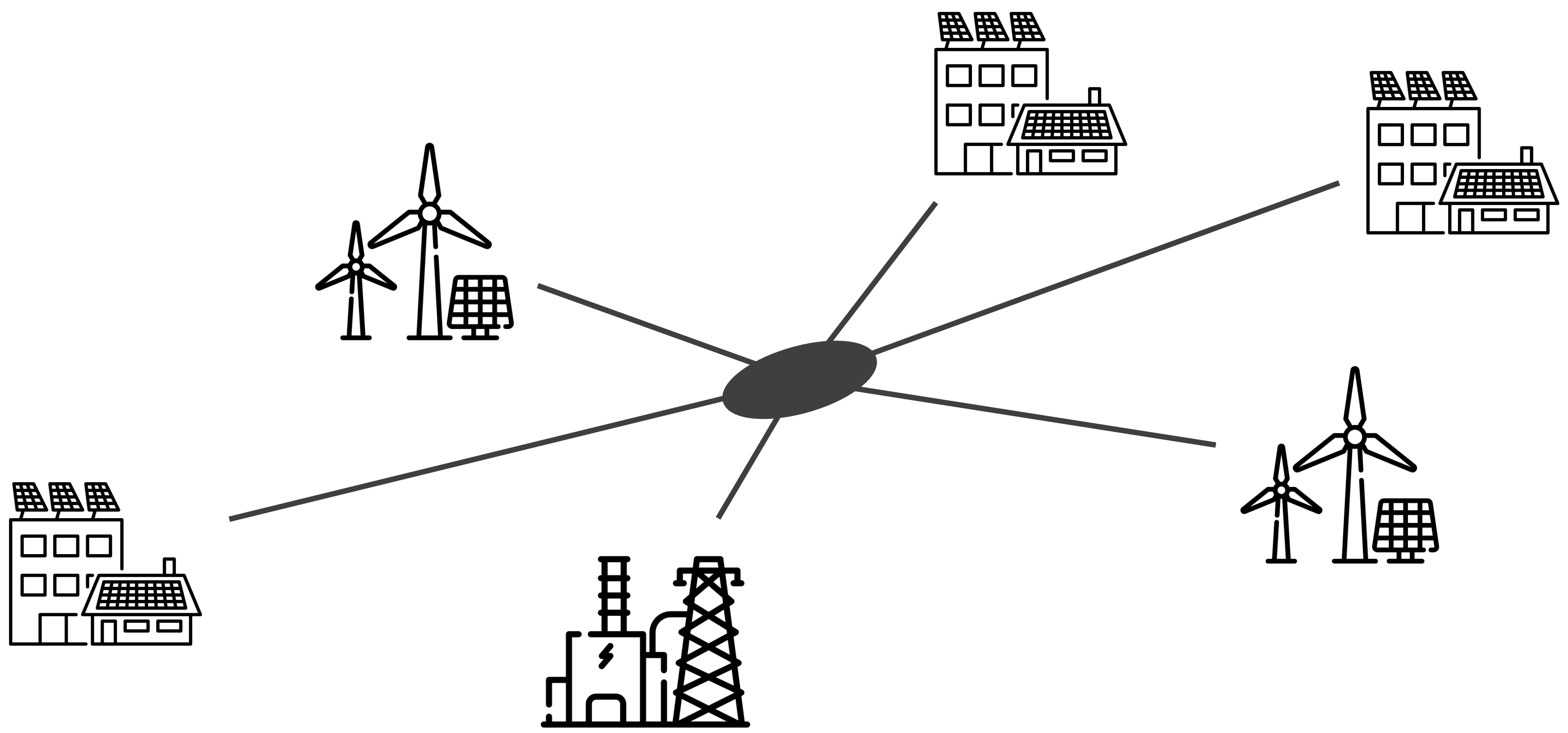
Goals:

- Demand satisfaction
- Buy energy at the lowest price

Sellers: Excess of energy that can be sold

Goals:

- Maximize revenues
- Store energy for future use



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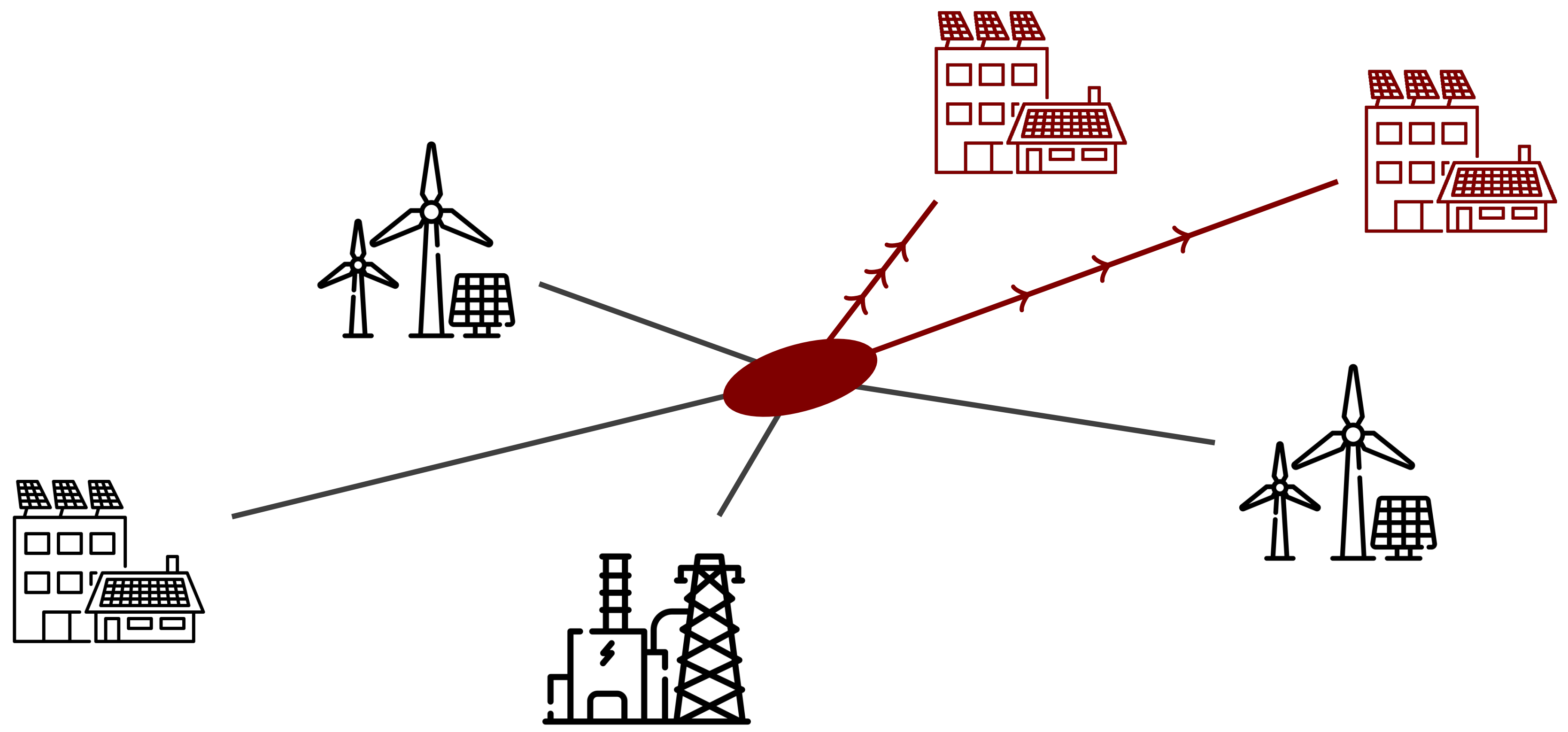
Buyer Detail



Decision Variable: $c_i \in [c_b, c_s]$

- Unit bid that buyer i is willing to pay
- Constrained by the main grid market prices

Energy received: follows a proportional sharing rule

$$E_i(c, w) = \hat{E}(w) \frac{c_i}{\sum_{i \in \mathcal{B}} c_i}$$

Note: $\hat{E}(w) := \sum_{j \in \mathcal{S}} \hat{E}_j w_j$ total energy sold, function of sellers decision variables and energy excesses $\hat{E}_j$

Cost function:

$$f_i^B := \epsilon_i^d \underbrace{\|E_i(c, w) - \bar{E}_i\|^2}_{\text{Demand satisfaction}} + \epsilon_i^b \underbrace{E_i(c, w)(c_i - c_s)}_{\text{Low energy cost}}$$

with $\bar{E}_i$ the energy demand

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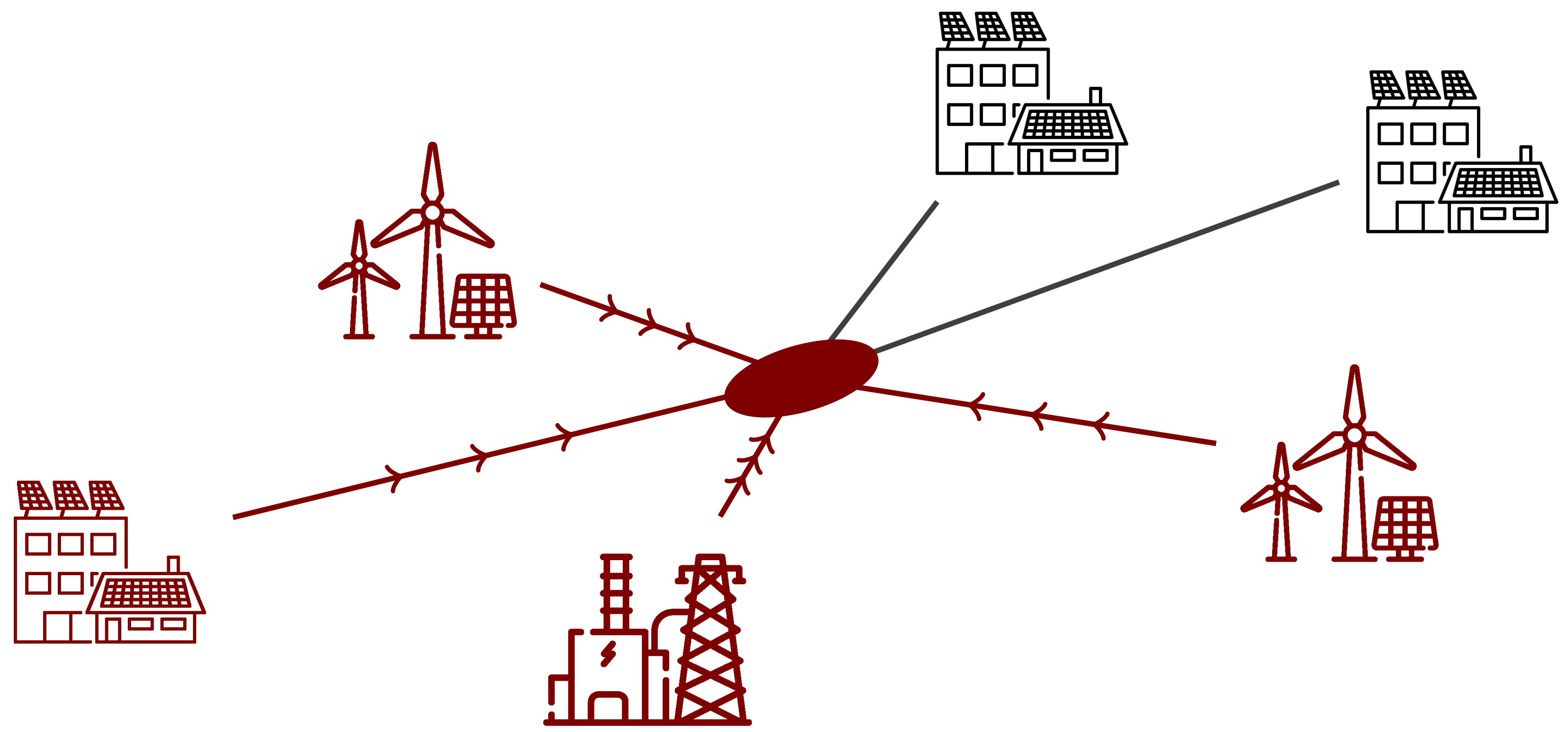
Seller Detail



Decision Variable: $w_j \in [0,1]$

- Percentage of energy to sell
- Consistency constraints

Cumulative and Unit Revenue: follows a proportional sharing rule

$$R(c,w) := \sum_{i \in \mathscr{B}} c_i E_i(c,w) \qquad \text{and} \qquad R_j(c,w) := R(c,w)\frac{\hat{E}_j w_j}{\hat{E}(w)}$$

Cost function:

$$f_i^S(c,w) := = \gamma_j^r \underbrace{R_j(c,w)}_{\text{Revenue maximisation}} - \gamma_j^s \underbrace{\ln\left(1 + \hat{E}_j(1-w_j)\right)}_{\text{Satisfaction from storage}}$$

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Distributed Aggregative Optimization Problem

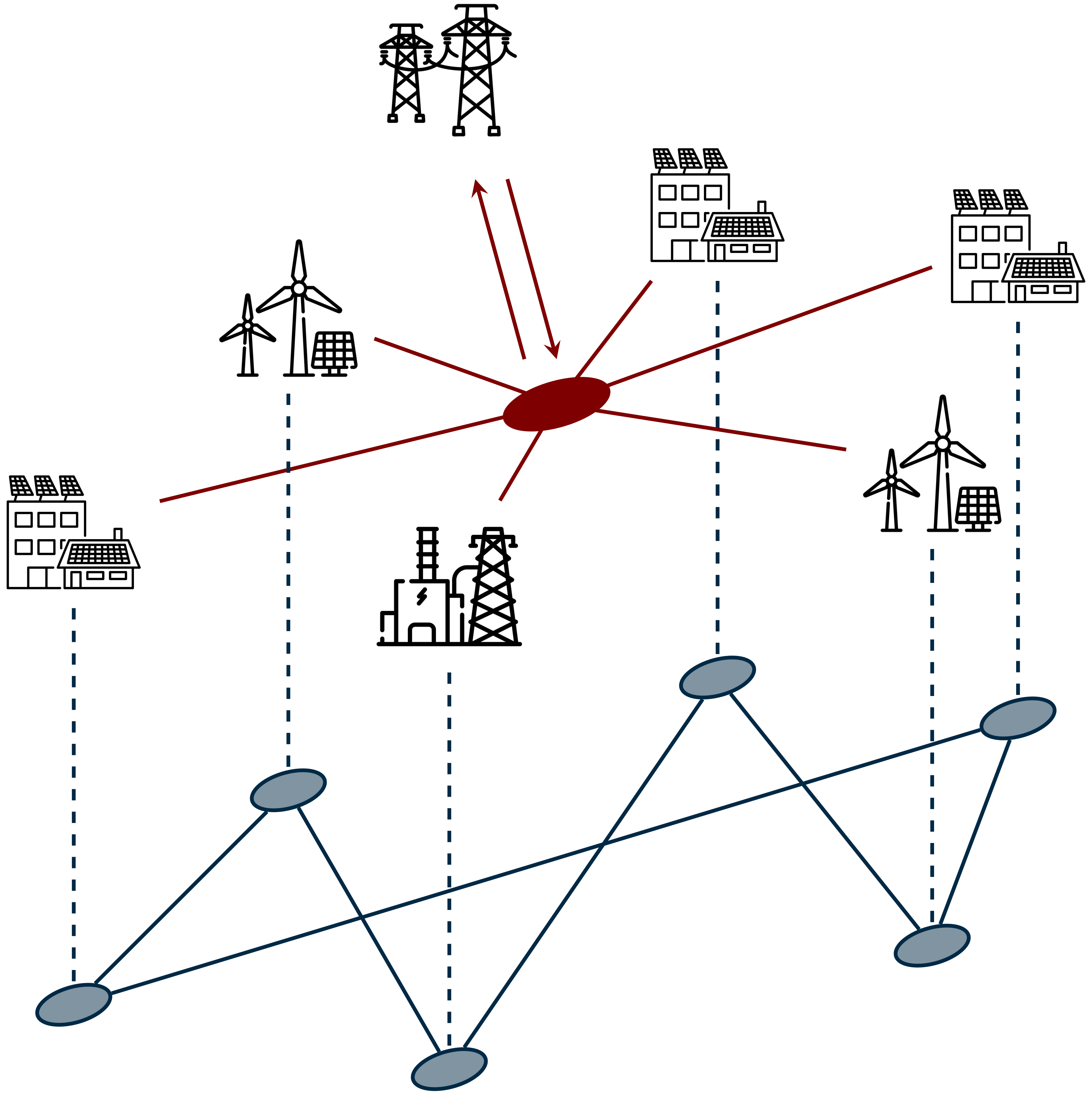
Remark: f_i^B and f_j^S depends on an aggregation of all decision variables

Optimization Problem:

$$\min_{\substack{c_1,\dots,c_I \\ w_{I+1},\dots,w_J}} \sum_{i\in\mathcal{B}} f_i^B(c_i, \sigma(c,w)) + \sum_{j\in\mathcal{S}} f_i^S(w_j, \sigma(c,w))$$

$$\text{subj. to} \quad c_i \in [c_b, c_s], \quad \forall i \in \mathcal{B}$$
$$w_j \in [0,1], \quad \forall j \in \mathcal{S}$$

where $\sigma(c,w) := \frac{1}{N}\left[\underbrace{\sum_{i\in\mathcal{B}} c_i}_{\text{Total bid}},\ \underbrace{\sum_{i\in\mathcal{B}} c_i^2}_{\propto R(c,v)},\ \underbrace{\sum_{j\in\mathcal{S}} \hat{E}_j w_j}_{\text{Total Energy Sold}}\right]^\top$



Solution Algorithm:

- Gradient-based update with local proxies for global quantities
- Consensus-based update to track global quantities

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Algorithm

Notation:

- Buyer: $x_i := c_i$ and $X_i := [c_b, c_s]$
- Seller: $x_i := w_i$ and $X_i := [0,1]$

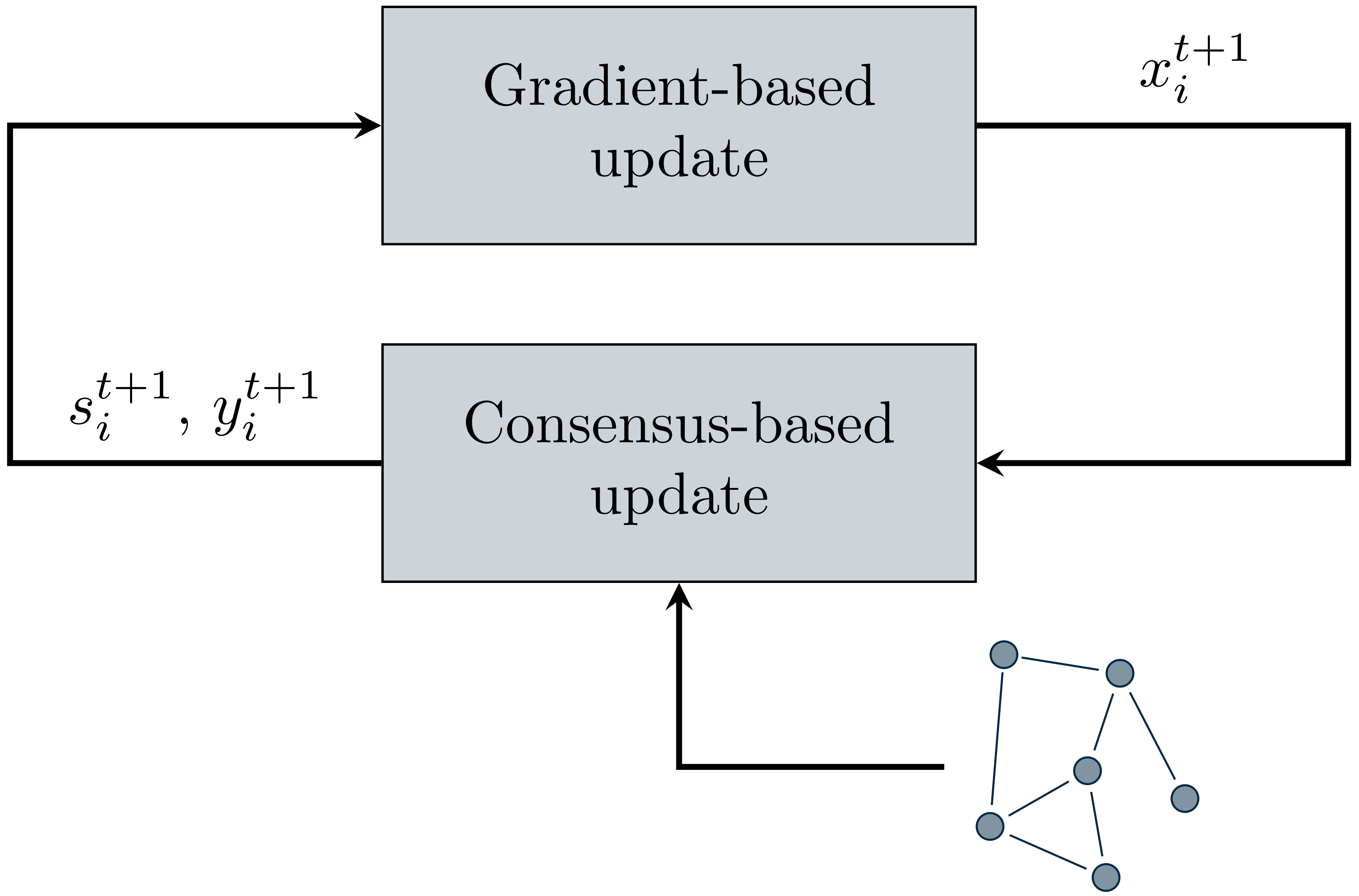
Gradient based Update:

$$\tilde{x}_i^t = P_{X_i}\Big[x_i^t - \gamma\left(\nabla_1 f_i(x_i^t, s_i^t) + \nabla\phi_i(x_i^t) y_i^t\right)\Big]$$

Consensus based Update:

$$s_i^{t+1} = \sum_{j\in\mathcal{N}_i} a_{ij} s_j^t + \phi_i(x_i^{t+1}) - \phi_i(x_i^t)$$

$$y_i^{t+1} = \sum_{j\in\mathcal{N}_i} a_{ij} y_j^t + \nabla_2 f_i(x_i^{t+1}, s_i^{t+1}) - \nabla_2 f_i(x_i^t, s_i^t)$$



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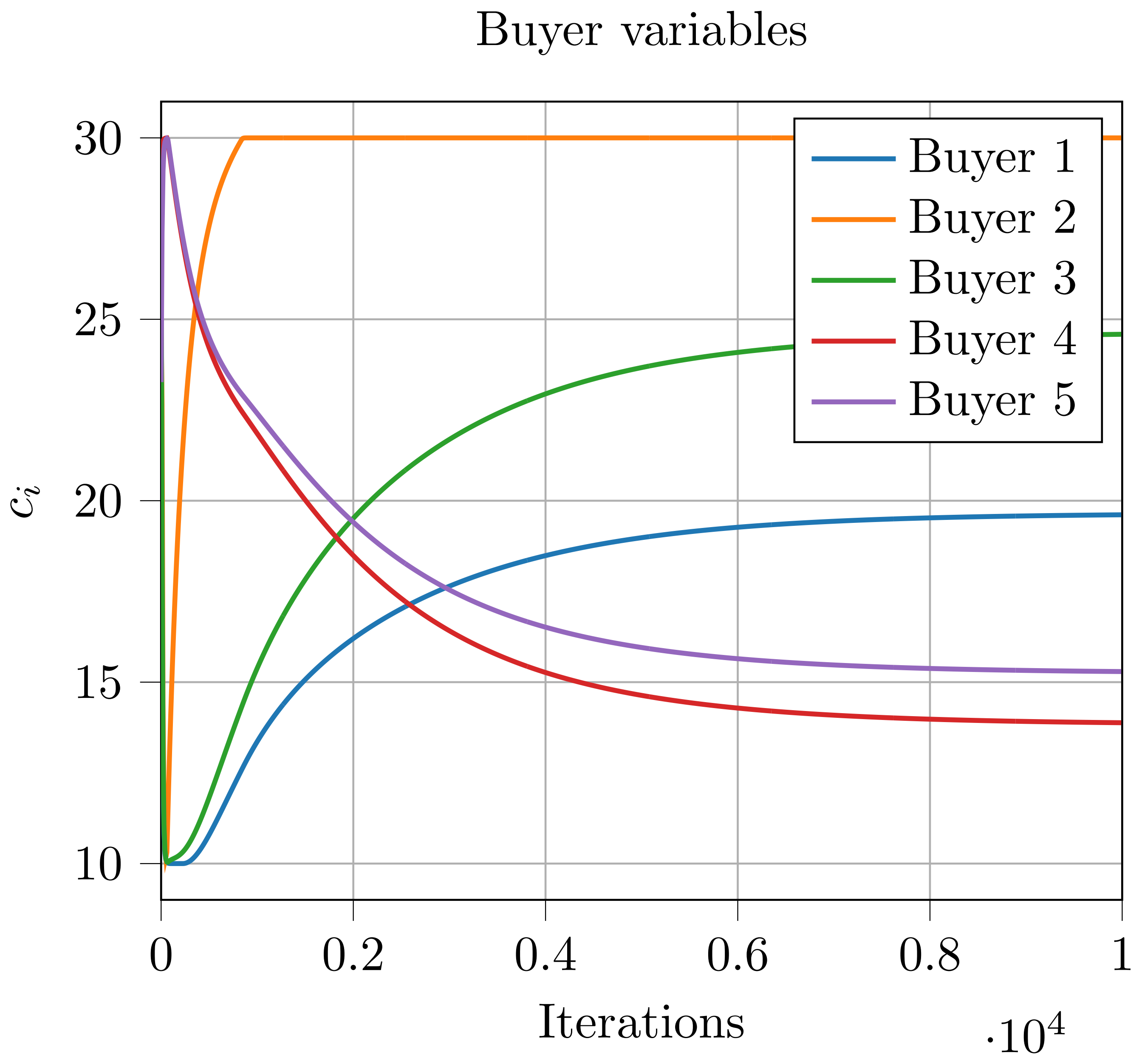
Numerical Simulation: Focus on Demand satisfaction

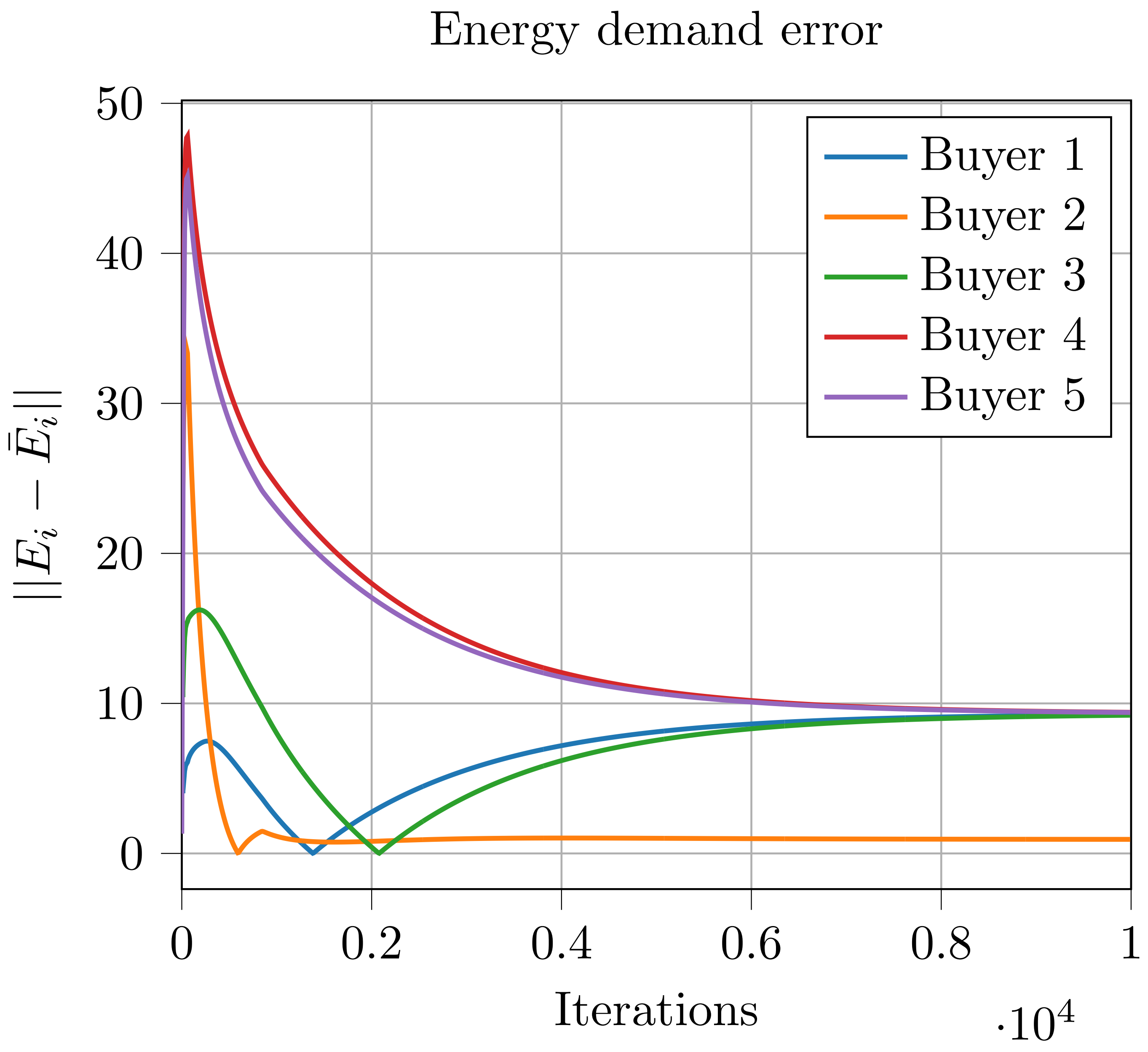
Desired Behavior:

Buyer 2 prioritizes demand satisfaction

Parameter Selection:

$$\varepsilon_2^d \gg \max\left\{\varepsilon_i^d, \varepsilon_i^b, \varepsilon_2^b, \gamma_j^r, \gamma_j^s\right\} \quad \forall i \in \mathscr{B}\setminus\{2\}, \forall j \in \mathscr{S}$$





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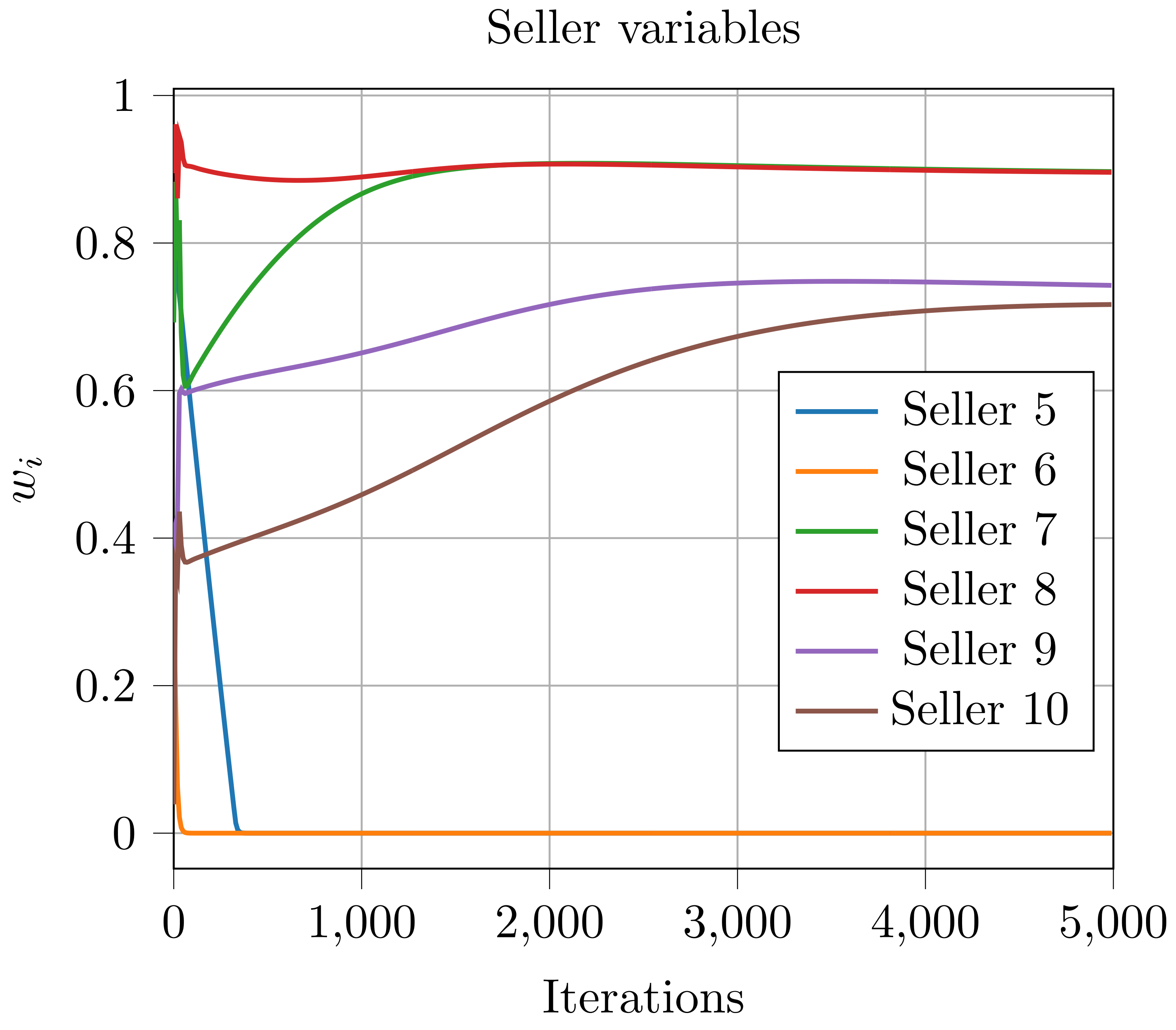
Numerical Simulation: Focus on Storage

Desired Behavior:

Sellers 5 and 6 prioritize energy storage

Parameter Selection:

$$\gamma_5^s, \gamma_6^s \gg \max\left\{\varepsilon_i^d, \varepsilon_i^b, \gamma_j^r, \gamma_5^r, \gamma_6^r, \gamma_j^s\right\} \quad \forall i \in \mathscr{B}, \forall j \in \mathscr{S} \setminus \{5,6\}$$



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Data-Driven Distributed Optimization via Aggregative Tracking and Deep-Learning

Data-driven Distributed Optimization

Distributed setup

- agents communicating over a graph
- agents access only local information

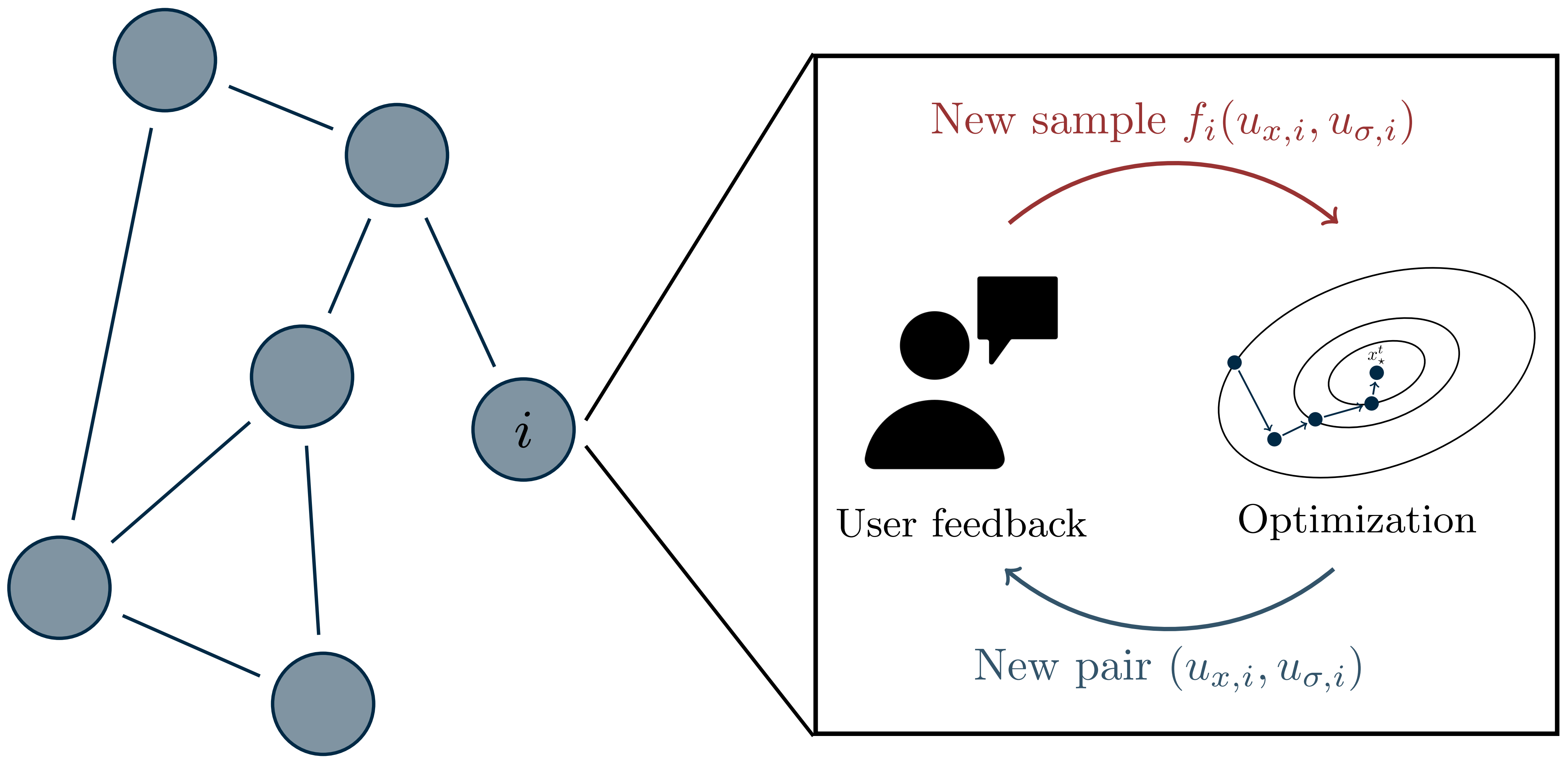
Optimization problem

$$\min_{x_1,\dots,x_N} \sum_{i=1}^{N} f_i(x_i, \sigma(x))$$

where $\sigma(x) := \frac{1}{N}\sum_{i=1}^{N} \phi_i(x_i)$ is called aggregative variable

Data-driven scenario

- Unknown local objectives
- One feedback of each at each iteration



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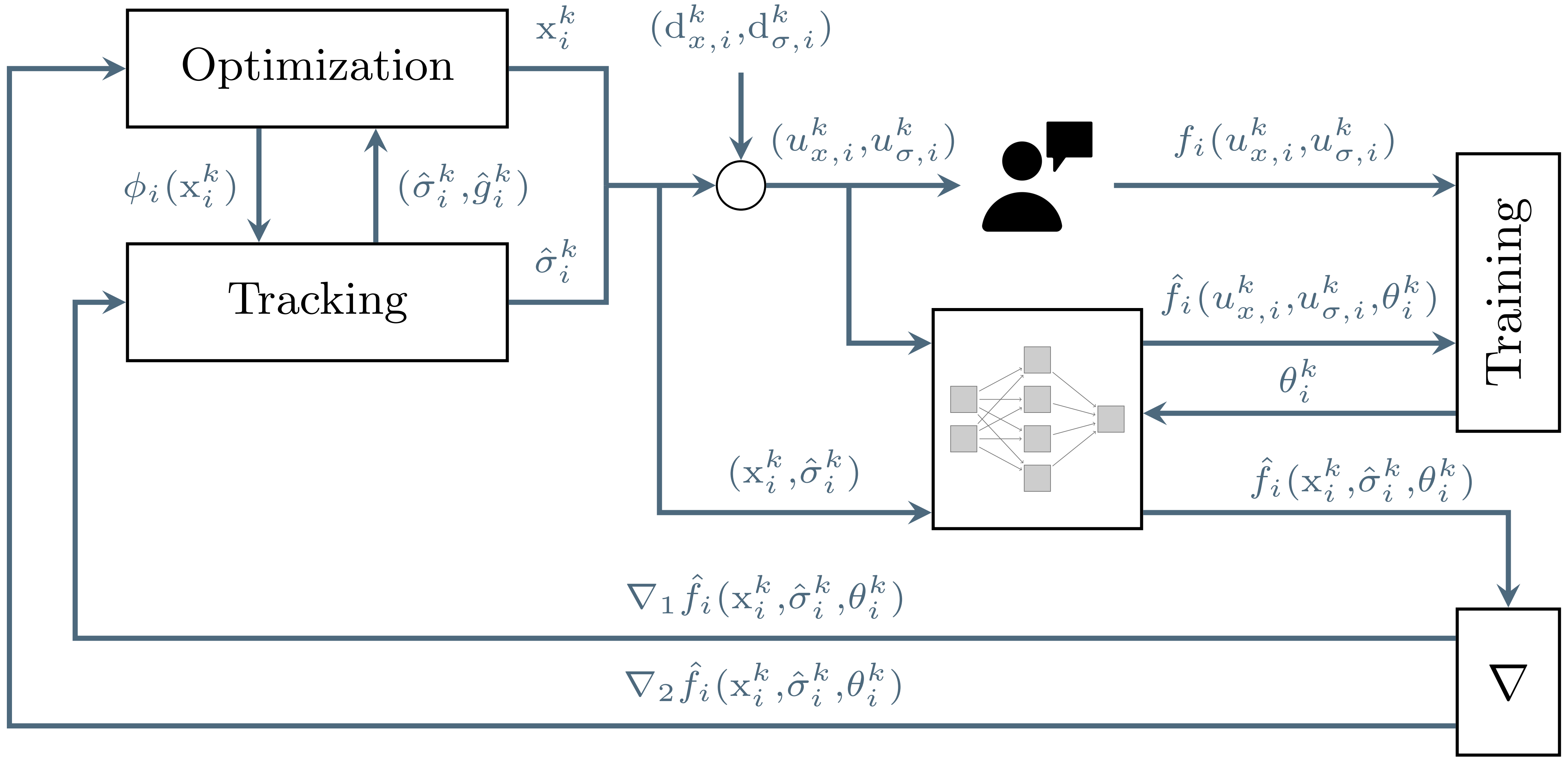
Distributed Strategy and Theoretical Guarantees

Solution Idea:

- Approximate the descent direction as $\nabla \hat{f}_i$
- Learning based on local neural networks
- Update the current solution estimate x_i^k
- Track $\sigma(x)$ and $\frac{1}{N}\sum_{i=1}^{N} f_i(x_i, \sigma(x))$ via w_i^k and z_i^k



Theoretical Guarantees:

- Convergence to a neighborhood of the optimum
- Proof based on timescale separation and averaging theory

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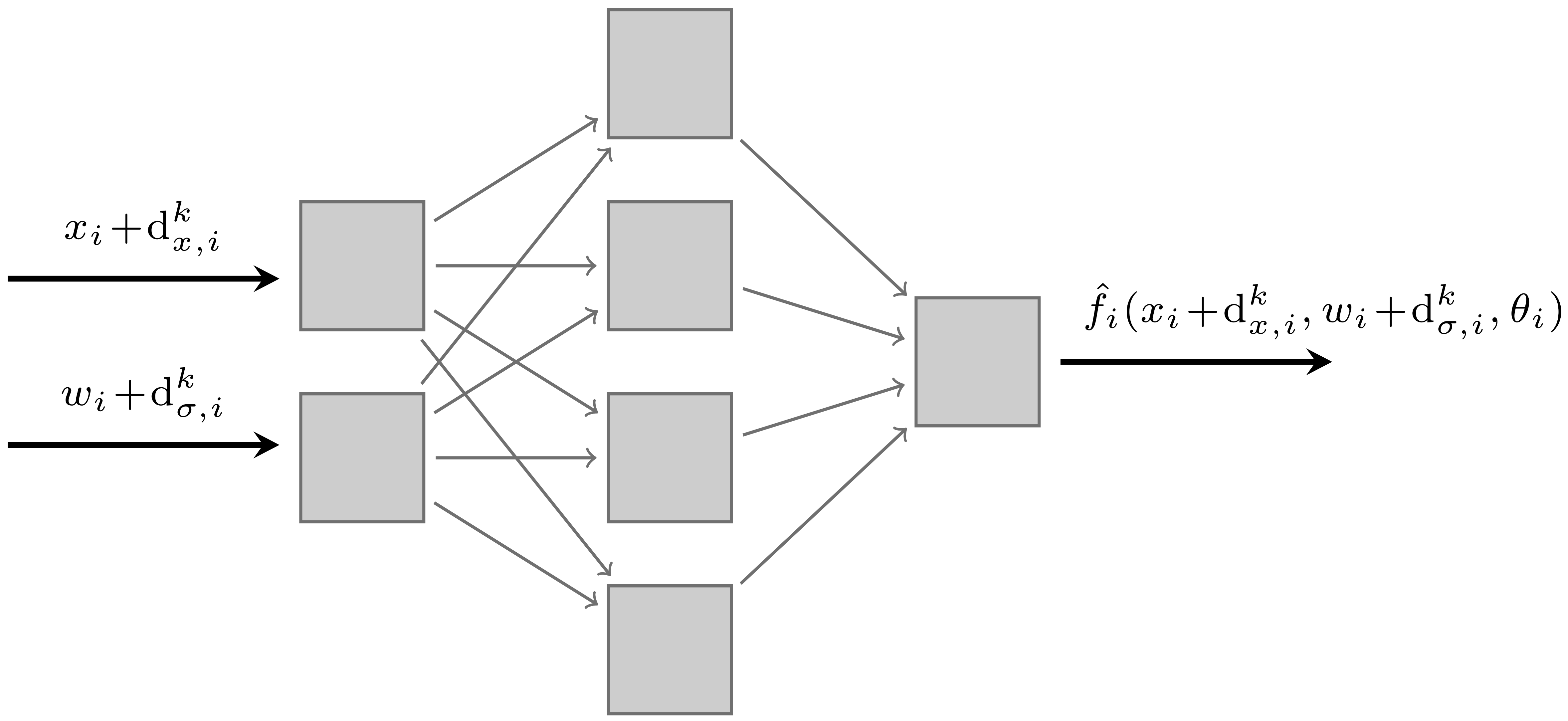
Learning Strategy

Idea: for each iteration k

- Given a neural network with parameter $\theta_i \in \mathbb{R}^{m_i}$
- Sample f_i in a point around the current $(x_i, \sigma(x))$
- Learn $f_i(\,\cdot\,,\cdot\,)$ from samples as $\hat{f}_i(\,\cdot\,,\cdot\,,\theta)$



Training cost function:

$$\ell_i(x_i^k, w_i, \theta_i) := \frac{1}{2} \left\| f_i\left(x_i^k + d_k^{x,i}, w_i + \hat{d}_k^{\sigma,i}\right) - \hat{f}_i\left(x_i^k + d_k^{x,i}, w_i + d_k^{\sigma,i}, \theta_i\right) \right\|^2$$

Gradient estimate: $\nabla f_i(\,\cdot\,,\cdot\,) \approx \nabla \hat{f}_i(\,\cdot\,,\cdot\,,\theta)$

$\nabla_1 f_i(x_i, w_i, \theta_i)$ proxy for $\nabla_1 f_i(x_i, w_i)$, $\qquad \nabla_2 f_i(x_i, w_i, \theta_i)$ proxy for $\nabla_2 f_i(x_i, w_i)$

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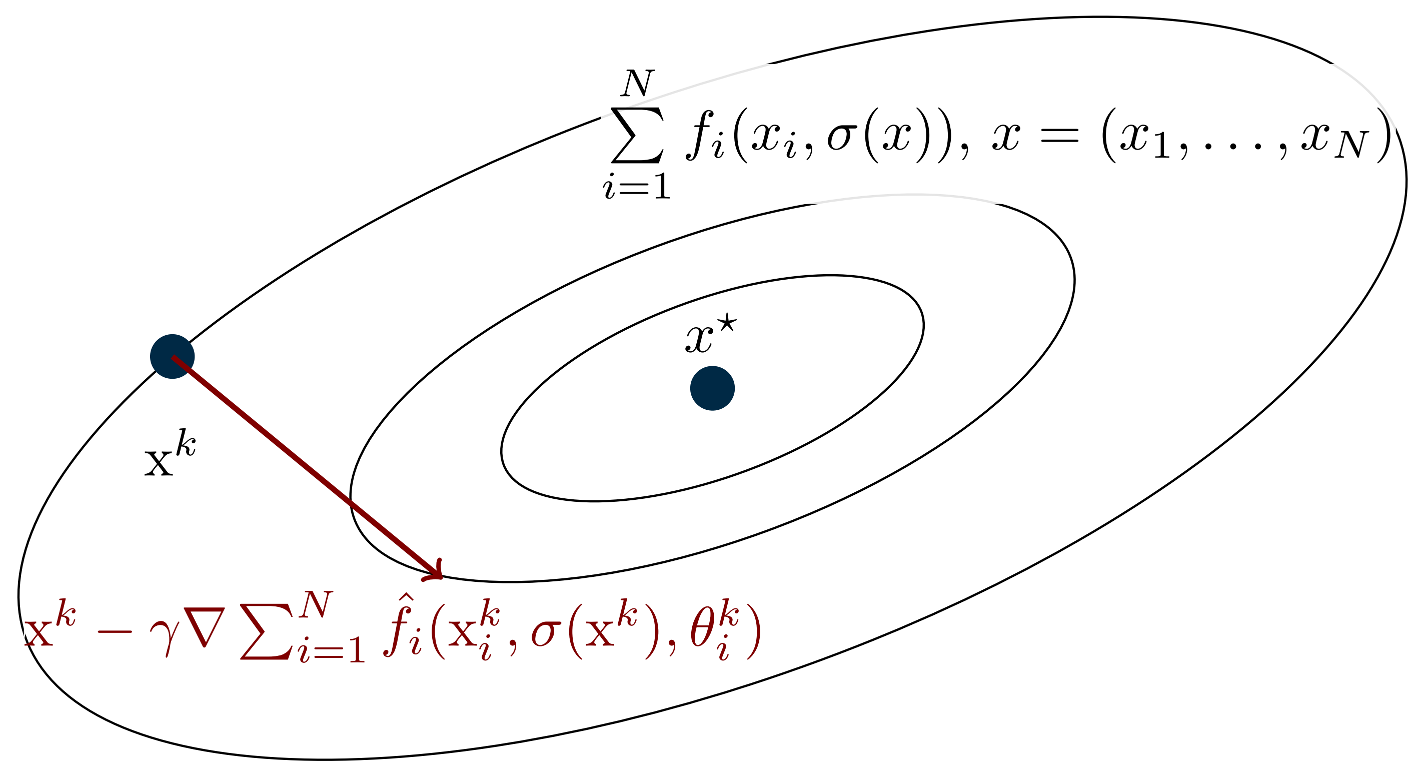
Optimization and Tracking Steps

Idea: for each iteration k

- Follow an approximated gradient method
- Track global quantities with local proxies $w_i^k, z_i^k \in \mathbb{R}^d$



Optimization Step:

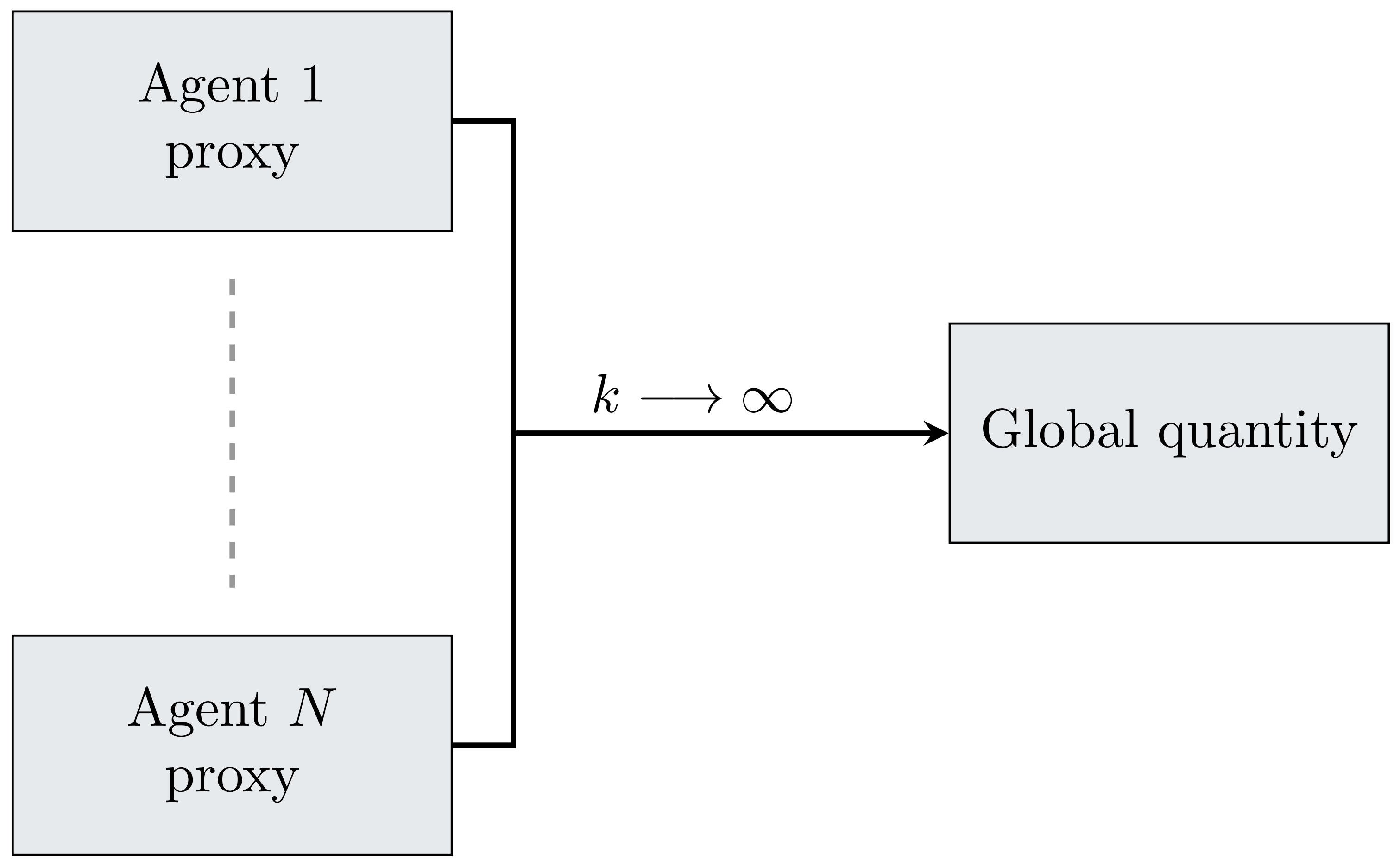
$$x_i^{k+1} = x_i^k - \gamma \nabla_{x_i} \hat{f}_i \left(x_i^k, w_i^k + \phi_i(x_i^k), \theta_i^k \right)$$

Tracking Step:

Consensus based update such that

$$w_i^k + \phi_i(x_i^k) \xrightarrow[k \to \infty]{} \sigma(x^k)$$

$$z_i^k + \nabla_2 \hat{f}_i\left(x_i^k, w_i^k + \phi_i(x_i^k), \theta_i^k\right) \xrightarrow[k \to \infty]{} \frac{1}{N} \sum_{j=1}^{N} \nabla_2 \hat{f}_j\left(x_j^k, \sigma(x^k), \theta_j^k\right)$$



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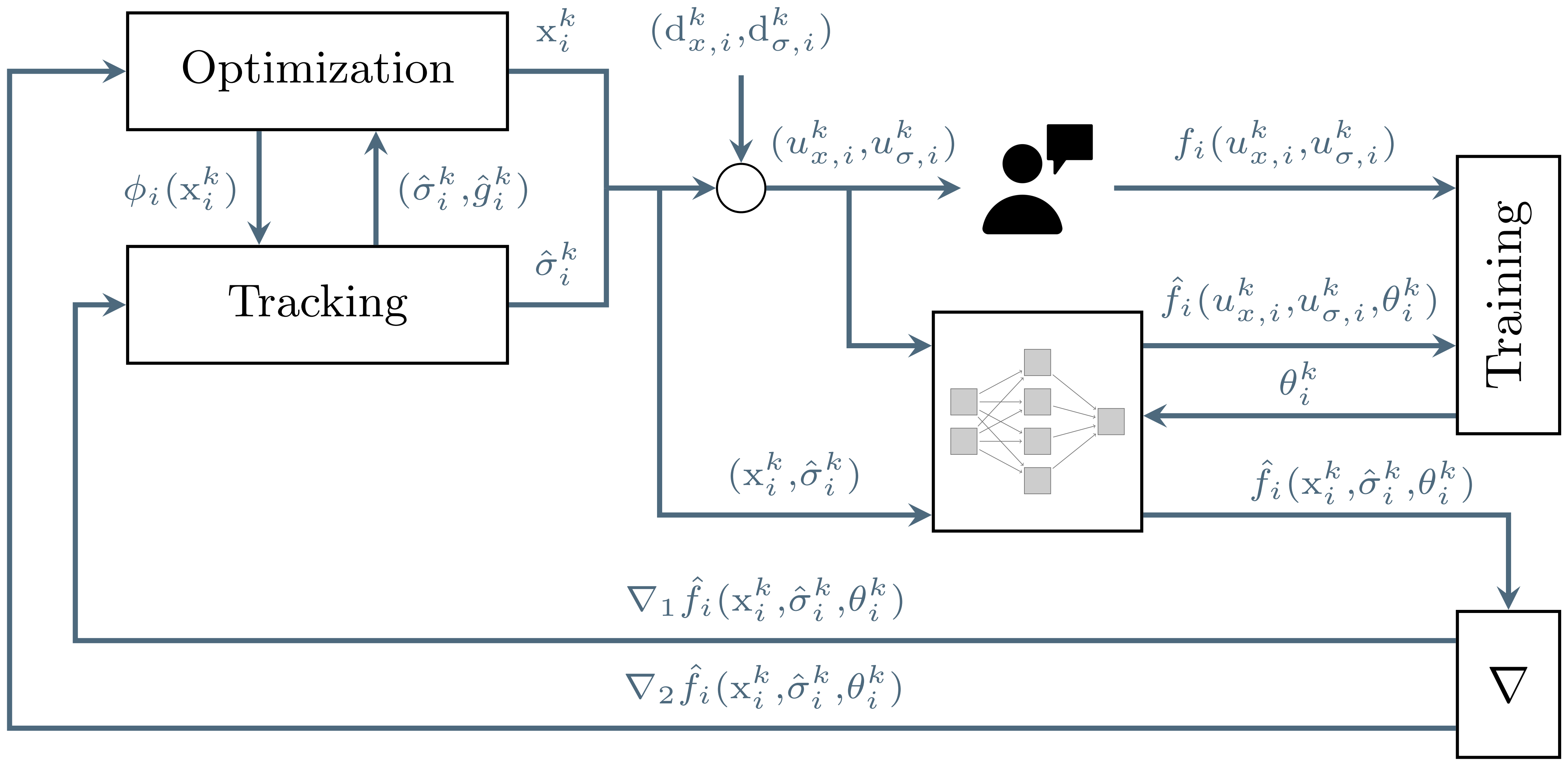
DEep-Learning aggregative TrAcking (DELTA)



Learning update

$$\theta_i^{k+1} = \theta_i^k - \gamma \nabla_3 \ell_i \left(x_i^k + d_{x,i}^k, w_i^k + \phi_i\left(x_i^k\right) + d_\sigma^k, \theta_i^k \right)$$

Optimization update

$$x_i^{k+1} = x_i^k - \gamma \Big[\nabla_1 \hat{f}_i\left(x_i^k, w_i^k + \phi_i(x_i^k), \theta_i^k\right) + \nabla \phi_i(x_i^k) \Big(z_i^k + \nabla^2 \hat{f}_i\left(x_i^k, w_i^k + \phi_i(x_i^k), \theta_i^k\right) \Big) \Big]$$

Tracking update

$$w_i^{k+1} = \sum_{j \in \mathcal{N}_i} a_{ij} \Big(w_j^k + \phi_j(x_j^k) \Big) - \phi_i(x_i^k),$$

$$z_i^{k+1} = \sum_{j \in \mathcal{N}_i} a_{ij} \Big(z_j^k + \nabla_2 \hat{f}_j \left(x_j^k, w_j^k + \phi_j(x_j^k), \theta_j^k \right) \Big) - \nabla_2 \hat{f}_i \left(x_i^k, w_i^k + \phi_i(x_i^k), \theta_i^k \right).$$

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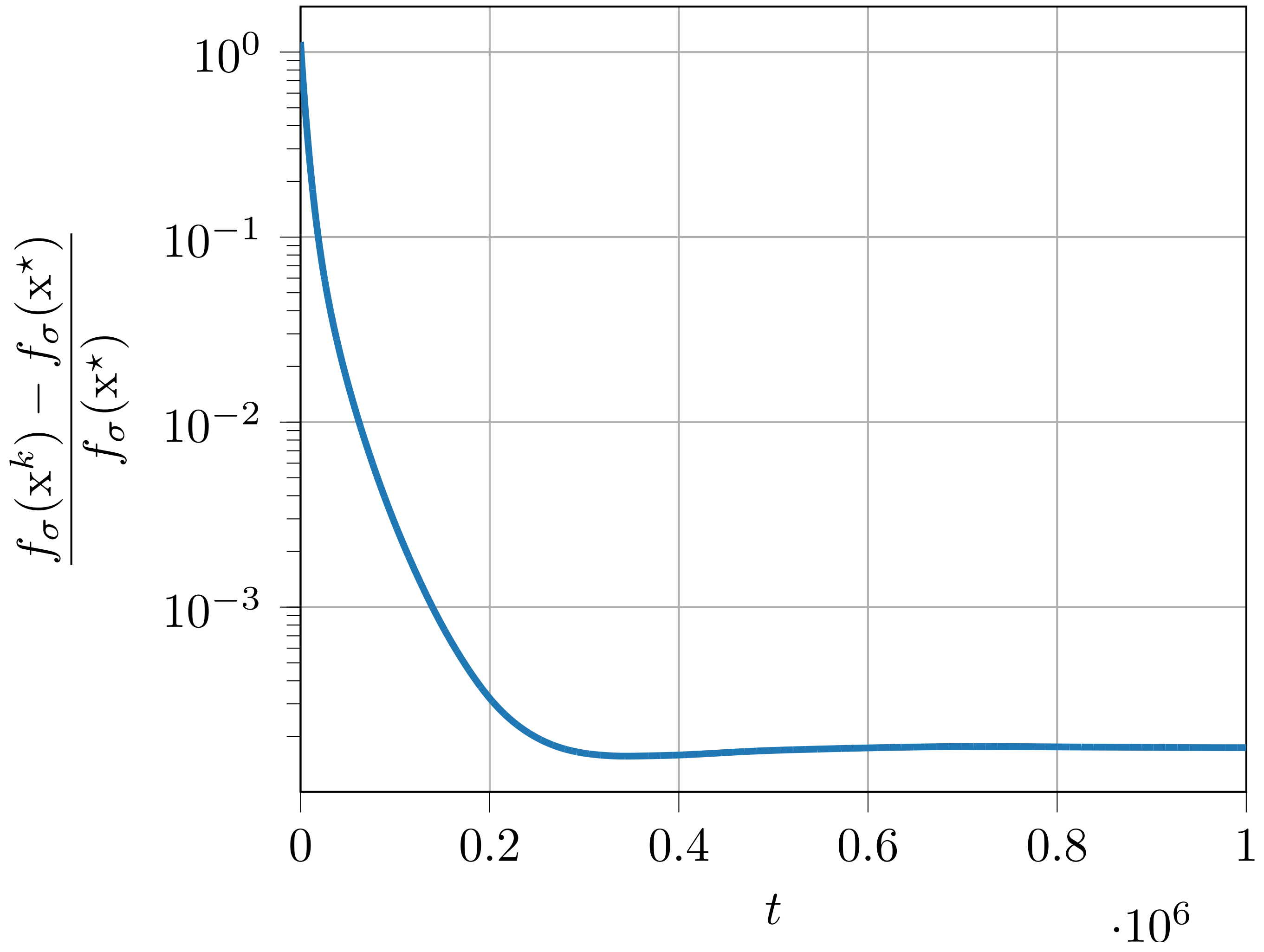
Numerical Simulations

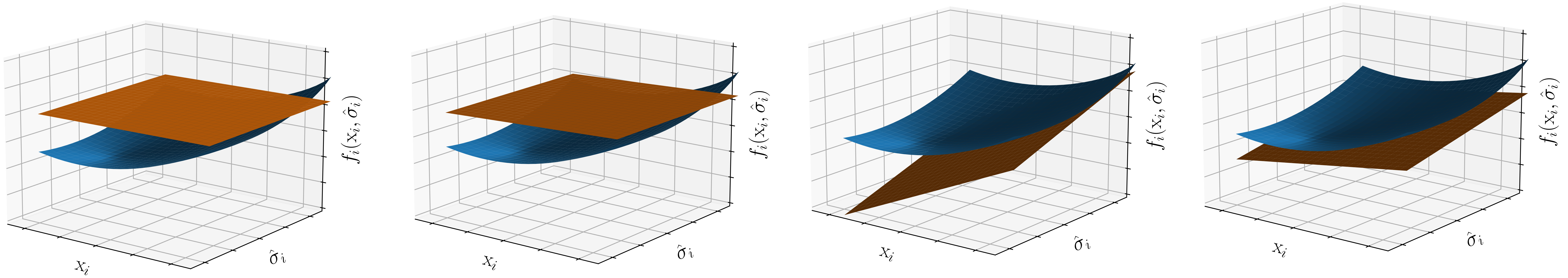
Setup:

- $N = 20$ agents
- Networks structure: 2 layer 300 neurons



Local f_i:

$$f_i\left(x_i, \sigma(x)\right) = \frac{1}{2}\left[\begin{bmatrix} x_i \\ \sigma(x) \end{bmatrix}^\top P_i \begin{bmatrix} x_i \\ \sigma(x) \end{bmatrix} + v_i^\top \begin{bmatrix} x_i \\ \sigma(x) \end{bmatrix} + a_i + e^{-b_i \begin{bmatrix} x_i \\ \sigma(x) \end{bmatrix} + c_i} + q_i\right]$$



$k = 0$ $k = 20$ $k = 500$ $k = 10^4$

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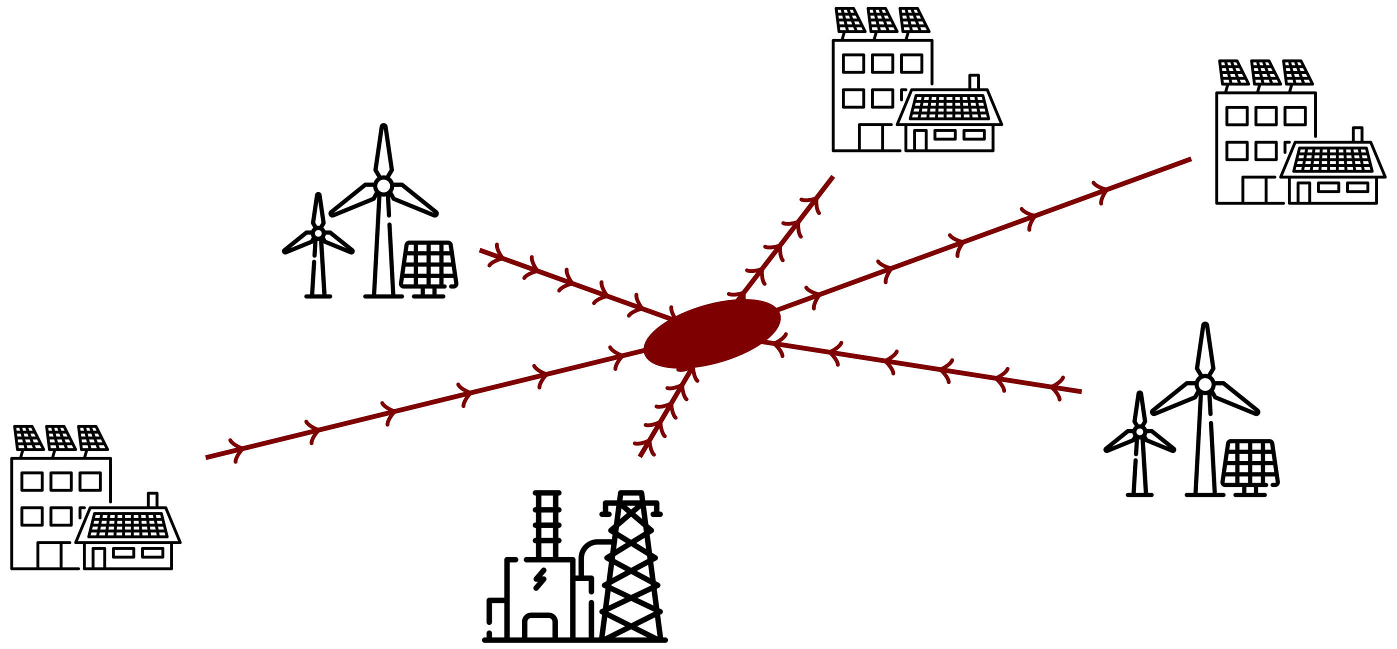
Distributed Learning and Optimization of a Multi-Agent Macroscopic Probabilistic Model

Distributed Learning and Optimization of a Multi-Agent Macroscopic Probabilistic Model

Multi-agents systems have been widely studied in optimization, e.g.,

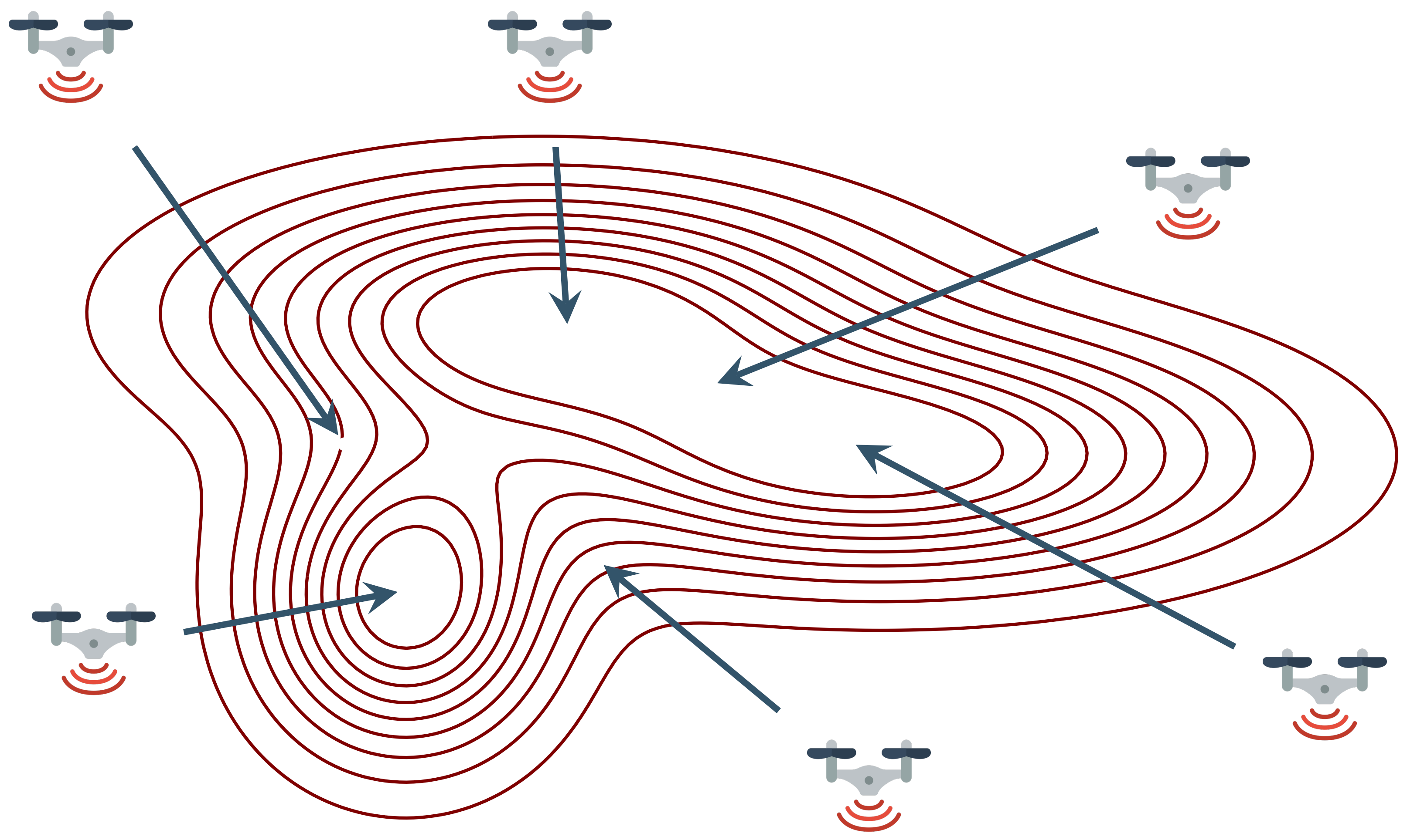
- Energy communities coordination
- Multi-robot applications



Agents can coordinate themselves to make a certain behavior emerge

Existing works based on two approaches to coordinate agents

- Centralized approach to optimize spatial distribution (based on PDEs)
- Distributed algorithms to coordinate single agents



Goal:

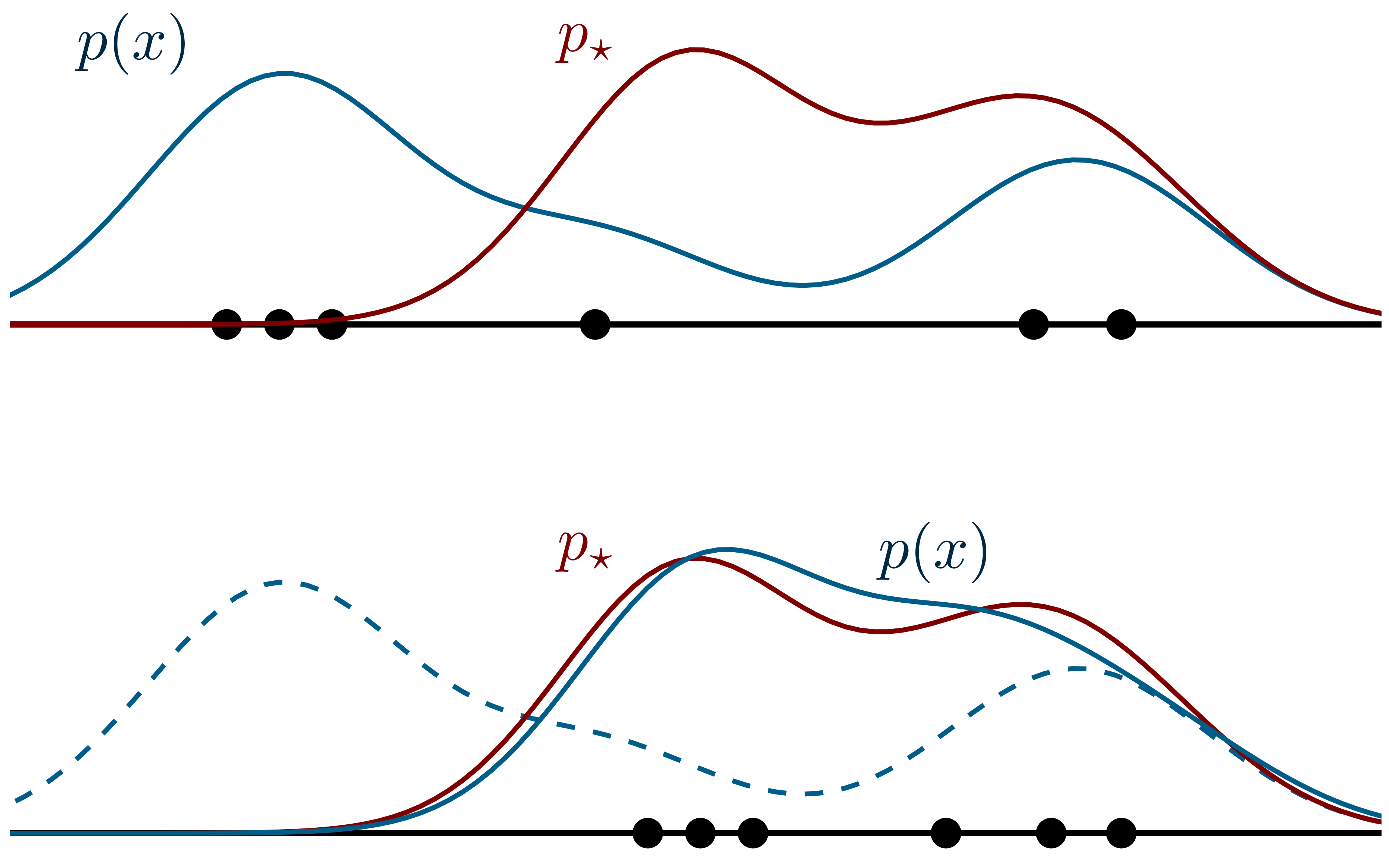
- Address the optimization in one step at a multi-scale level
- Act directly on the single agents to optimize the behavior of the ensamble

Brumali, Carnevale, Notarstefano (2025). Distributed learning and optimization of a multi-agent macroscopic probabilistic model. European Journal of Control, 101332.

Problem Setup

Setup:

- N interacting agents modeled as a continuum
- System described by a macroscopic probabilistic model $p(x)$
- Discretized workspace into C cells



Goal:

Act on microscopic states x_i to achieve a macroscopic behavior $p_\star$

Optimization Problem:

$$\min_{x_1,\ldots,x_N} \sum_{c=1}^{C} \ell\big(p^c(x)\big)$$

with $p^c(x)$ agents macroscopic model at cell c, $\ell(p^c(x))$ performance index (Kullback-Leibler divergence)

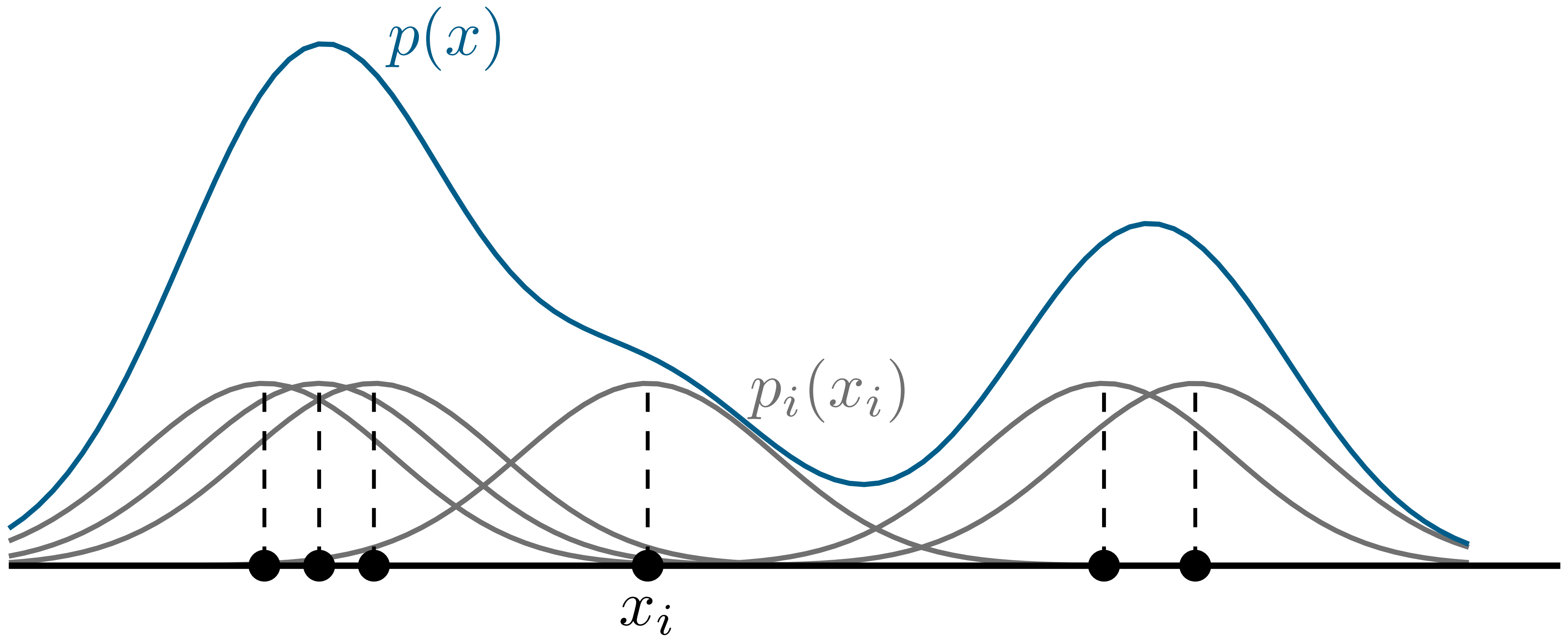
Brumali, Carnevale, Notarstefano (2025). Distributed learning and optimization of a multi-agent macroscopic probabilistic model. European Journal of Control, 101332.

Solution Strategy

Assumption: for each cell c

- Agents posses local models $p_i^c(x_i)$
- Kernel Density Estimation for macroscopic model $p^c(x)$

Macroscopic probabilistic model: $p^c(x) = \frac{1}{N}\sum_{i=1}^{N} p_i^c(x_i)$



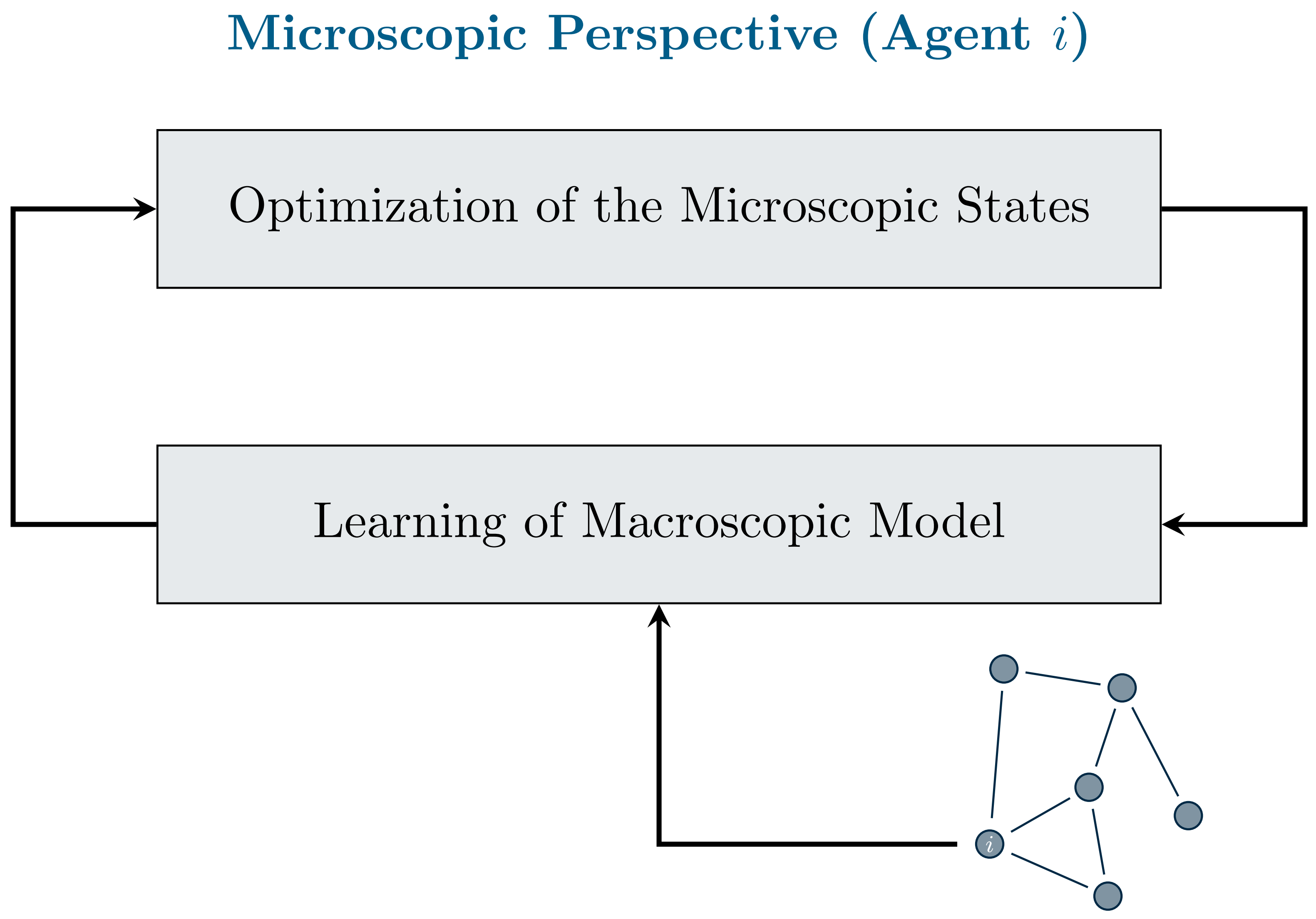
Algorithm for agent i:

- Microscopic state update:

$$x_i^{k+1} = x_i^k - \gamma \frac{1}{N} \nabla p_i(x_i^k) \frac{d}{dp}\ell(p)\Big|_{p=P_{\mathscr{C}}(w_i^k + p_i(x_i^k))}$$

- Macroscopic model learning:

$$w_i^{k+1} = \sum_{j\in\mathcal{N}_i} a_{ij} w_j^k + p_j(x_j^k) - p_i(x_i^k)$$



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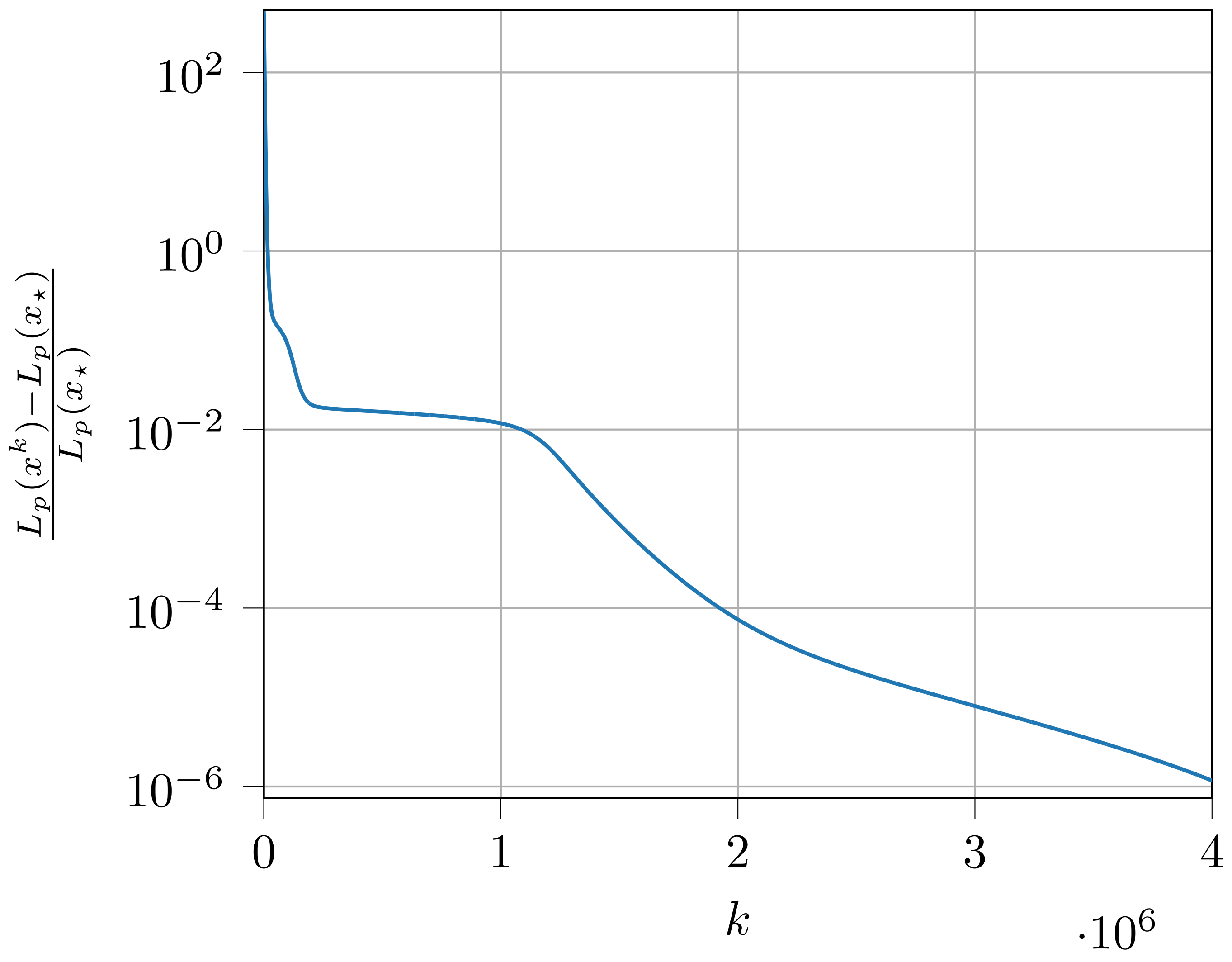
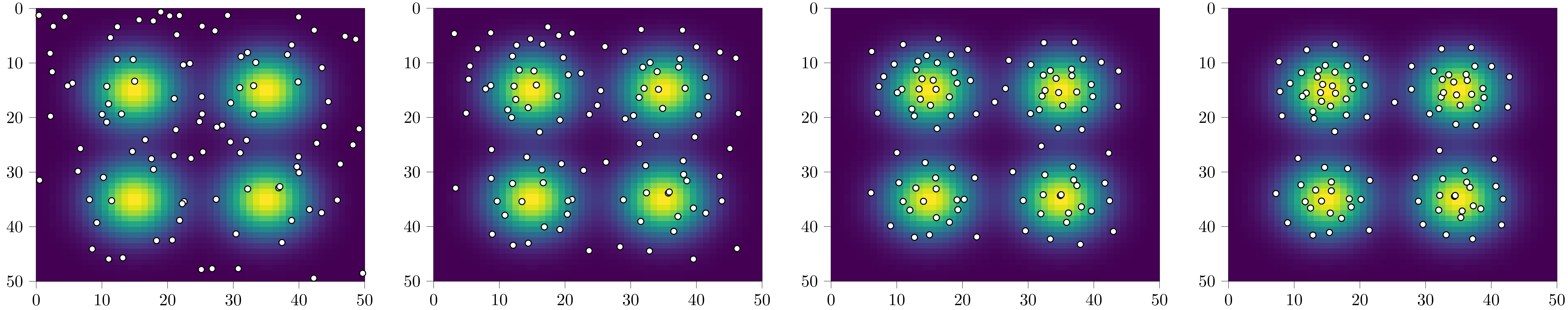
Numerical Simulation

Scenario: Sensor network deployment problem for event detection



Simulation setup:

- Space $C := [0,100] \times [0,100]$ discretized with $C = 2500$
- Event PDF $p_\star$ mixture of 4 Gaussians
- $N = 100$ agents with Gaussian $p_i(x_i)$



$k = 0$ $\quad$ $k = 20000$ $\quad$ $k = 50000$ $\quad$ $k = 100000$

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Application of Distributed Optimization to the management of active and reactive powers in sustainable microgrids

Joint work with UNIGE

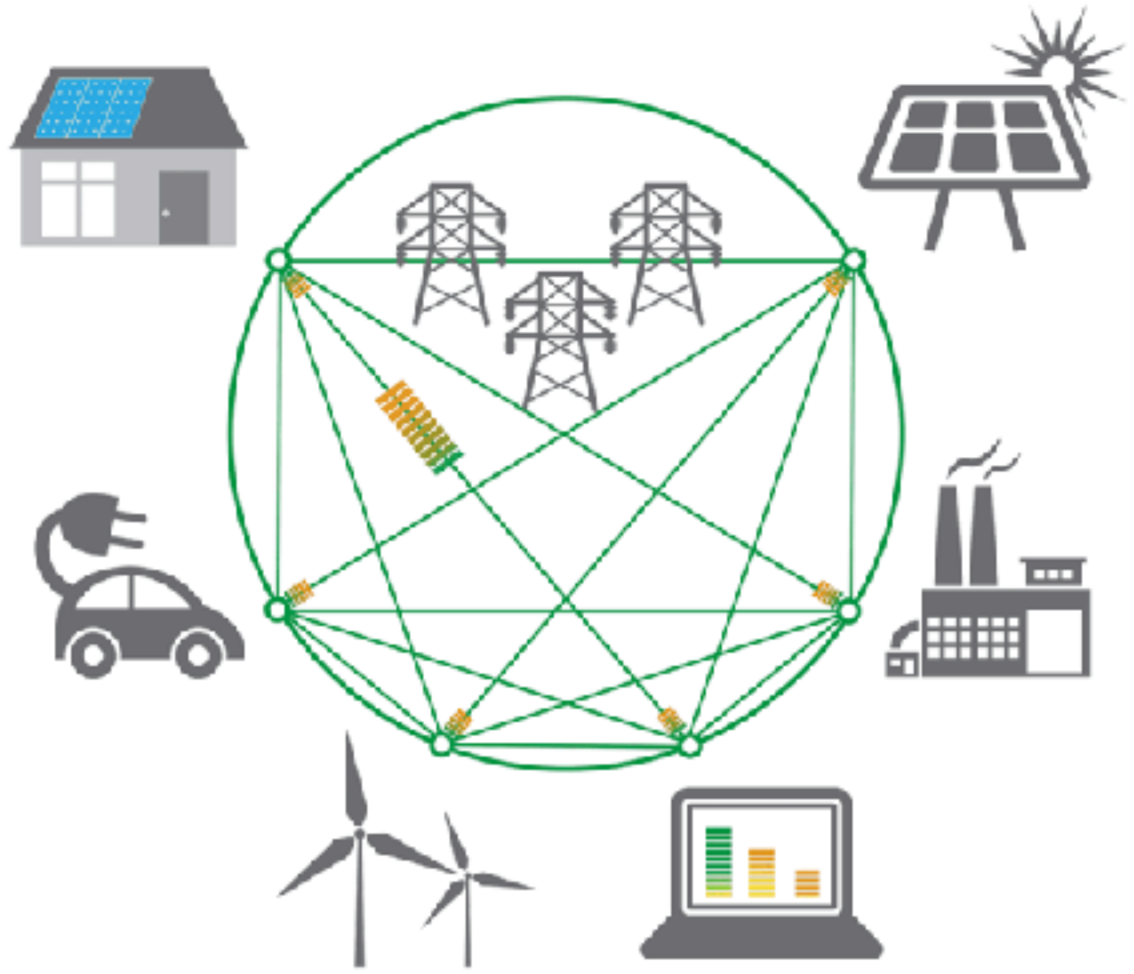
Application Setting

Consider a microgrid system with N nodes:

- H controllable microturbines
- L renewable sources
- K storage systems
- Main grid
- Boiler

Distributed Setup:

- Each node is a different agent
- Only local information available
- Graph based communication



Goal: Design and implement a distributed strategy to optimize power production satisfying all constraints

Joint work with the University of Genova "Distributed Optimization Algorithm for the management of active and reactive powers in sustainable microgrids"

Agent Model: Microturbine

Decision Variables:

- $p^{el}_{h,t} \in [\underline{p}^{el}_{h,t}, \bar{p}^{el}_{h,t}]$ electrical power produced at time t
- $F^{utx}_{h,t}$, $F^{tx}_{h,t}$ untaxed and taxed fuel used by boilers at time$t$

Constraints: at time t

- $F^{utx}_{h,t} = (1 - ff)\,\beta\, p^{el}_{h,t}$ with ff and β taxation parameters
- $F_{h,t} = F^{utx}_{h,t} + F^{tx}_{h,t}$ with $F_{h,t}$ total fuel used by boilers
- $p^{pe}_{h,t} = F_{h,t}\, L_{hv}$ with $p^{pe}_{h,t}$ primary energy for the microturbines

Cost Function:

$$J(p^{pe}_{h,t}, F^{utx}_{h,t}, F^{tx}_{h,t}) = \Delta \sum_{t=0}^{T-1} \left(F^{utx}_{h,t} K_{utx} \; + \; F^{tx}_{h,t} K_{tx} \; + \; C_t p^{pe}_{h,t} \right)$$

Where Δ interval length, K_{utx}, K_{tx} and C_t fuels and emissions cost

Joint work with the University of Genova "Distributed Optimization Algorithm for the management of active and reactive powers in sustainable microgrids"

Agent Model: Renewable source

Each renewable produce $\bar{p}_{l,t}^{res}$ of active power at time t

Decision Variables:

- $p_{l,t}^{res}$ active power exploited at time t
- $q_{l,t}^{res}$ reactive power produced at time t

Constraints:

Use at most the produced power

- $p_{l,t}^{res} \in [0, \bar{p}_{l,t}^{res}]$
- $q_{l,t}^{res} \in [\underline{q}_{l,t}^{res}, \bar{q}_{l,t}^{res}]$

Joint work with the University of Genova "Distributed Optimization Algorithm for the management of active and reactive powers in sustainable microgrids"

Agent Model: Storage Unit

Decision Variables:

- $p^s_{k,t} \in [\underline{p}^s_{k,t}, \overline{p}^s_{k,t}]$ active power exchanged with storages at time t
- $q^s_{k,t} \in [\underline{q}^s_{k,t}, \overline{q}^s_{k,t}]$ reactive power exchanged with storages at time t

Constraint: SoC e_k constraints

- $e_{k,t+1} = a_k e_{k,t} + \eta_k p^s_{k,t} \Delta$
- $e_{k,t} \in [\underline{e}_{k,t}, \overline{e}_{k,t}]$

Where $\eta_k \in [0,1]$ is the charging/discharging efficiency $a_k \in [0,1]$ a decay factor

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Agent Model: Main Grid

Decision Variables:

- p_t^{grid}, q_t^{grid} Active and reactive power exchanged between units and grid
- $p_t^{\text{grid},i}$, $p_t^{\text{grid},o}$ Power bought and sold with the main grid

Constraint:

- $p_t^{\text{grid},i} - p_t^{\text{grid},o} = p_t^{\text{grid}}$
- $p_t^{\text{grid},i}, p_t^{\text{grid},o} \geq 0$
- $p_t^{\text{grid}} \in \left[\underline{p}_t^{\text{grid}}, \overline{p}_t^{\text{grid}}\right]$ and $q_t^{\text{grid}} \in \left[\underline{q}_t^{\text{grid}}, \overline{q}_t^{\text{grid}}\right]$

Cost Function:

$$J(p_t^{\text{grid},i}, p_t^{\text{grid},o}) = \Delta \sum_{t=0}^{T-1} \left(B\, p_t^{\text{grid},i} - S\, p_t^{\text{grid},o}\right)$$

With B and S the buying and selling prices respectively

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Agent Model: Boiler

Decision Variables:

- $p_t^{pe,b}$ Primary energy fed to the boiler
- $p_t^{th,b}$ Thermal power produced by the boiler

Constraint:

$p_t^{pe,b}\,\eta_B = p_t^{th,b}$ with $\eta_B \in [0,1]$ the boiler efficiency

Cost Function:

$$J(p_t^{pe,b}, p_t^{th,b}) = \Delta \sum_{t=0}^{T-1} \left(E\, p_t^{th,b} + C\, p_t^{pe,b} \right)$$

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Electrical and Thermal Balance

The system must satisfy these constraints depending on all agents variables

Active and Reactive Power Balance:

$$\sum_{h\in H} p_{h,t}^{el} + \sum_{l\in L} p_{l,t}^{res} - \sum_{k\in K} p_{k,t}^{s} + p_t^{grid} = p_t^d + p_t^{veh}$$

$$\sum_{l\in L} q_{l,t}^{res} - \sum_{k\in K} q_{k,t}^{s} + q_t^{grid} = q_t^d + q_t^{veh}$$

Where p_t^d, q_t^d, p_t^{veh}, q_t^{veh} are the active and reactive power exchanged with the load

Thermal Power Balance:

$$\sum_{h\in H} p_{h,t}^{th} + p_t^{th,b} + \sum_{l\in L} p_{l,t}^{res} \in [\overline{D}^t, \underline{D}^t]$$

With $p_{h,t}^{th} = \bar{\mu}_h \, p_{h,t}^{el}$, where $\bar{\mu}_h$ is a conversion parameter

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Distributed Optimization Problem

Notation:

- $x_i \in X_i$ decision variables of unit i with associated cost $J_i(x_i)$
- $h_i(x_i)$ and $g_i(x_i)$ influence of x_i in the electric and thermal balance
- $b := \text{col}(p_t^d + p_t^{veh}, q_t^d + q_t^{veh})$ and $\kappa := \text{col}(-\underline{D}^t, \bar{D}^t)$

Constrained Coupled Optimization Problem:

$$\begin{aligned} \min_{x_1,\ldots,x_N} \quad & \sum_{i=1}^{N} J_i(x_i) \\ \text{s.t.} \quad & x_i \in X_i, \quad i = 1,\ldots,N, \\ & \sum_{i=1}^{N} h_i(x_i) = b, \quad \sum_{i=1}^{N} g_i(x_i) \leq \kappa \end{aligned}$$

Solution Strategy:

Distributed Primal Decomposition

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Solution Algorithm:

Idea:

- recast the problem into a master-subproblem architecture
- See b and κ as shared resources and introduce allocation vectors $y_{\text{eq},i}$ and $y_{\text{in},i}$

Initialization: $y^0_{\text{eq},i}, y^0_{\text{in},i} : \sum_{i=1}^N y^0_{\text{eq},i} = \kappa, \quad \sum_{i=1}^N y^0_{\text{in},i} = b, \quad M > 0$ sufficiently large.

For $k = 0,1,\dots$

Step 1: Compute $(x_i, \rho_i, \mu_i, \lambda_i)$ solving

$$
\begin{aligned}
\min_{x_i \in X_i, \rho_i \geq 0} \; & f_i(x_i) + M\rho_i \\
\text{s.t. } \mu_i : \; & g_i(x_i) \leq y^k_{\text{in},i} + \rho_i \mathbf{1}_s, \\
\lambda_i : \; & |h_i(x_i) - y^k_{\text{eq},i}| \leq \rho_i \mathbf{1}_p,
\end{aligned}
$$

Step 2: Receive multipliers (μ_j, λ_j) from neighbors and update

$$
y^{k+1}_{\text{eq},i} = y^k_{\text{eq},i} + \sum_{j \in \mathcal{N}_i} (\lambda_i - \lambda_j), \qquad y^{k+1}_{\text{in},i} = y^k_{\text{in},i} + \sum_{j \in \mathcal{N}_i} (\mu_i - \mu_j)
$$

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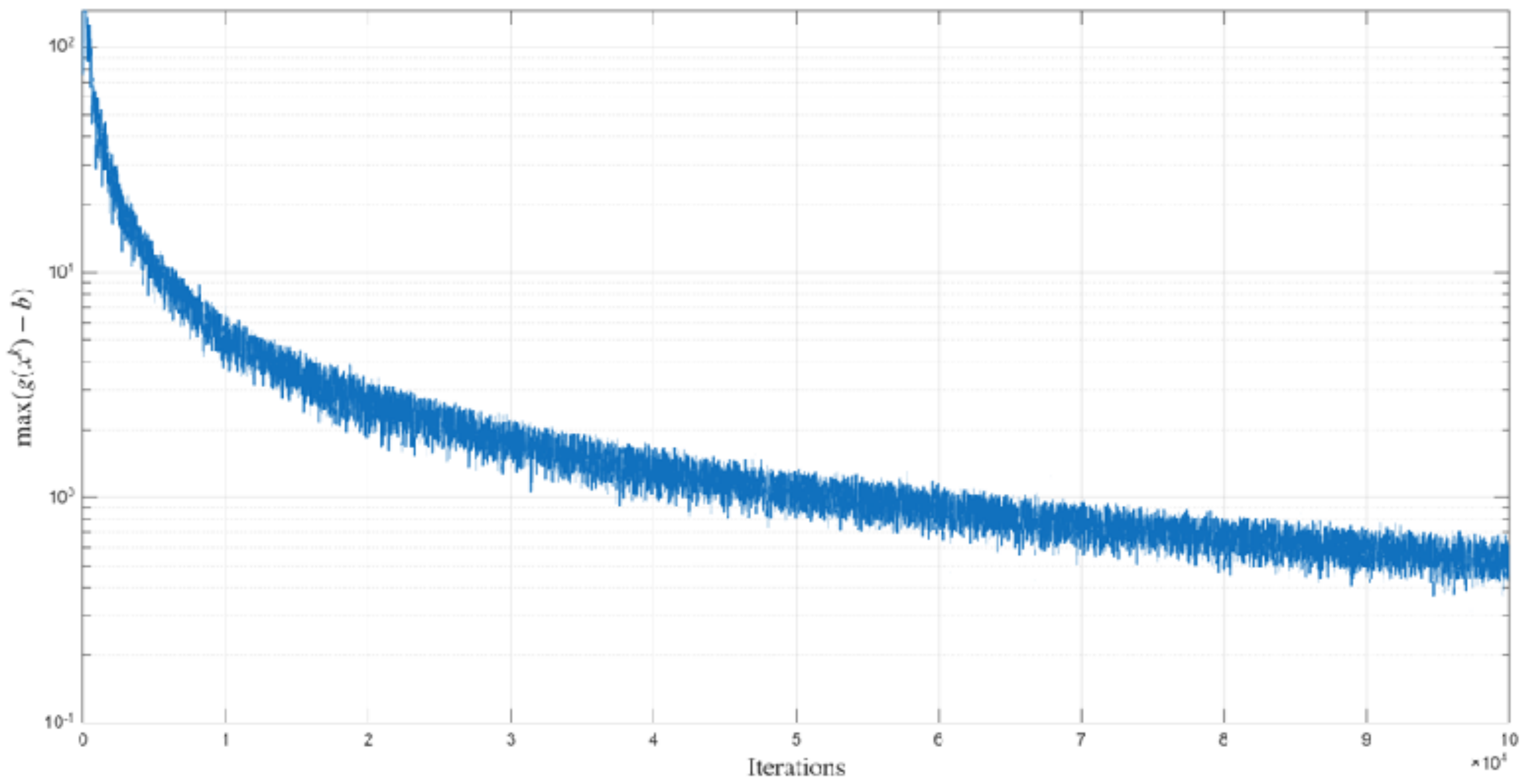
Numerical Simulation

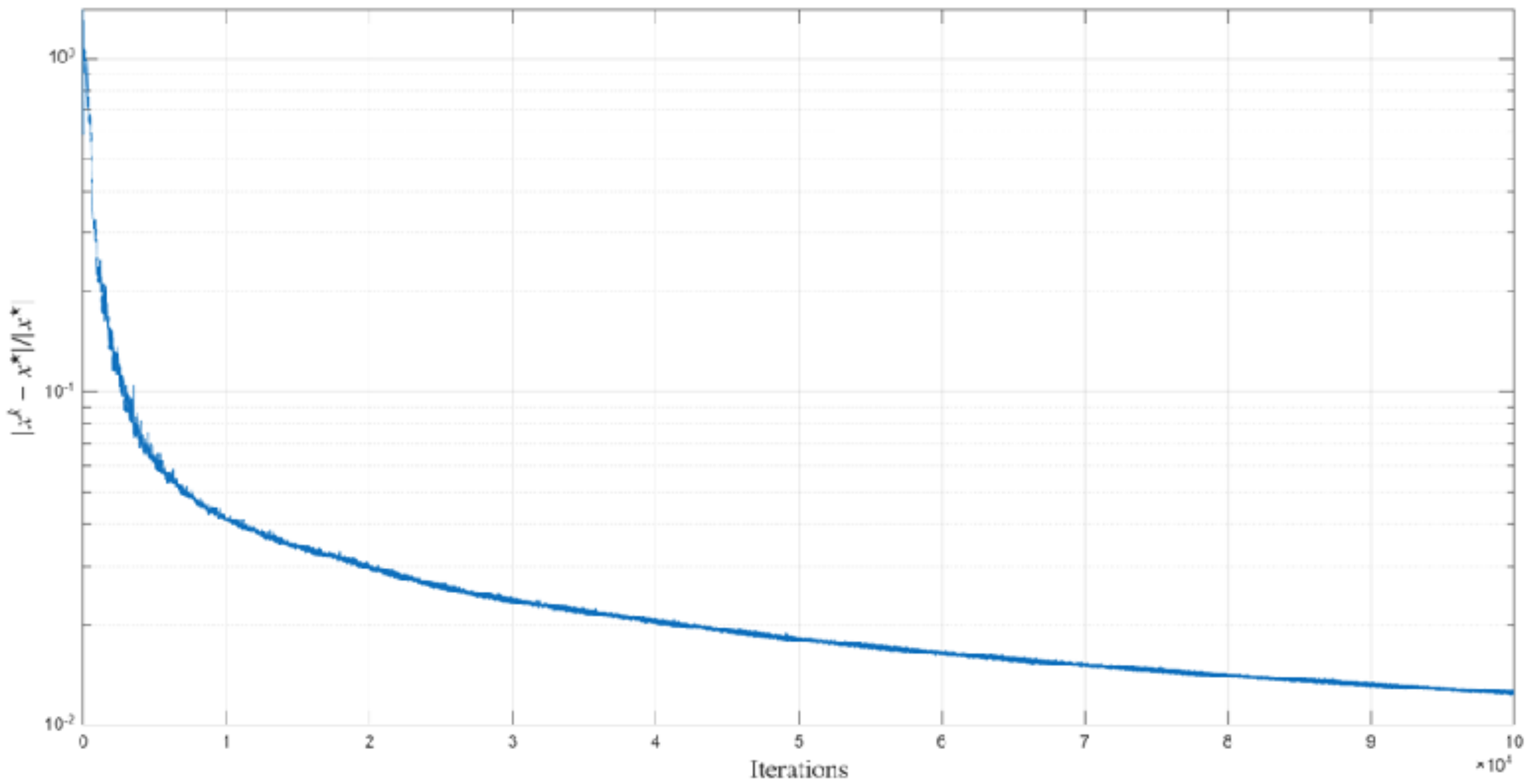
Setup: for $N = 8$ agents and $T = 96$

- $L = 3$ renewable sources
- $H = 2$ turbines element
- $K = 1$ storage element

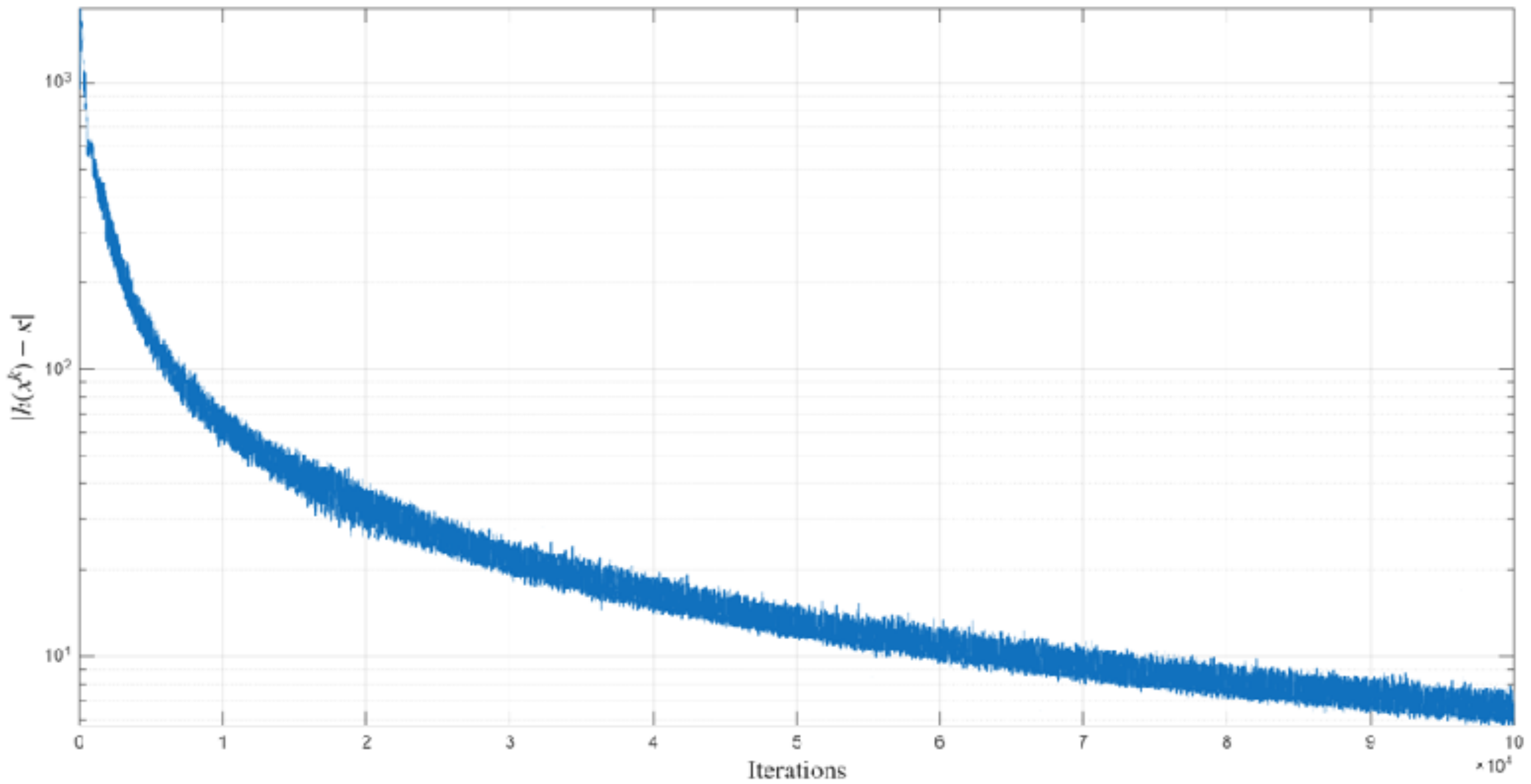
Thermal energy violation



Relative distance from the solution $x^\star$



Power balance violation



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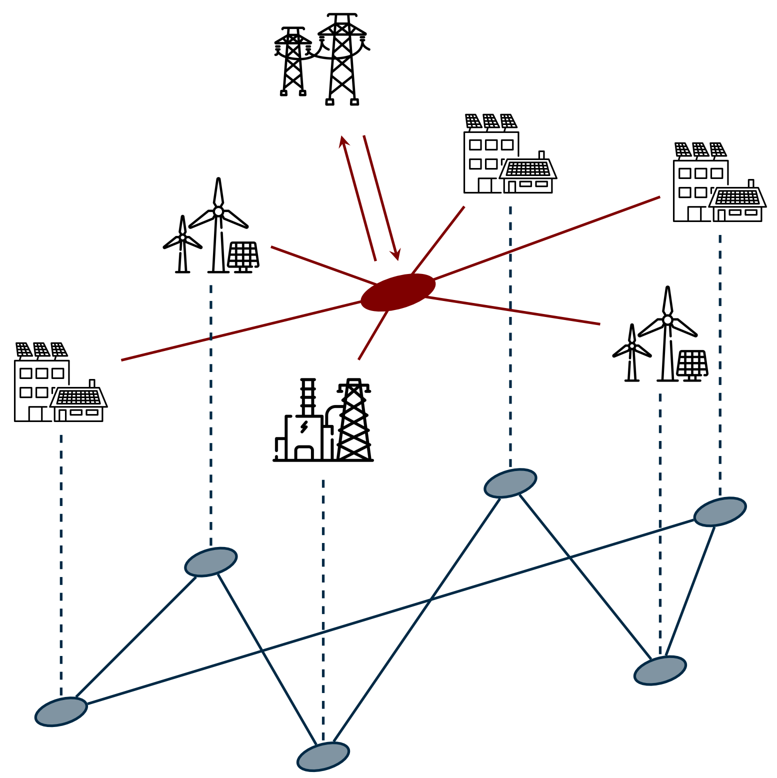
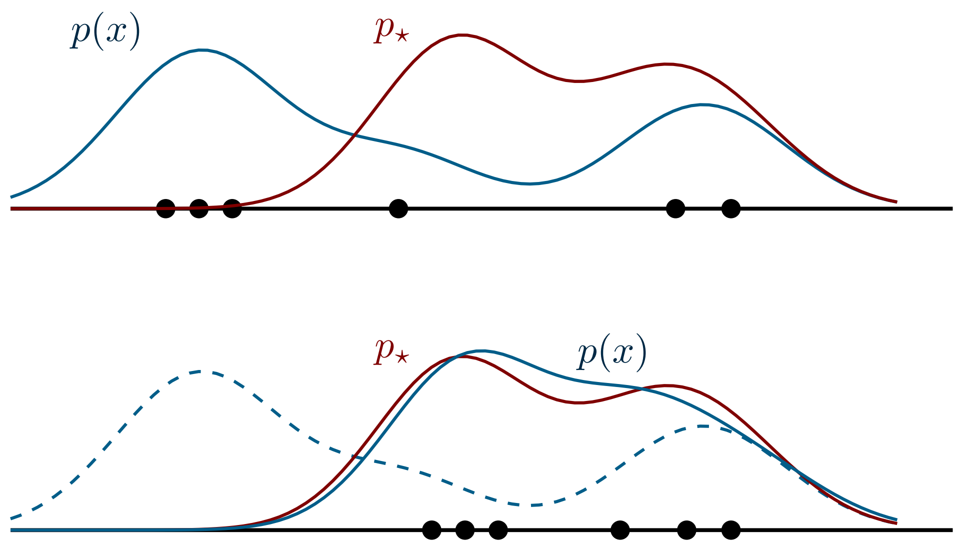
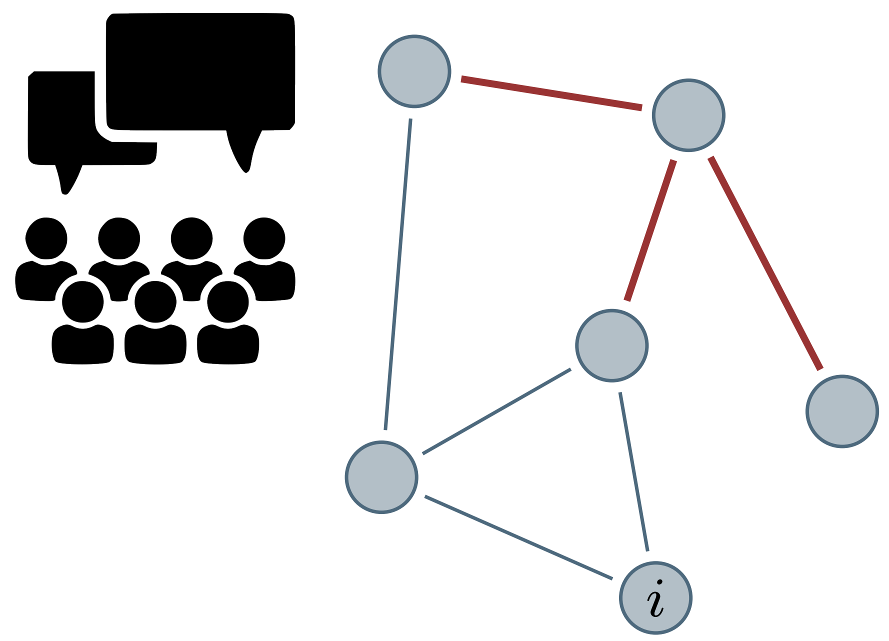
Sum up

Distributed Algorithm for Coordination in Energy Communities



Distributed learning and optimization in aggregative settings





Application of distributed optimization to microgrid testbed