Learning and Market Design for Prosumers in Energy Communities

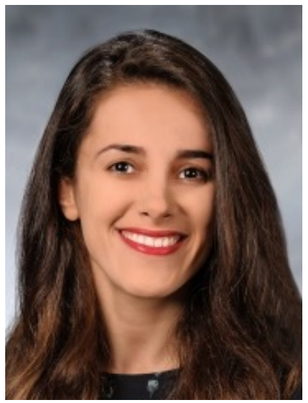
Jalal Kazempour and Lesia Mitridati (DTU)

DTU PES Summer School
May 21, 2026

All Credits Go to:

Collaborators:

Bennevis Crowley
(former PhD, DTU)



Mahnoosh Alizadeh
(Associate Professor,
UC Santa Barbara)

Flex CEC Project:

FLEX CEC

FlexCEC = **Flex**ibility from **C**ititzen **E**nergy **C**ommunities

Aim: unfold the potential of CECs in Denmark and harness flexibility from the participating citizens and businesses with flexible energy production and consumption

Project Partners & Funding Agency:

enyday · DTU · Energi Danmark · BY&HAVN · PowerLab DK · Kommune København · EUDP

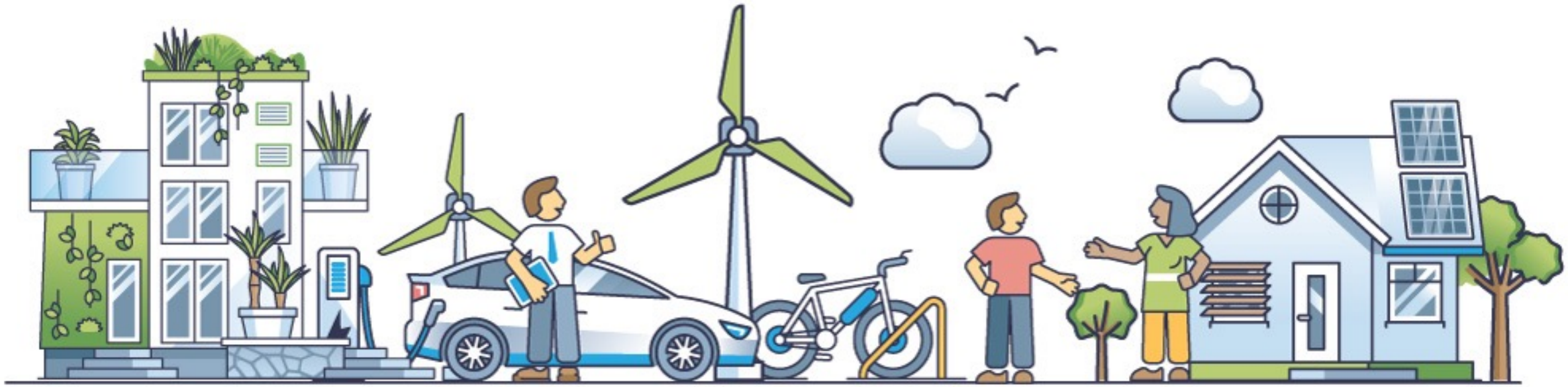
What are Citizen Energy Communities (CECs)?

*"**Citizen energy communities (CECs)** constitute a new type of entity **based on voluntary and open participation**, effectively **controlled by its members**; whose primary purpose is to **provide environmental, economic or social benefits to its members and the local area** where it operates rather than to generate financial profits"*

Energy Communities are becoming a reality…

- Backed by EU legislations under the “Clean Energy Package” and “REPowerEU Plan”
- Objective of achieving **1 energy community per municipality** with a population of more than 10 000 by 2025

Question: How many energy communities currently exist in Europe?



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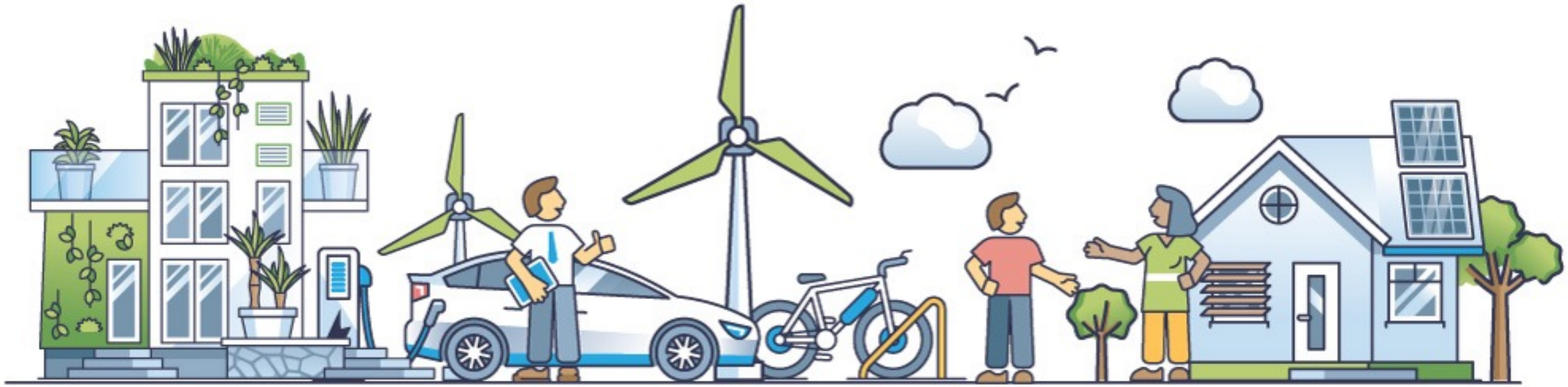
Over 2.500 active CECs and 2.000.000 citizens!

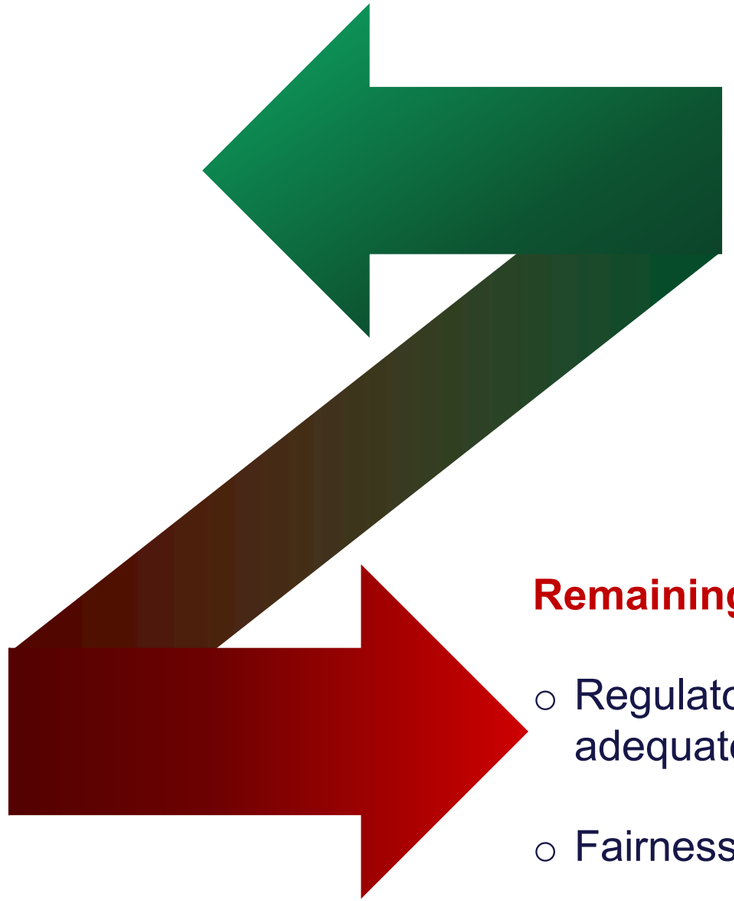
Source: RESCOOP EU



The Role of Citizen Energy Communities (CECs)

Potential benefits:

- Empower prosumers and facilitate market access (economic benefits)
- Address social & environmental concerns of prosumers (non-economic benefits)
- Provide local flexibility services - enhance grid stability and delay investments
- Advance social acceptance of RES



Remaining barriers:

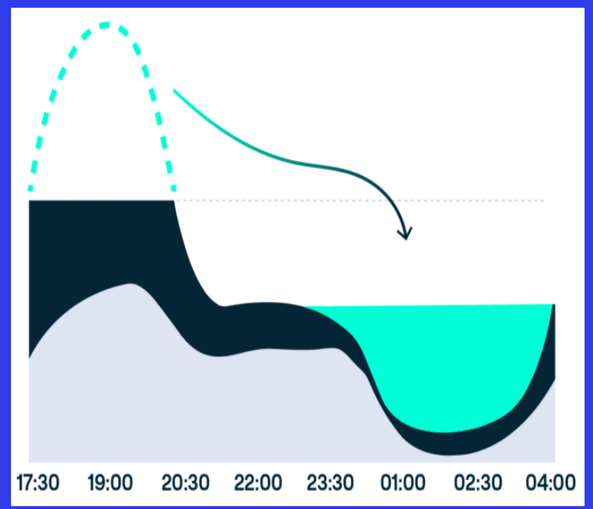
- Regulatory and market frameworks providing adequate incentives
- Fairness and equitable distribution of benefits
- Communication burden for prosumers
- Privacy leakage and cybersecurity concerns

Research Directions

(not in this talk)

Research direction 1

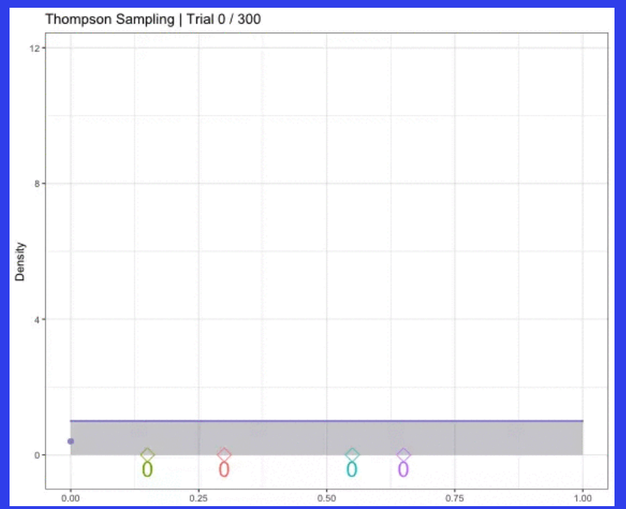
Quantify the benefits and viability of energy communities



Source: Ohme

Research direction 2

Efficiently coordinate prosumers in energy communities, under uncertainty on their preferences



Source: Wikipedia

Research direction 3

Ensure balance between prosumers' privacy and efficient & safe grid operations

Source: ChatGPT

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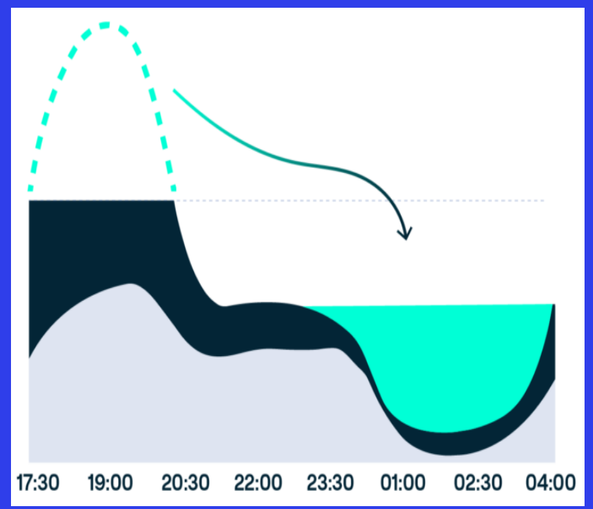

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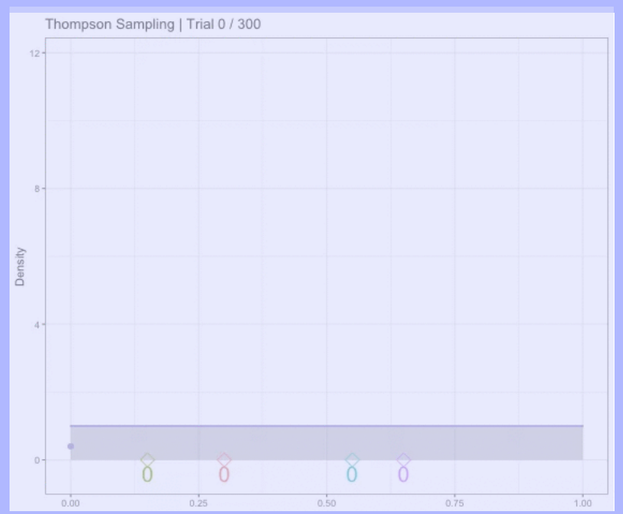

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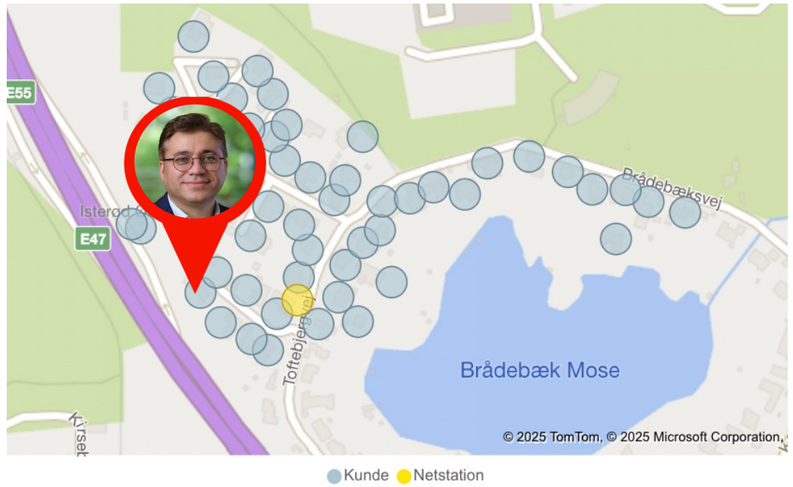
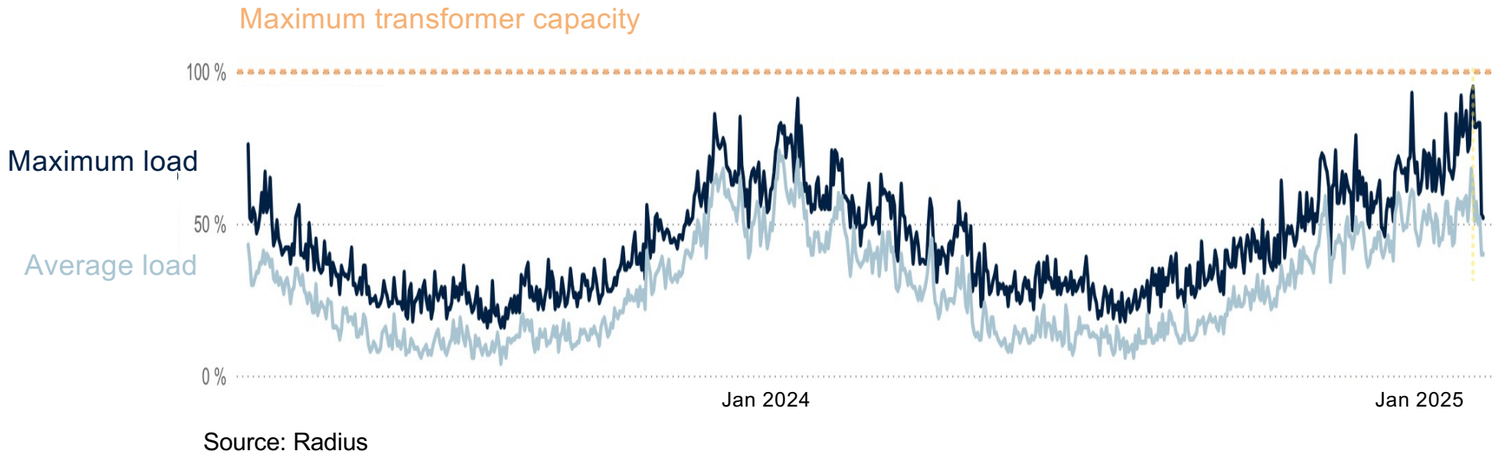
Motivating Example: Energy Community Providing Flexibility Services to DSO

Example of distribution grid nearing full capacity in Denmark





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Question: What are the potential benefits of CECs providing local grid services? Is there a viable business model for them?

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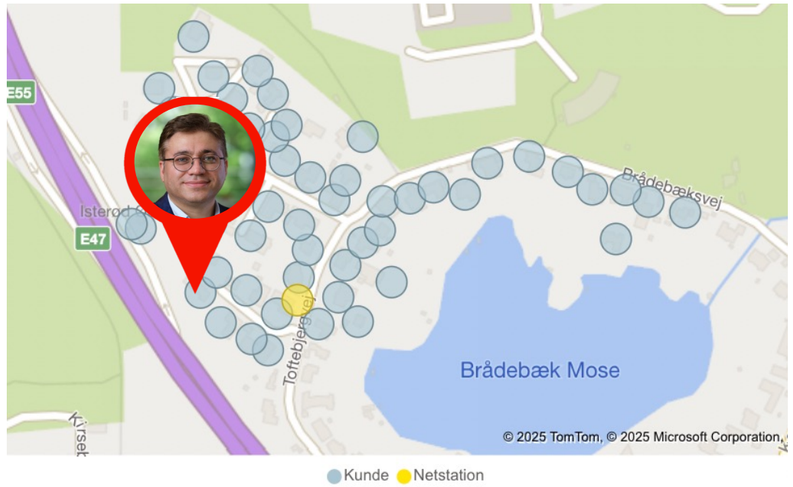

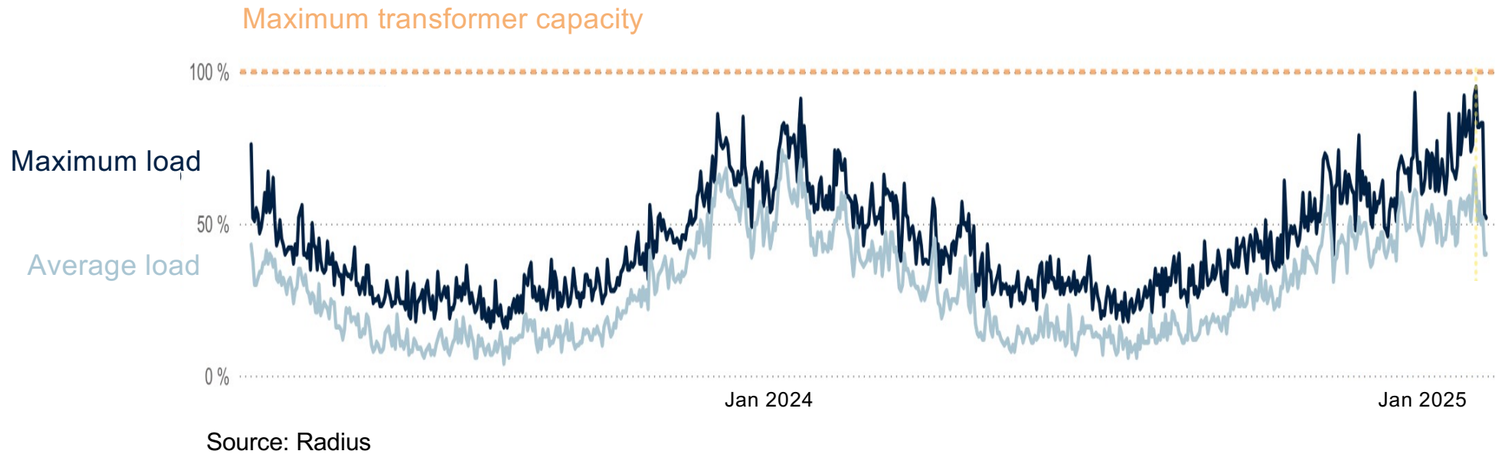

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Question: What are the potential benefits of CECs providing local grid services? Is there a viable business model for them?

Our objective: Provide a framework to quantify (best-case) flexibility available from CECs and their benefits for the local community and the grid operator

Proposed Framework: CEC providing capacity limitation services

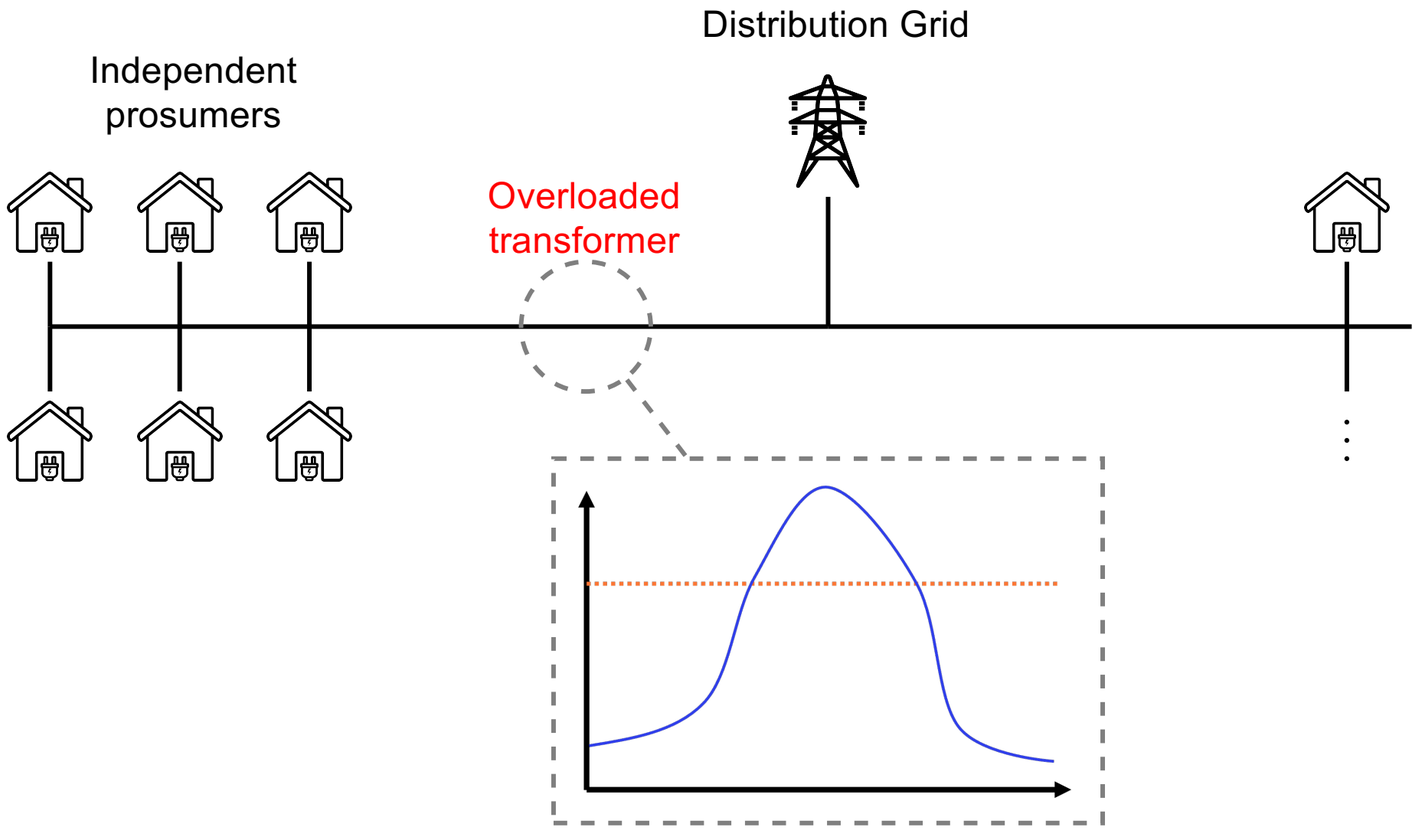

Illustration of distribution grid congestion without any service delivery from an energy community.

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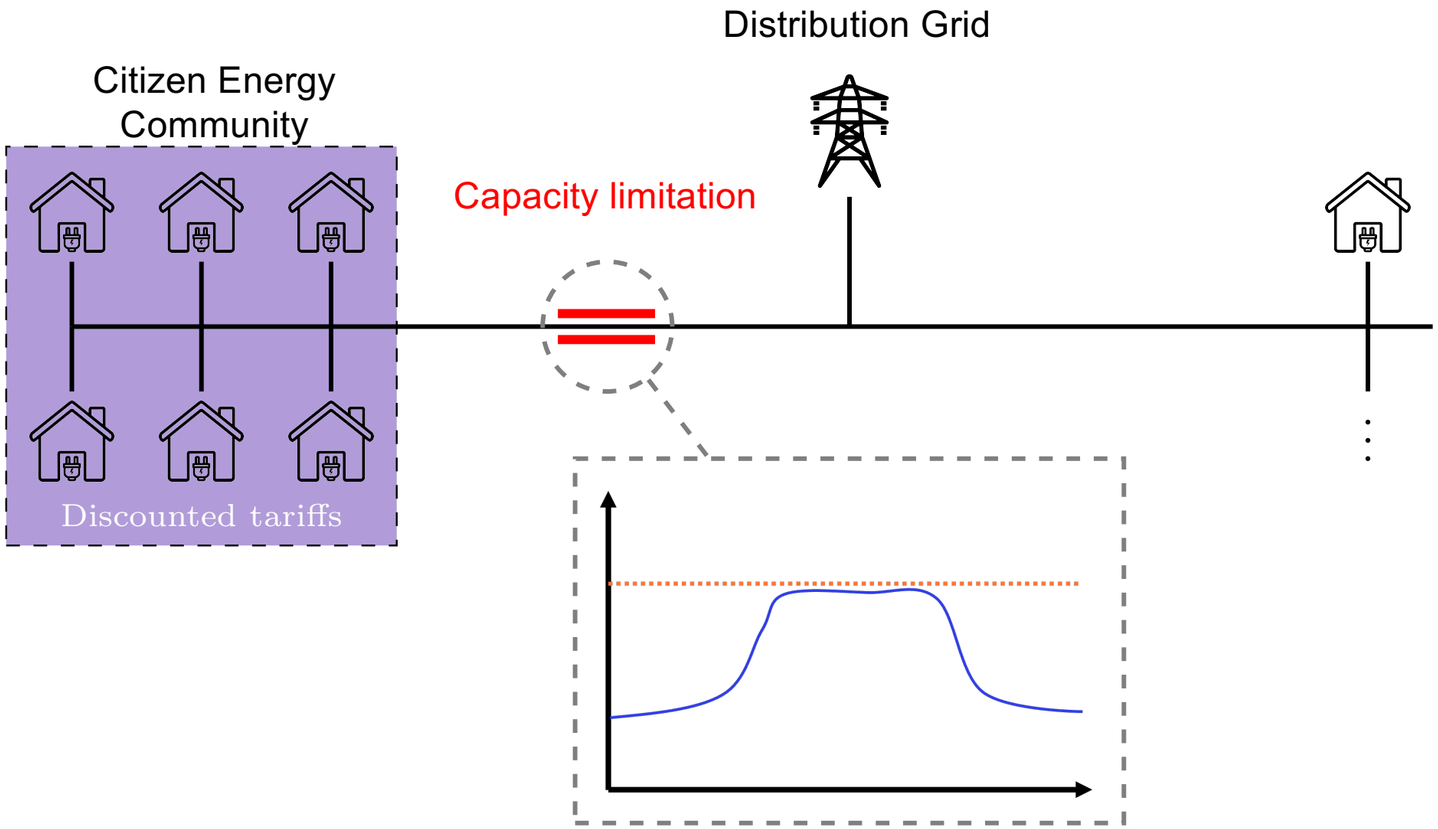


Illustration of how an energy community can help alleviate congestion in distribution networks by providing capacity limitation services.

Proposed Framework: CEC providing capacity limitation services

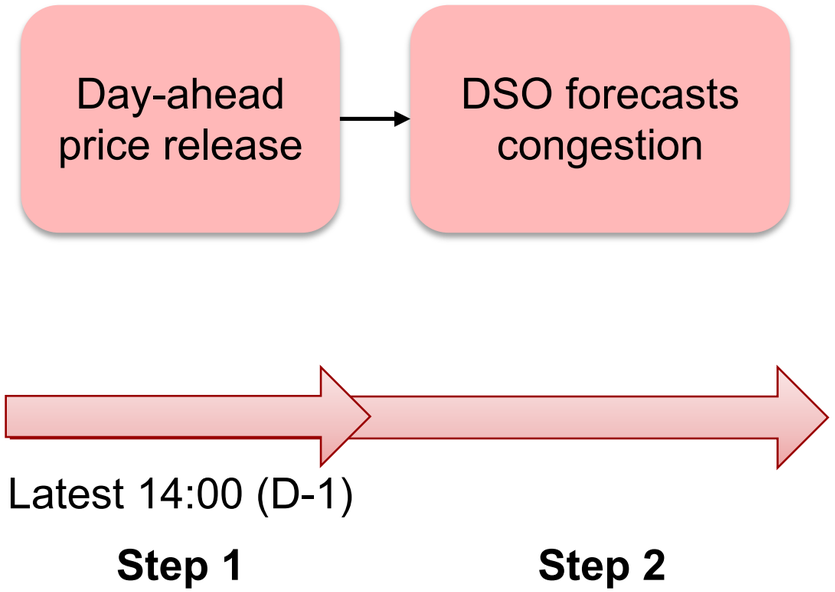
Day-ahead price release

Latest 14:00 (D-1)

Step 1

This process occurs the day before operation - not in real-time!

Proposed Framework: CEC providing capacity limitation services



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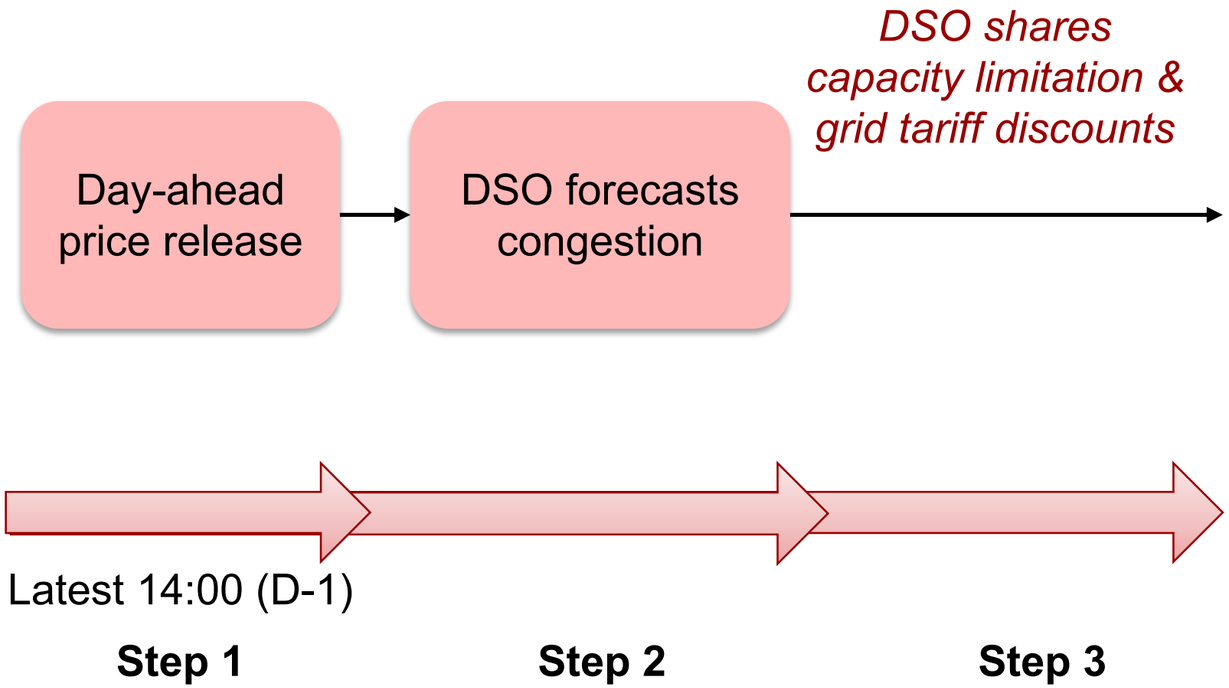

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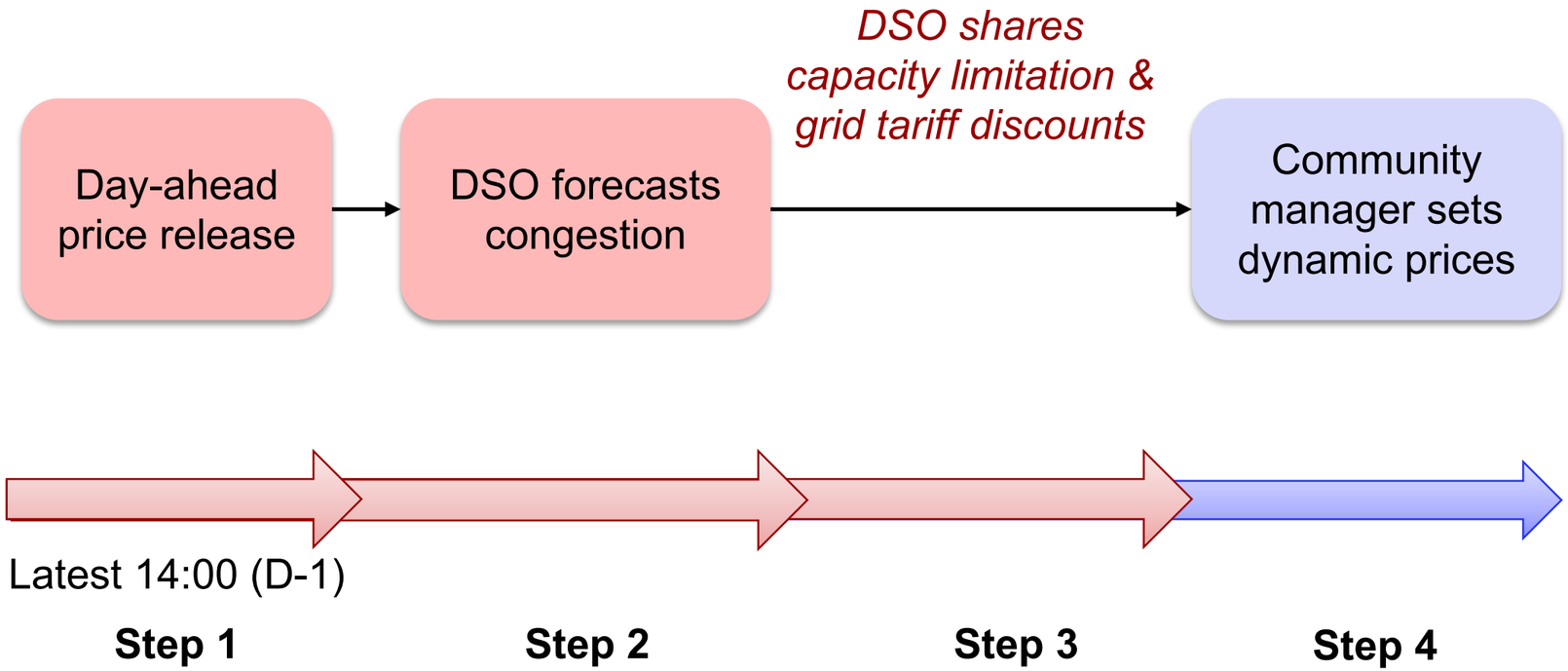

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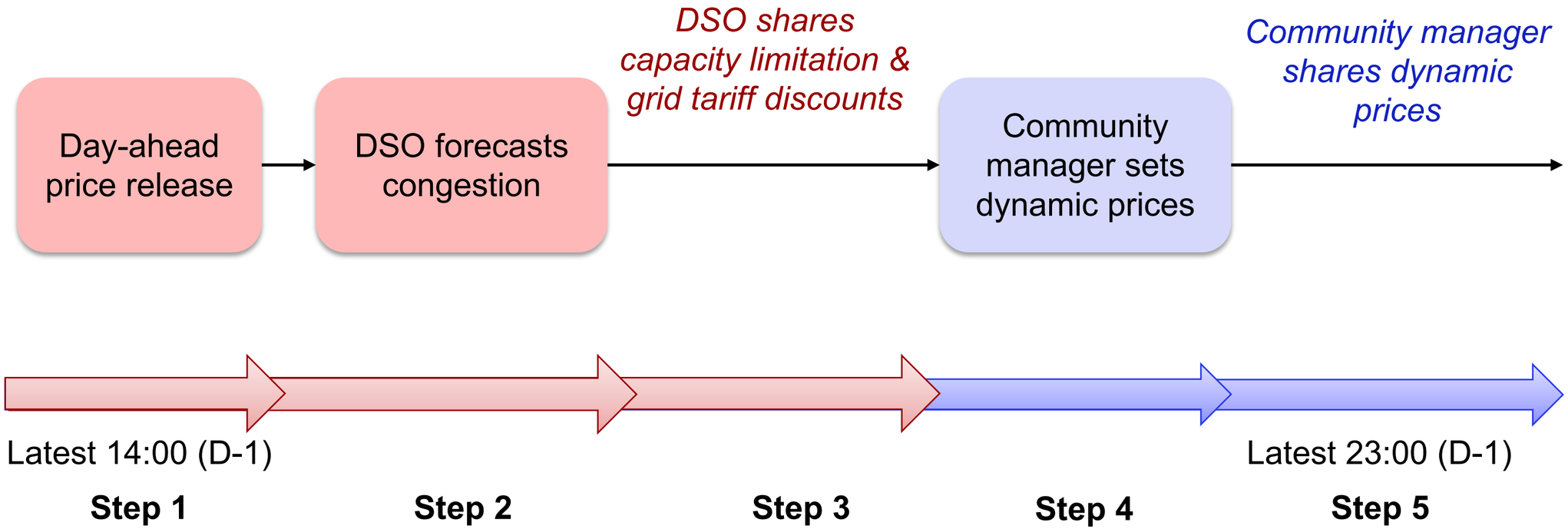

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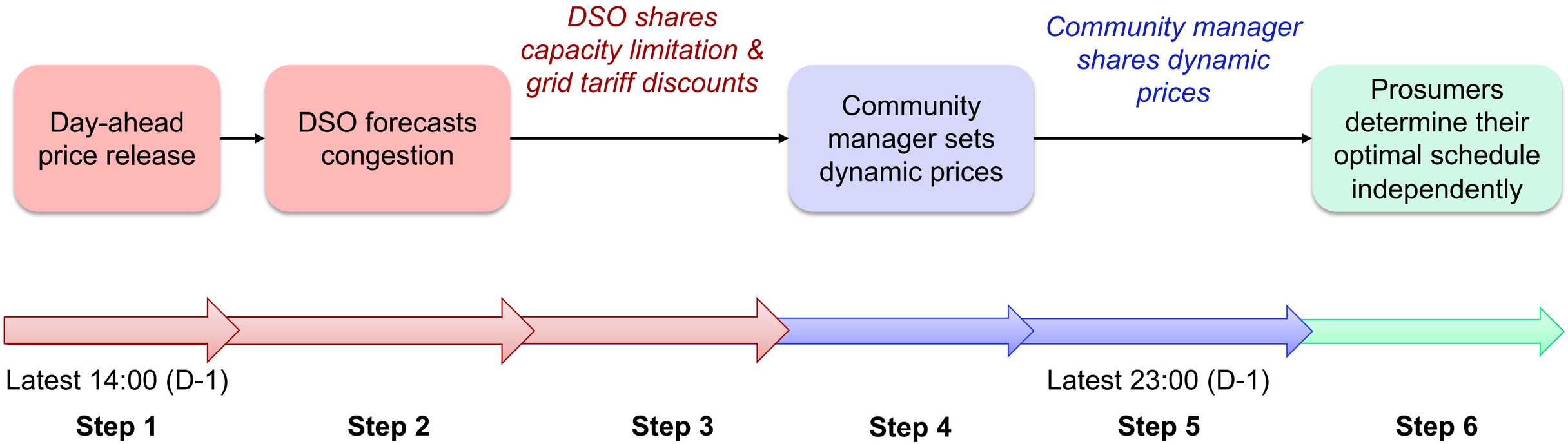

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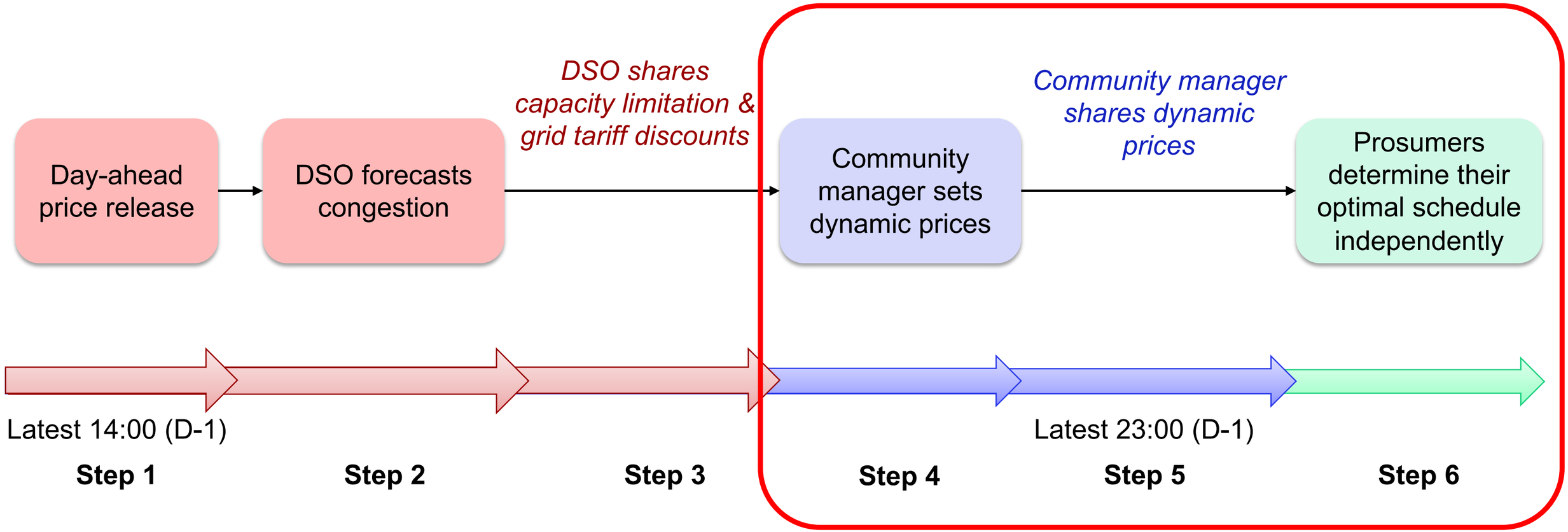

We focus on the community manager's problem:
Price setting (known capacity limitation & tariff discounts)

This process occurs the day before operation - <u>not</u> in real-time!

What do we mean by Dynamic Prices?

Static pricing

- Constant throughout the day
- Same for all prosumers
- Changes only in long-term horizon

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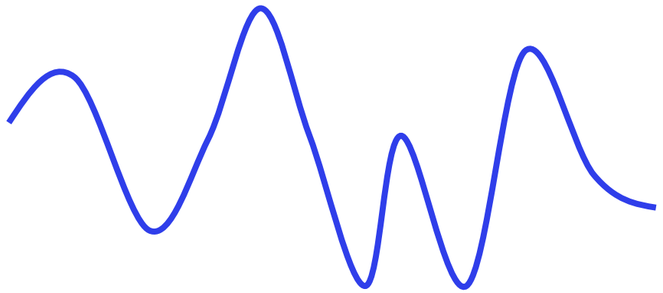
Time dynamic pricing



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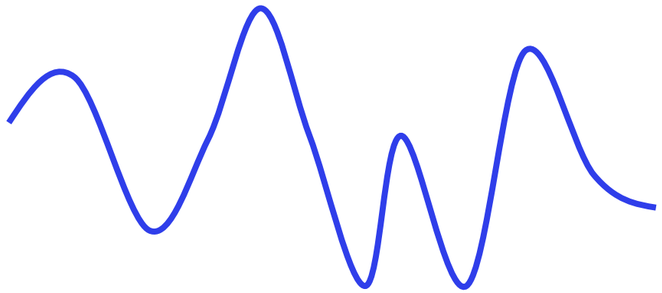

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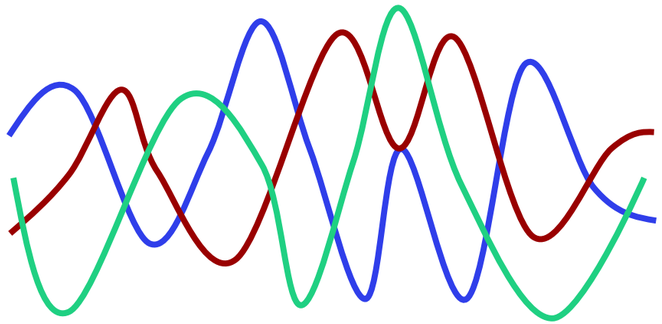
Time-and-space dynamic pricing



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Optimal Price Setting: A Game Theoretic Approach

Community manager (leader):
sets prices

Stackelberg game: Non-cooperative sequential game in which the leader (community manager) must anticipate the reaction of follower (prosumers)

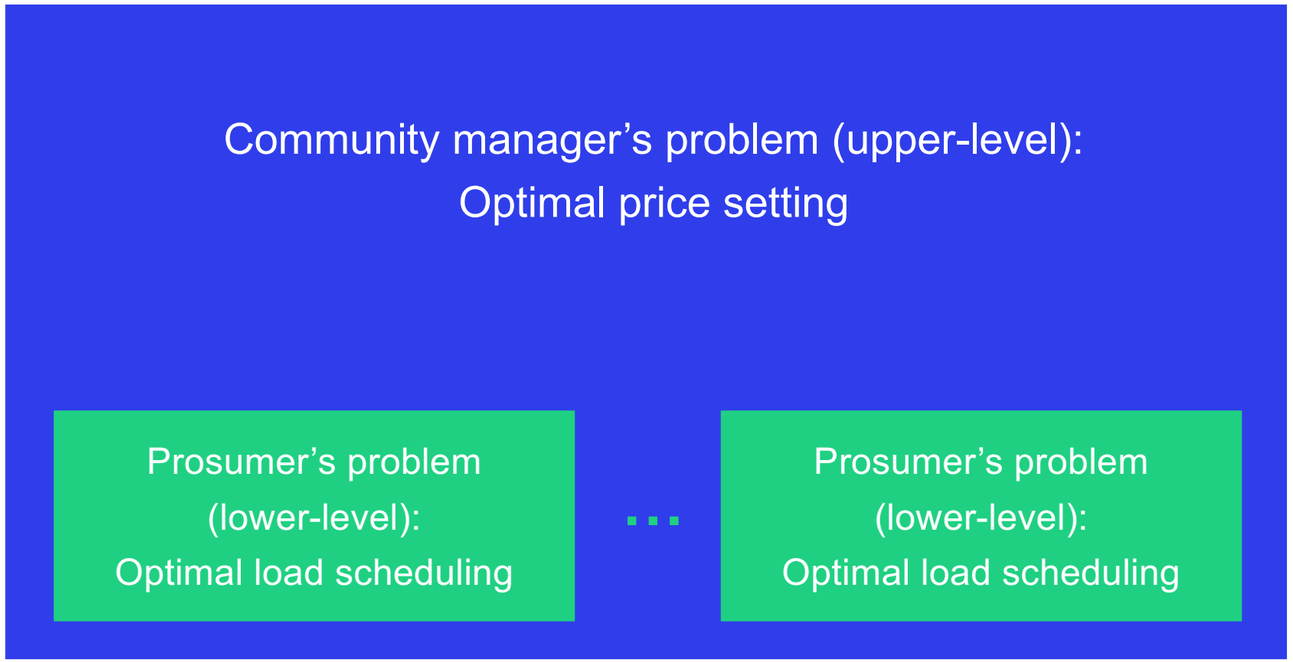
Optimal Price Setting: A Game Theoretic Approach

Prosumer (follower):

Schedules flexible assets and loads

Stackelberg game: Non-cooperative sequential game in which the leader (community manager) must anticipate the reaction of follower (prosumers)

Optimal Price Setting Problem: Bilevel Formulation



A bilevel program integrates the followers' best response within the leader's decision-making problem.

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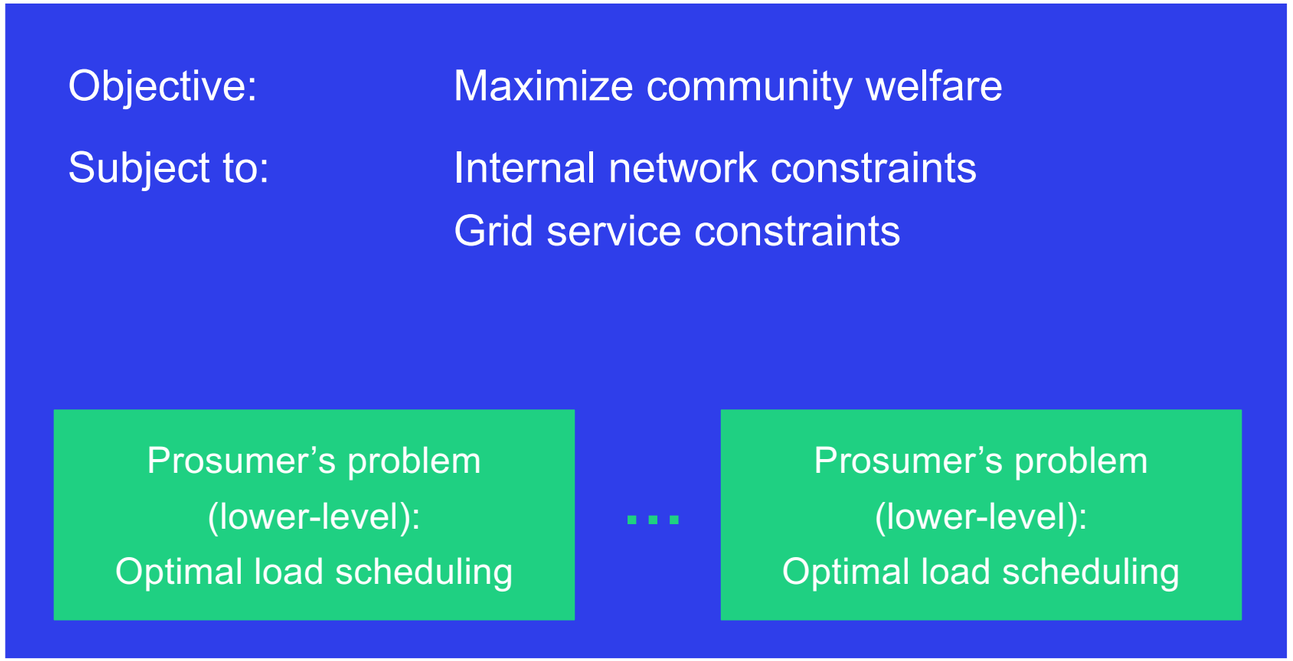

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Optimal Price Setting Problem: Bilevel Formulation

Objective: Maximize community welfare

Subject to: Internal network constraints

Grid service constraints

Individual rationality constraints

Prosumer's problem (lower-level): Optimal load scheduling

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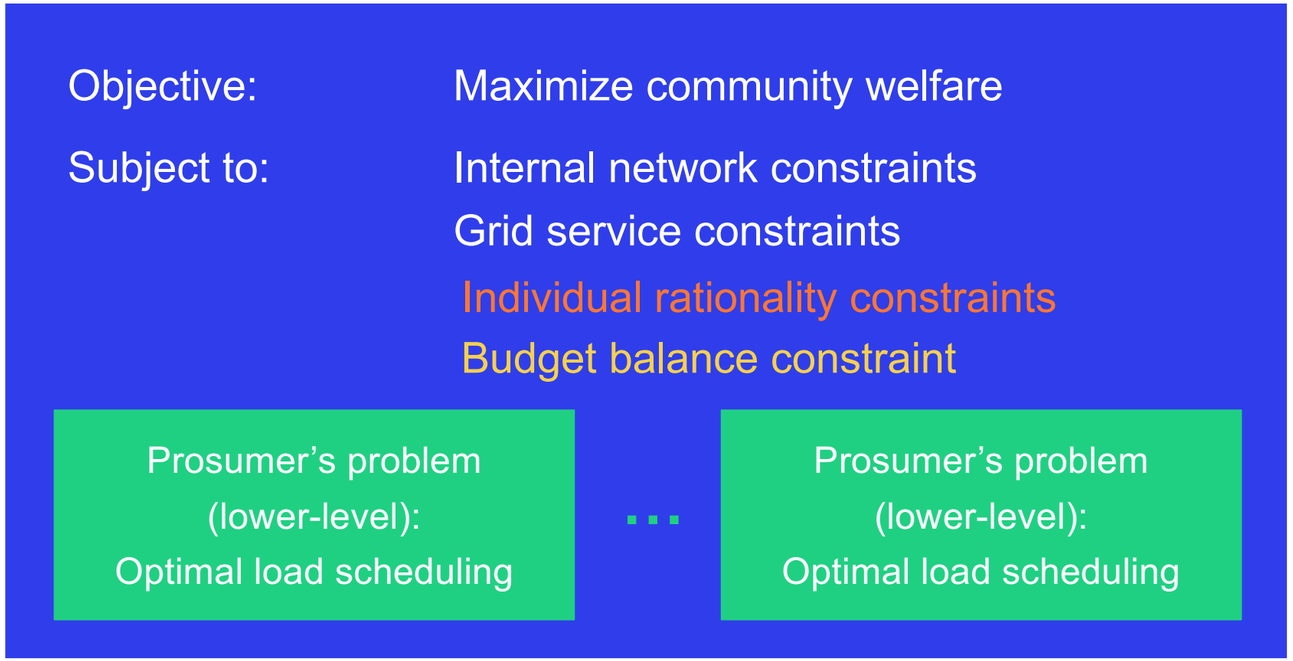

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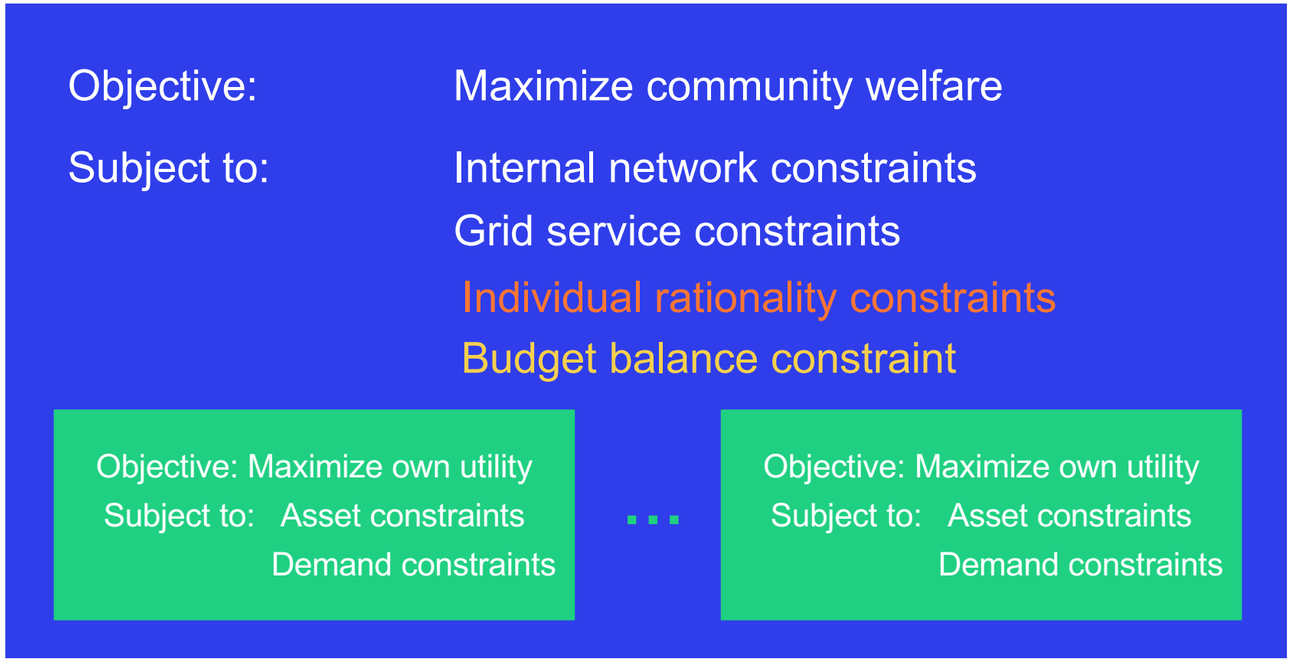

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Budget balance constraint

Optimality (KKT) conditions of prosumer's problem

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A bilevel program integrates the followers' best response within the leader's decision-making problem.

Benefits of CECs providing Grid Services

Benefits for Grid Operator

Can this energy community effectively help reduce congestion in the distribution grid?

Benefits for Community

Are the community members incentivized to act flexibly?
Are they ALL satisfied with the results?

Benefits of CECs providing Grid Services

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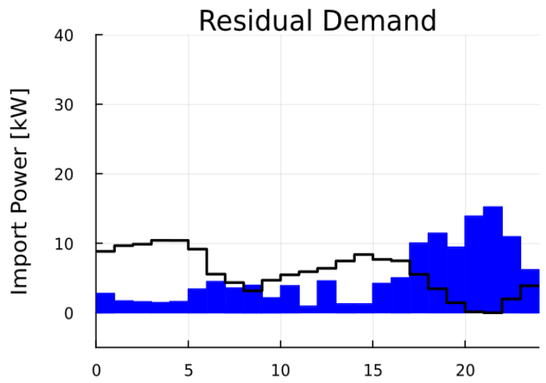

✓ Evening peak exceeds grid capacity limits

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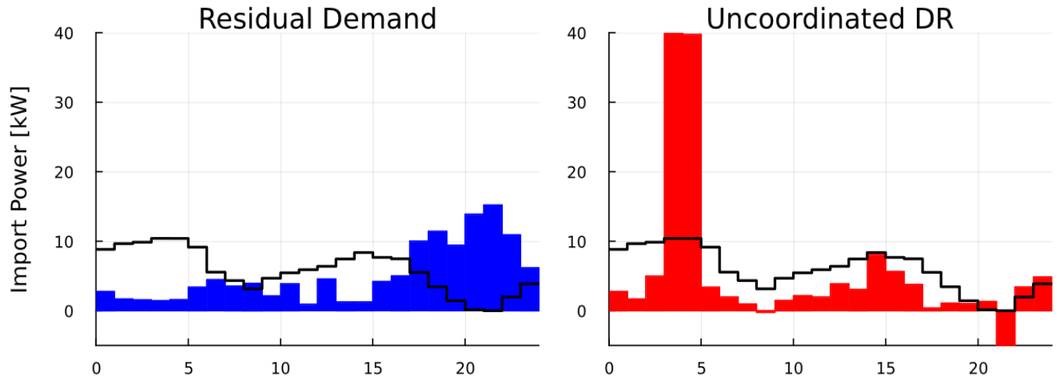

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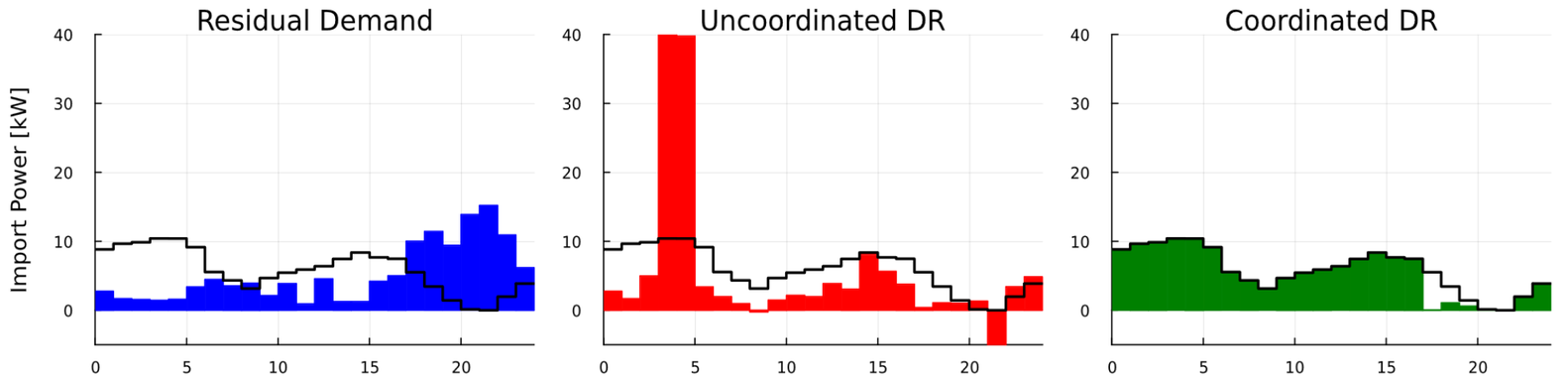

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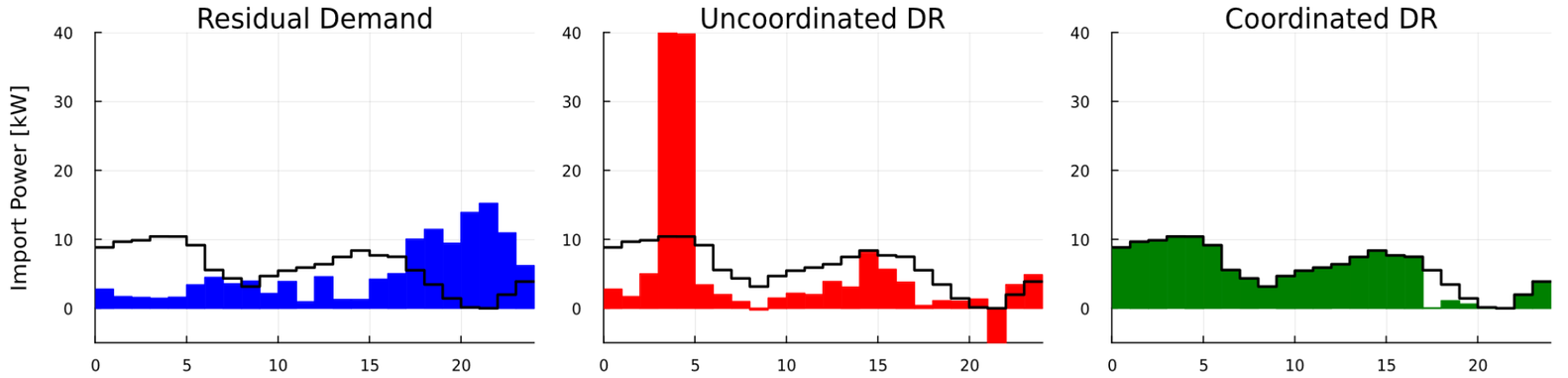

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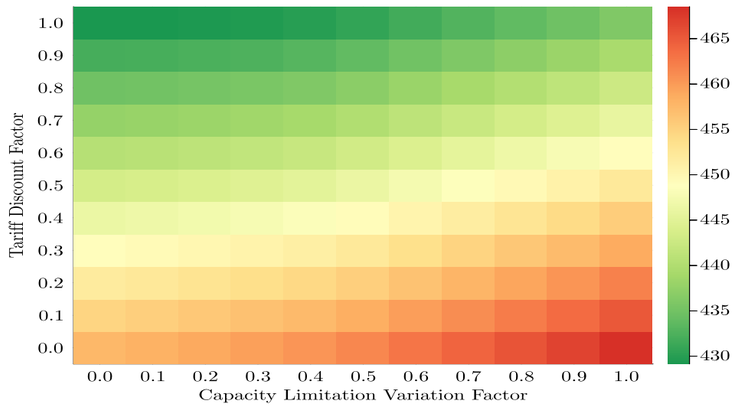

✓ Higher discounts and lower variability increase benefits for community

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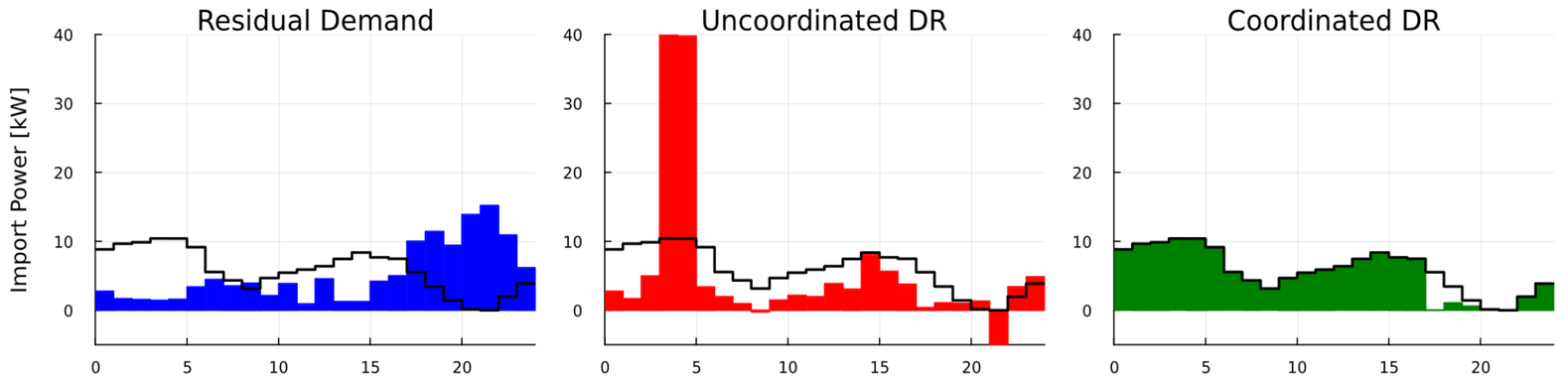

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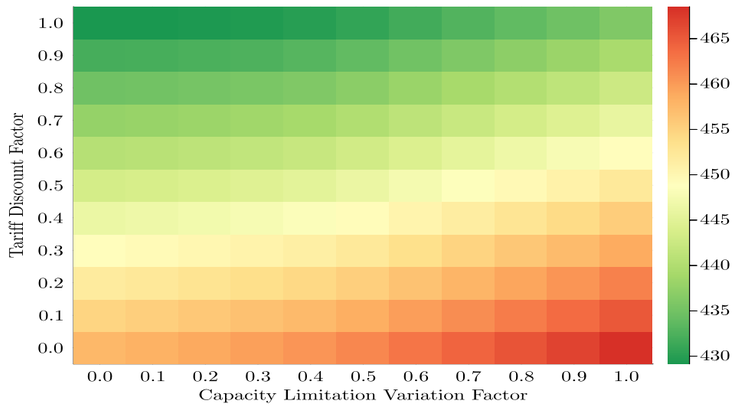
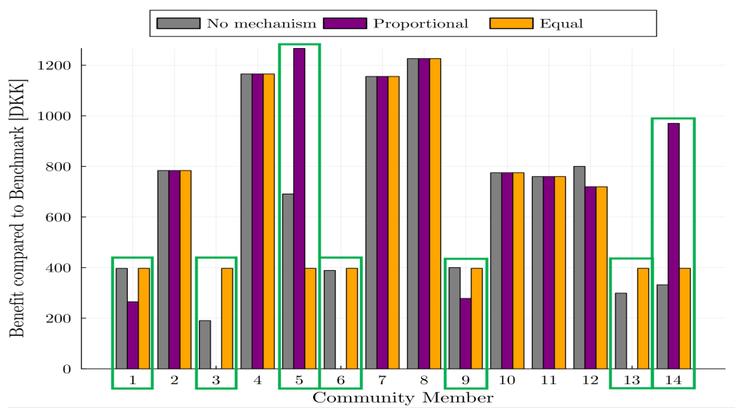




✓ Higher discounts and lower variability increase benefits for community

✓ Fairness promotion successful for the prosumers with positive residual demand

Key Takeaways

[Paper B]

Energy communities have the ***potential*** to deliver **grid services** that benefit the system operator.

The prosumers in energy communities ***can*** achieve desirable **socio-economic goals**.

Key Takeaways

Energy communities have the ***potential*** to deliver **grid services** that benefit the system operator.

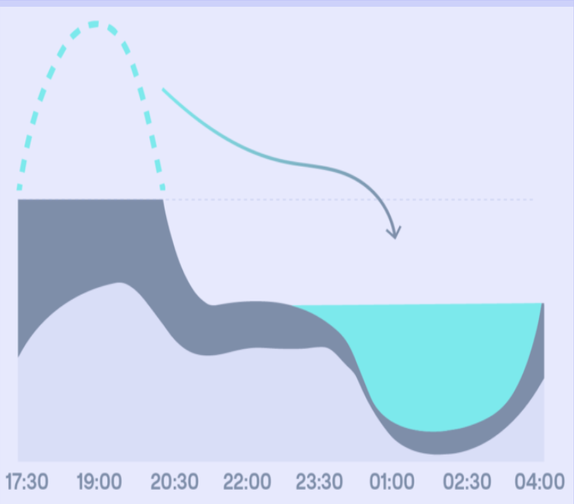
The prosumers in energy communities ***can*** achieve desirable **socio-economic goals**.

The community manager needs a practical framework to coordinate these prosumers and harness these *potential* benefits!

Research Directions

Research direction 1

Quantify the benefits and viability of energy communities



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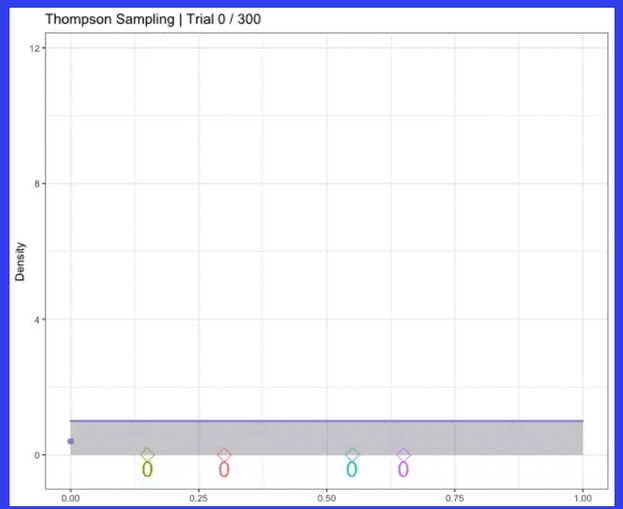

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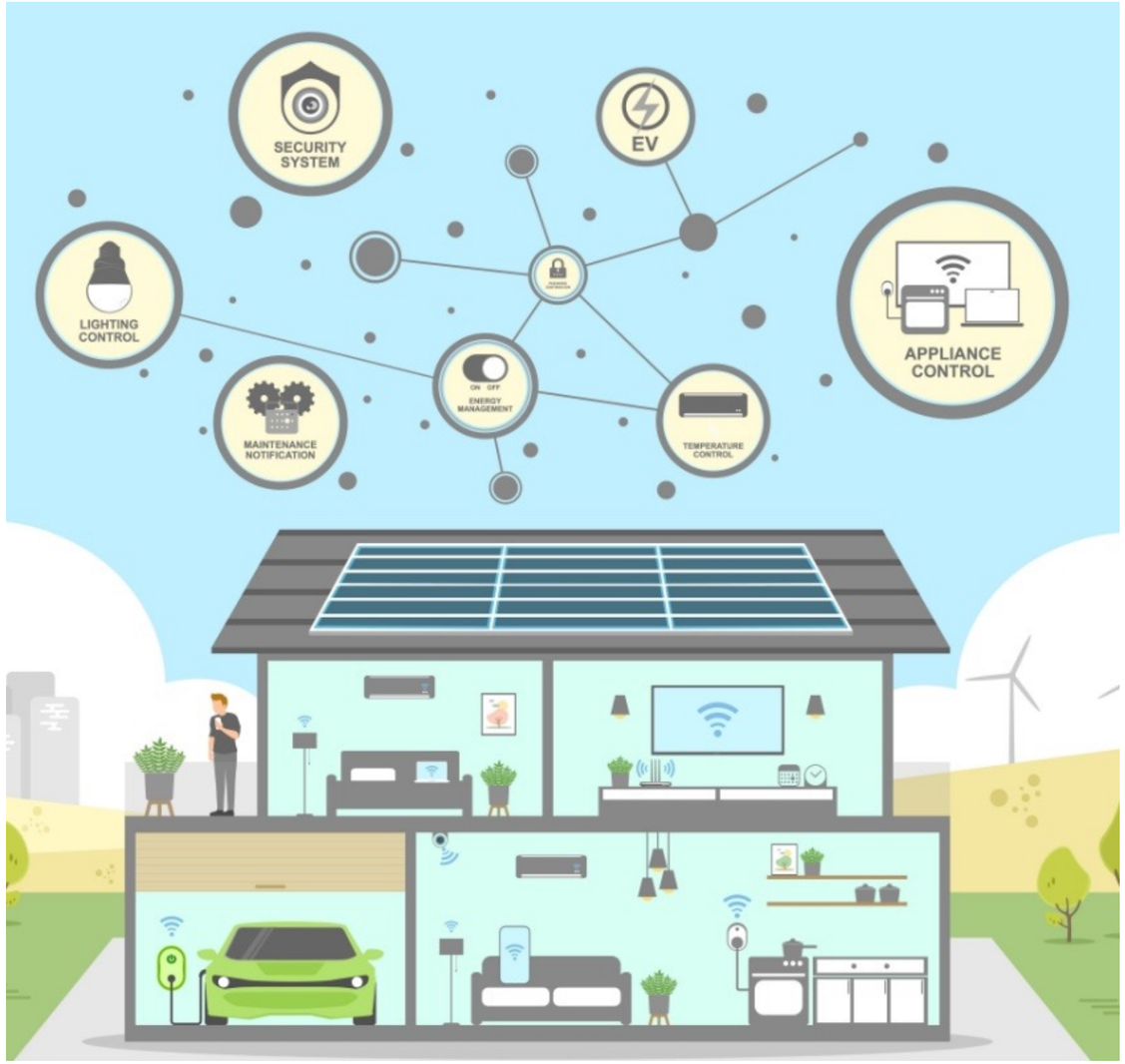
What do we mean by prosumer *preferences*?



Prosumers have complex and heterogeneous "preferences":

- *Do they want to reduce their energy procurement costs, increase self-consumption, and/or reduce their CO2 emissions?*
- *At what time are they at home and able to shift load?*
- *What flexible assets do they have in their homes?*
- *What temperature do they keep their homes at? How sensitive are they to temperature changes?*
- *Do they have an electric vehicle? When do they use it? How anxious are they regarding having a low state of charge?*
- *…*

Why is it important to better *understand* these preferences?

They shape welfare

The same price affects each prosumer differently. Ignoring comfort, schedules, or EV needs can leave them worse off.

They drive behavior

Heterogeneous prosumers respond differently to prices to optimize their own utilities.

They enable coordination

Modelling these preferences lets the community manager align individual incentives and steer individual behavior toward a common goal.

Aligned individual utilities → coordinated responses → social-welfare-maximizing outcomes

Let’s discuss…

If you were the community manager, how would you (practically) coordinate prosumers to provide grid services?

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Would you compensate them (e.g. contract) for letting you directly control their assets?

Would you set time-of-use prices to incentivize them shift loads to low-price hours?

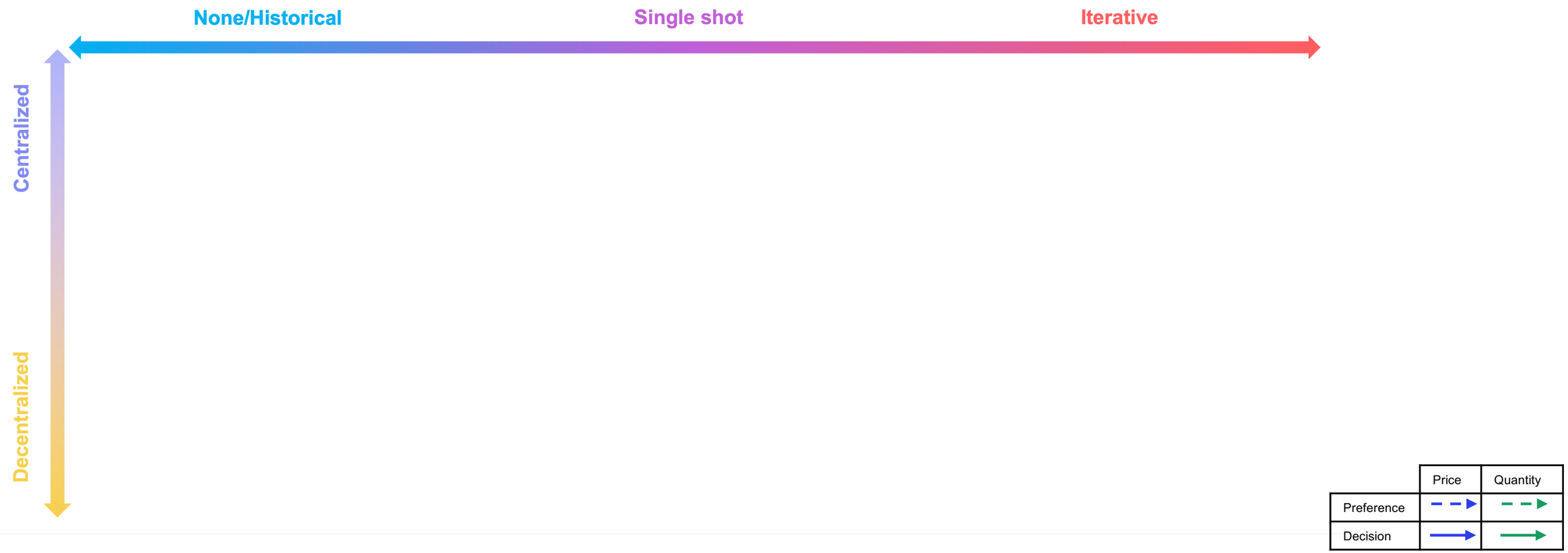
Would you ask them about their preferences & find a social-welfare maximizing solution?

… How?

Overview of Local Energy Coordination Mechanisms

Local Energy Coordination Mechanisms differ along two main architectural axes:

- **Decision-making** (centralized vs. decentralized): who determines quantities and prices
- **Preference-elicitation** (none vs. single-shot vs. iterative): whether and how often members exchange preferences over those quantities and prices



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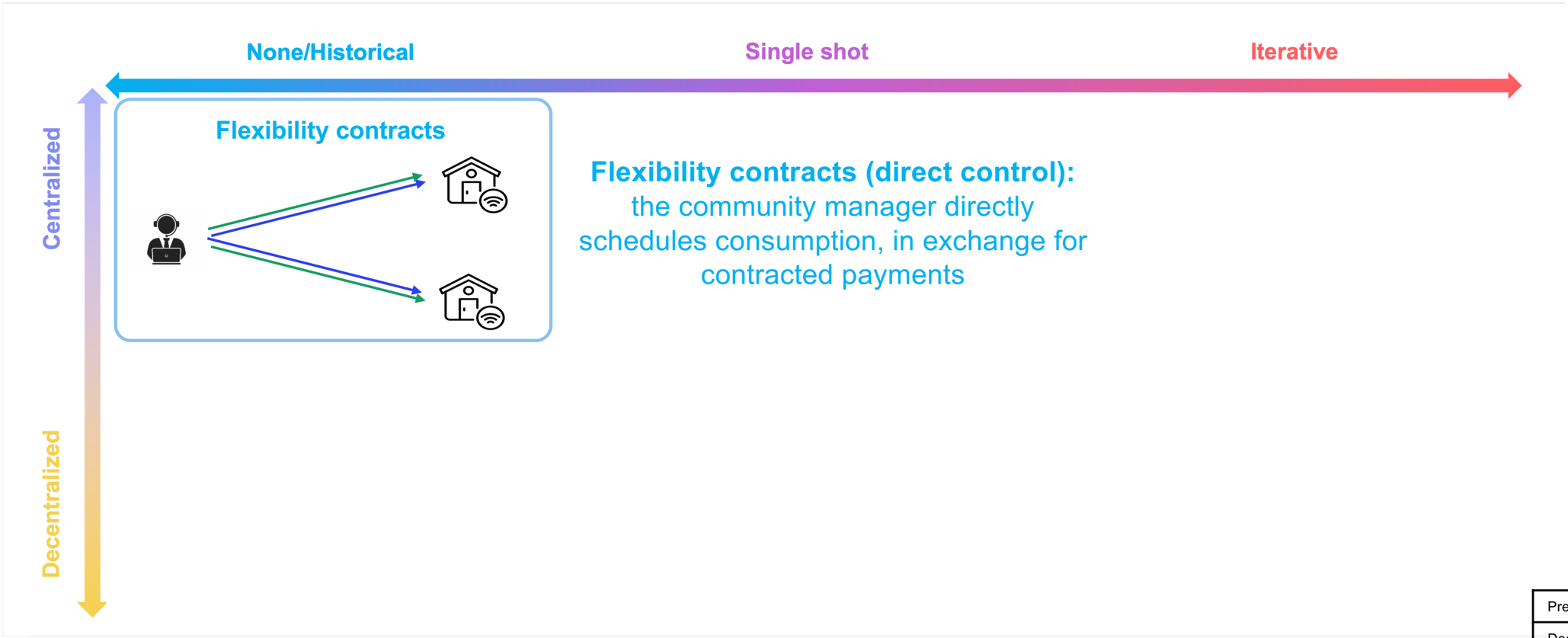

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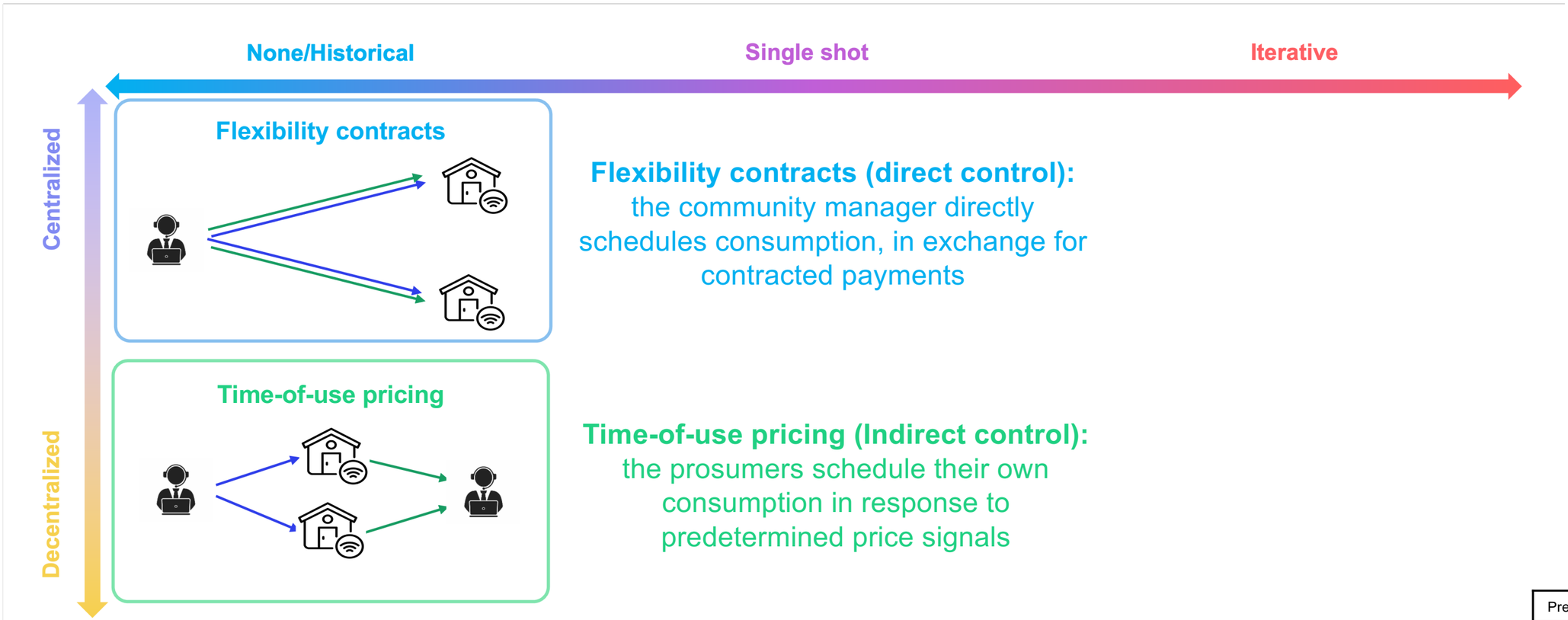

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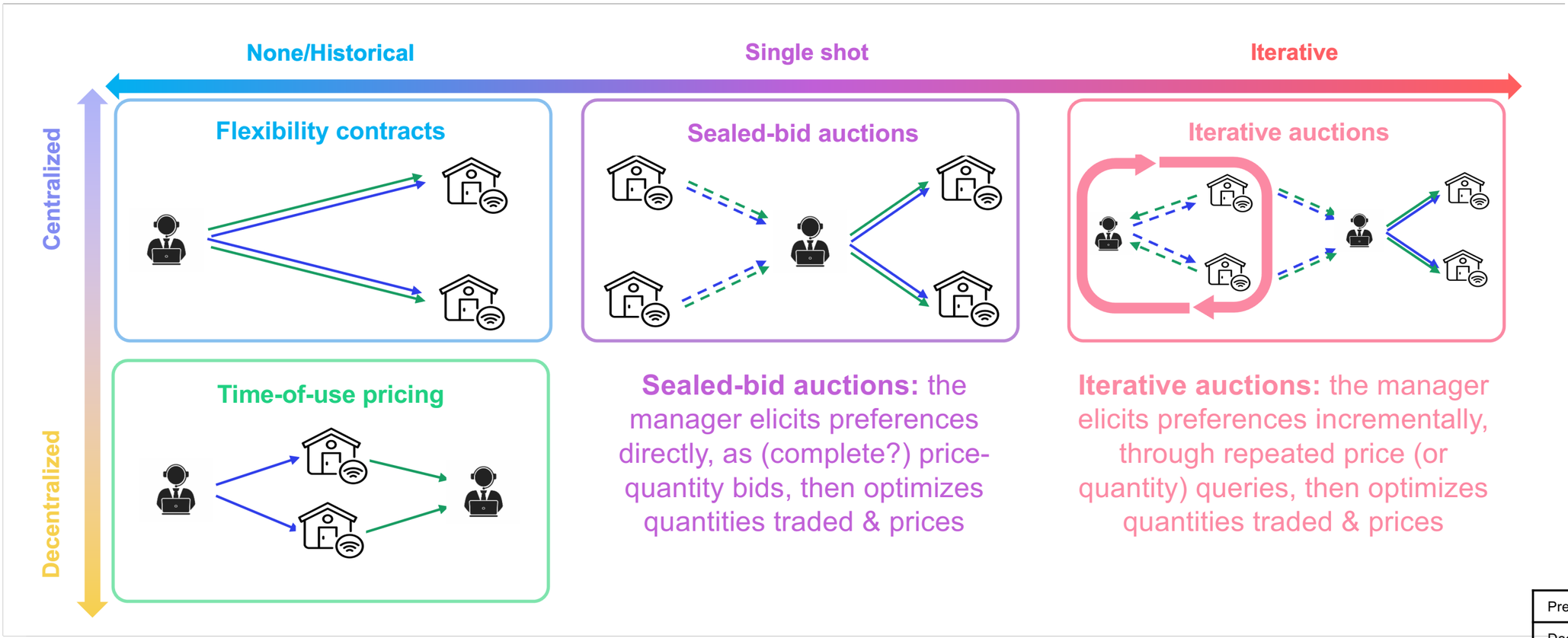

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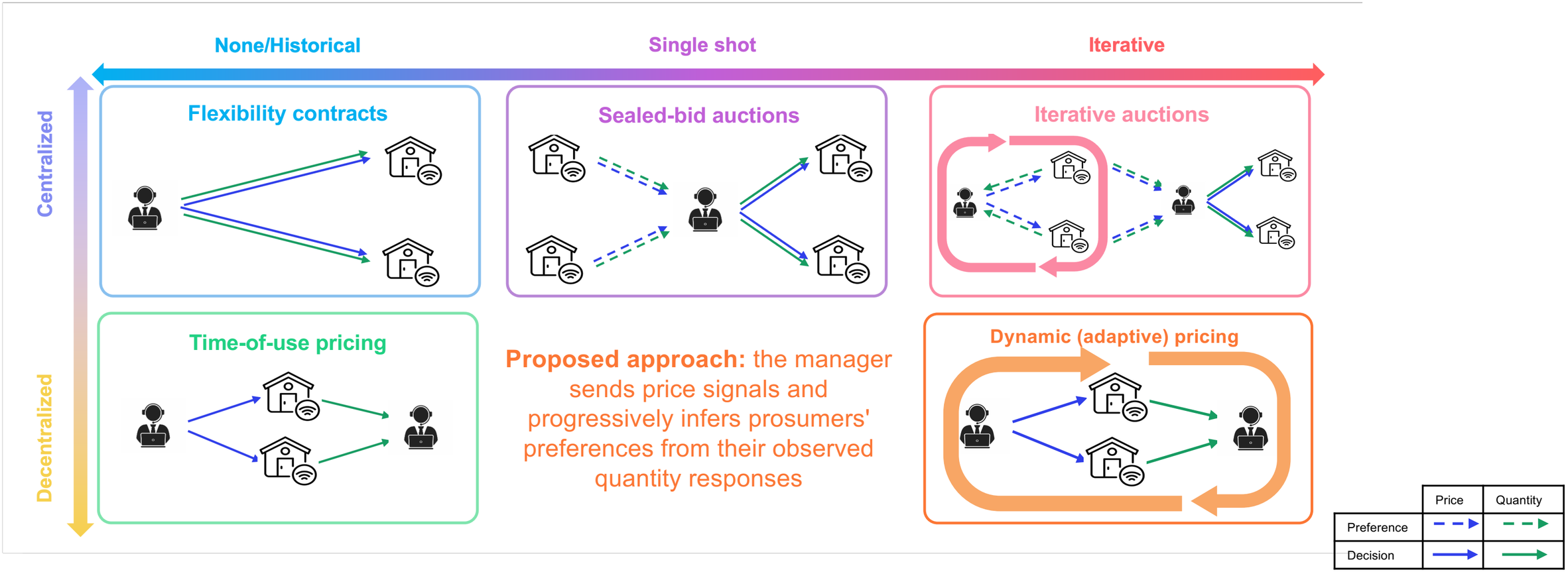
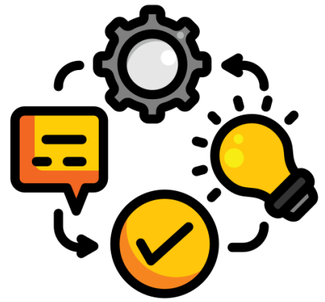


Proposed Framework: Learning preferences while optimizing prices

Main objective: Design a **dynamic pricing mechanism** that jointly learns prosumer preferences based on their response to price signals & how to set optimal price signals

Learning from large historical data sets



Learning while gathering data over time

Modeling Prosumer Preferences

- A prosumer’s household demand profile is an aggregation of multiple different **"signatures”**.
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We still assume perfect rationality and a single objective (cost minimization or utility maximization)

Online Learning & Bandit Framework

Goal: Learn the **weights** associated with each (predefined) signature, for each prosumer, based on their aggregate response to price signals

Signature - battery
true weight (θ_B): Battery size

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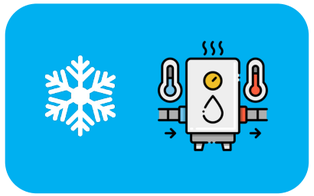
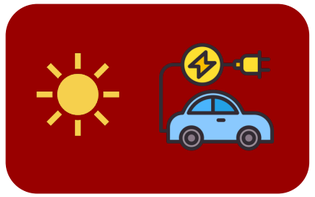


Signature – EV, day
True weight ($\theta_{EV,d}$): energy charged between 9am-5pm



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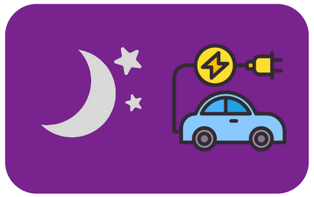

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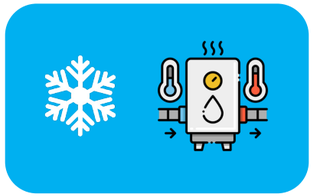

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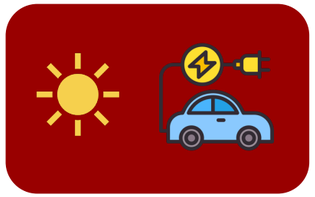

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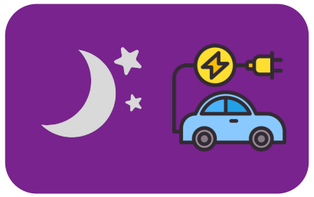

Prior knowledge about weights: prior distributions

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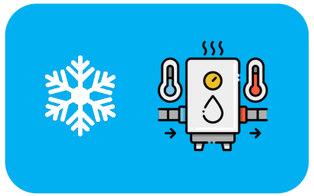

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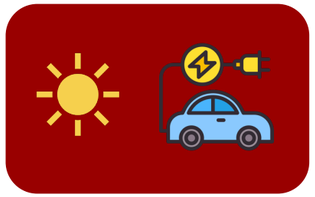

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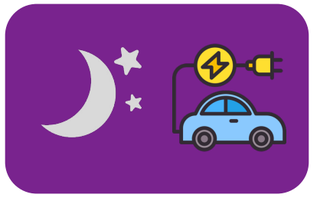

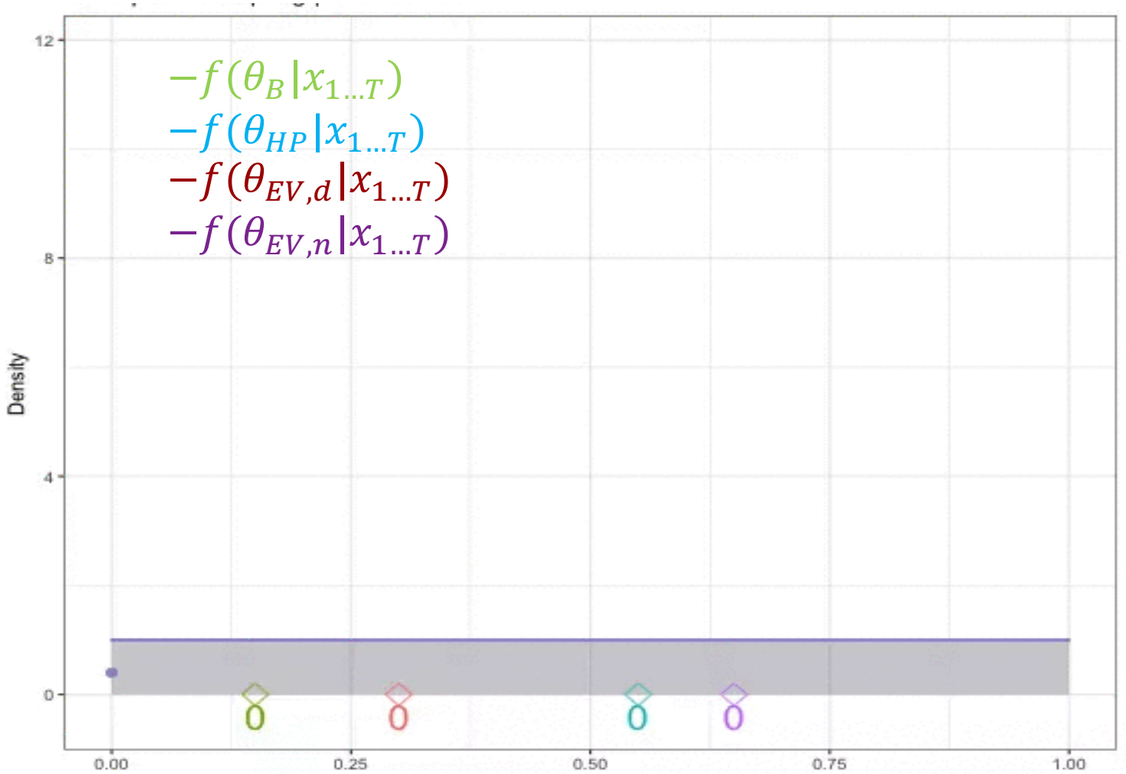

Update prior knowledge after each observation: Compute posterior distributions

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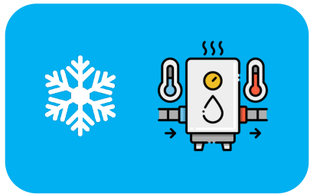

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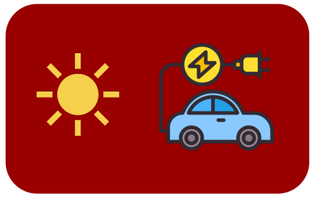

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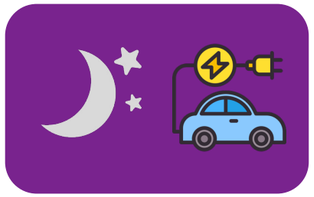
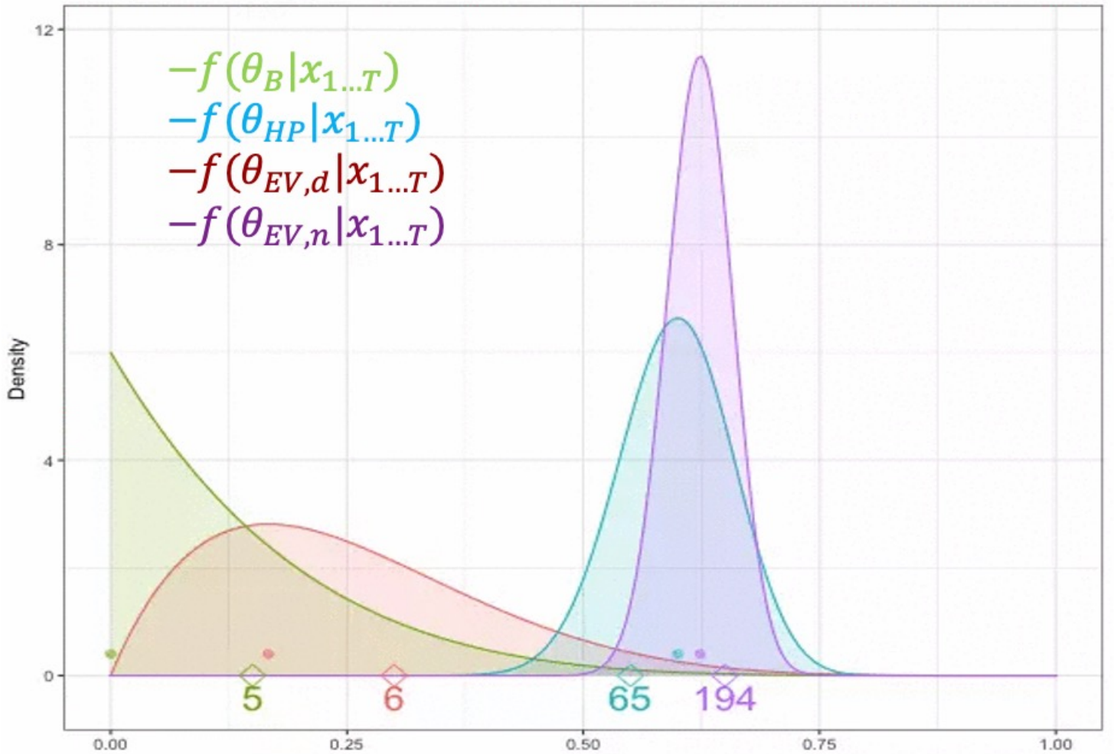
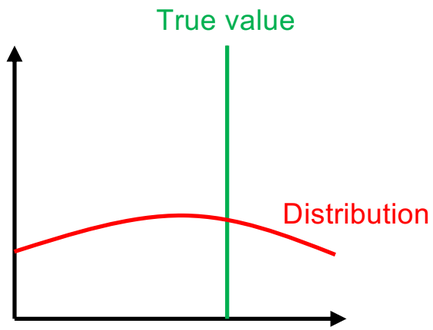




Learned weights: posterior ditributions converge towards "true" weights

Thompson Sampling Algorithm

Prior distributions over unknown weights



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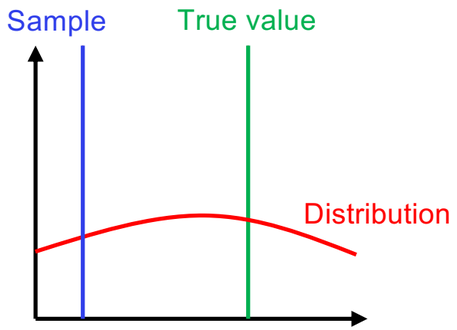
Prior distributions over unknown weights

↓

Sample values from distributions & set optimal prices



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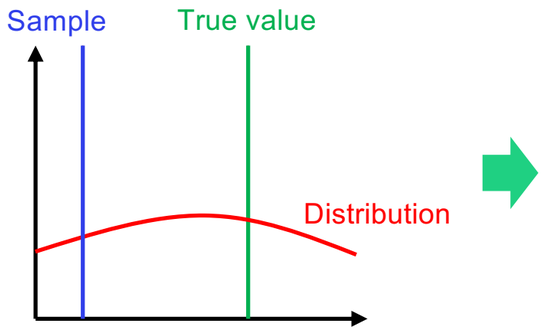
Prior distributions over unknown weights

Sample values from distributions & set optimal prices

Observe best response from prosumers



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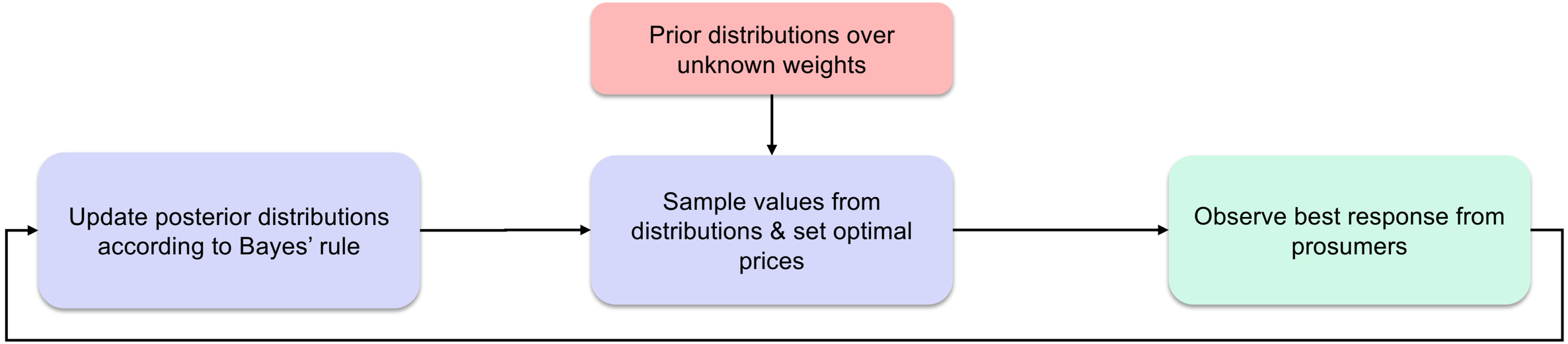

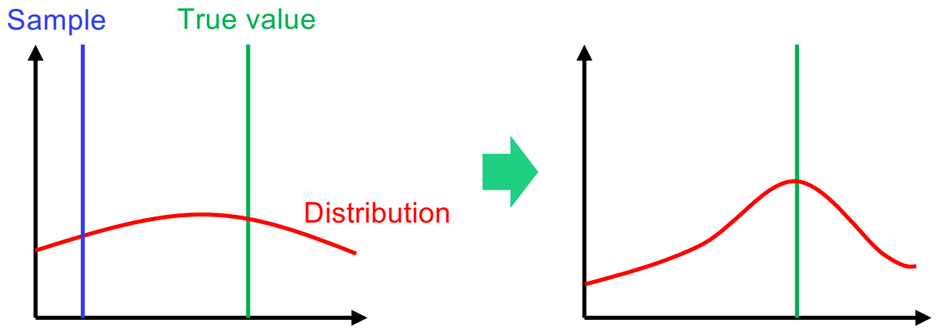

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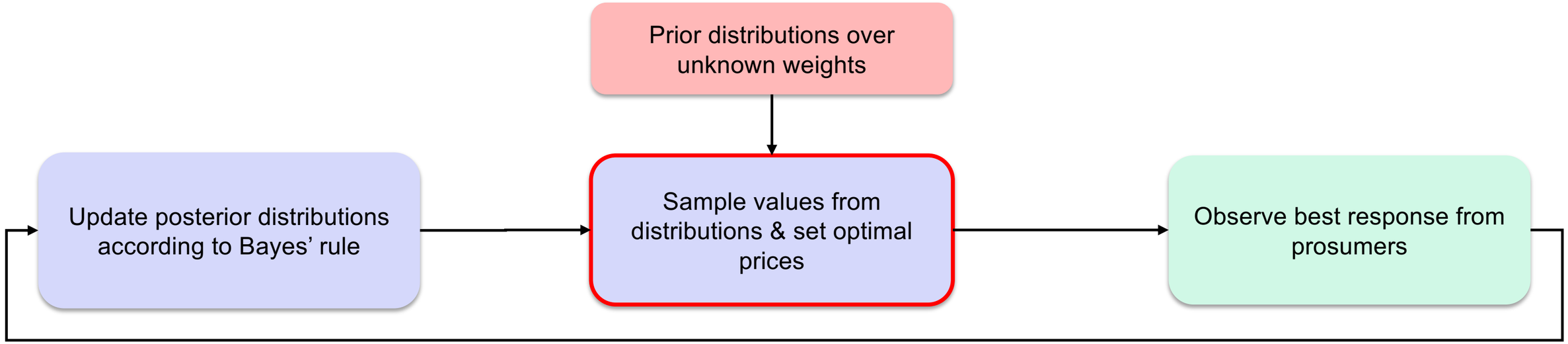

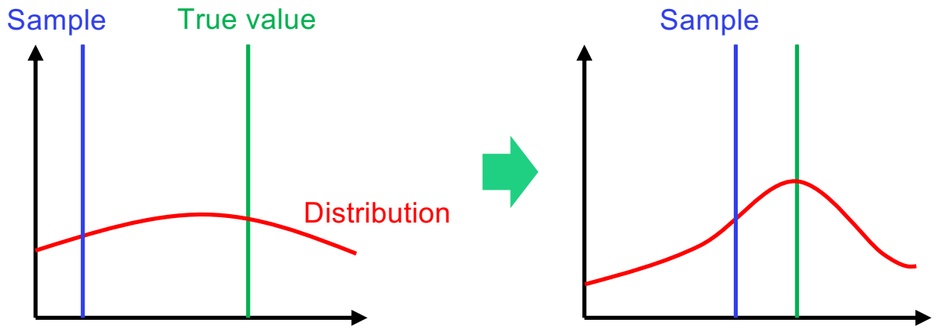

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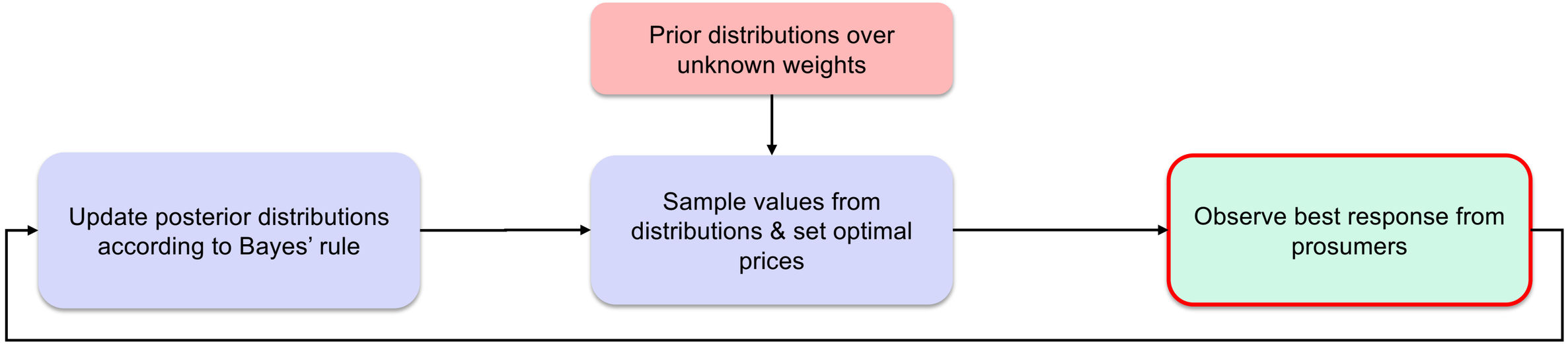

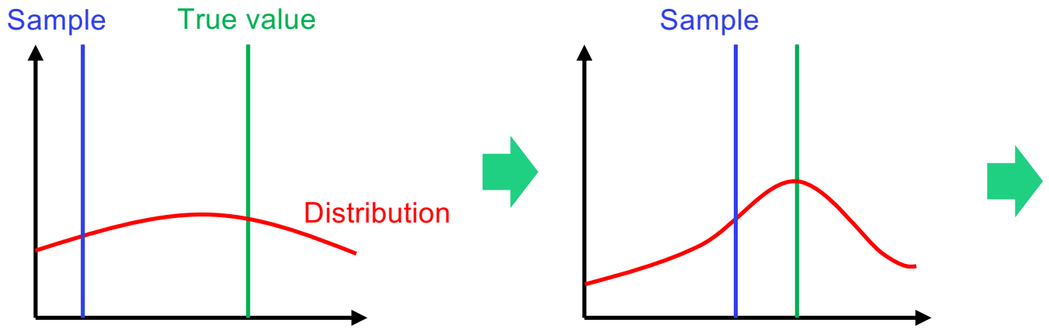

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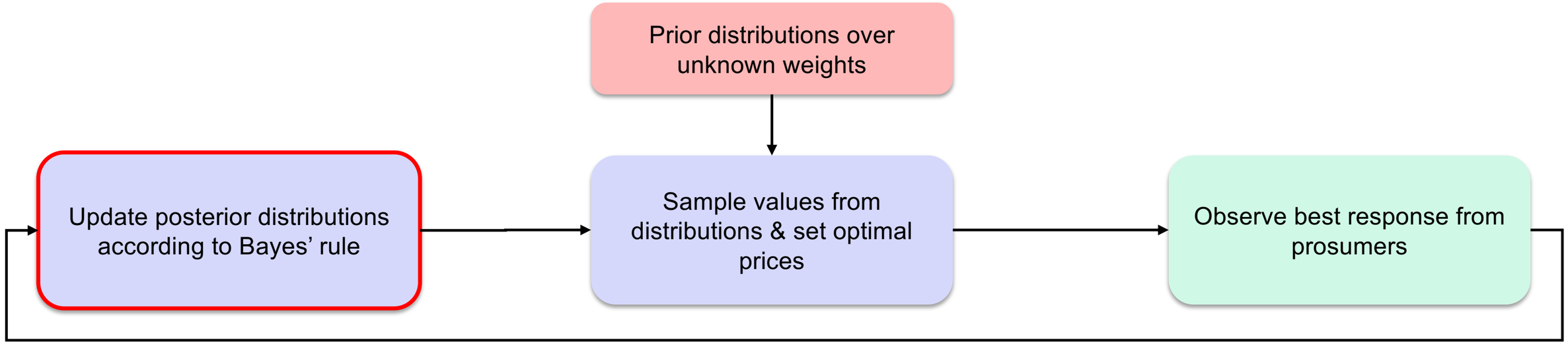

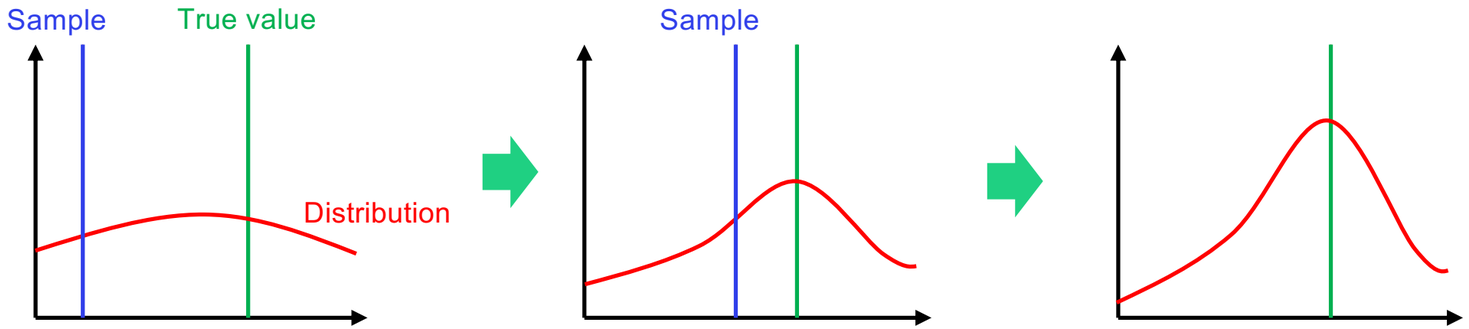

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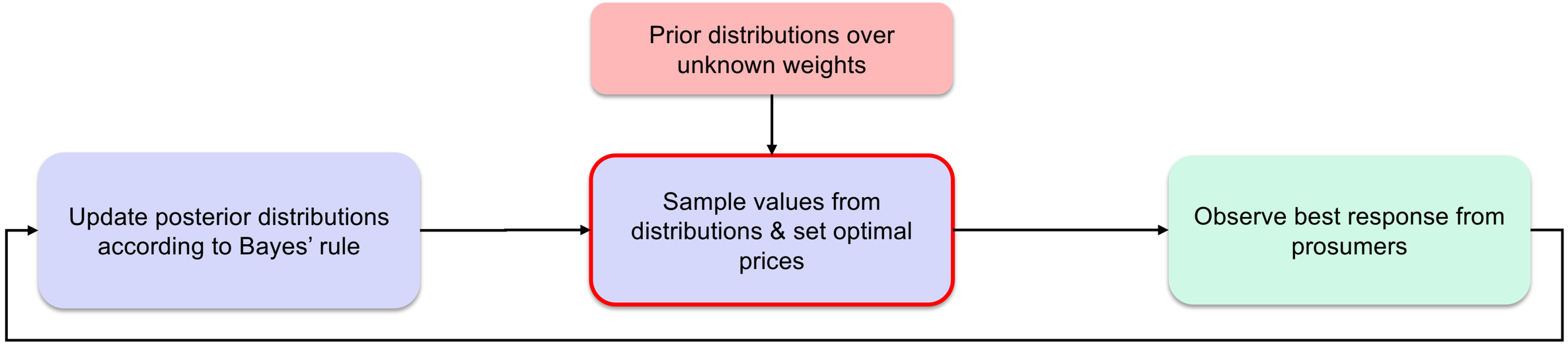

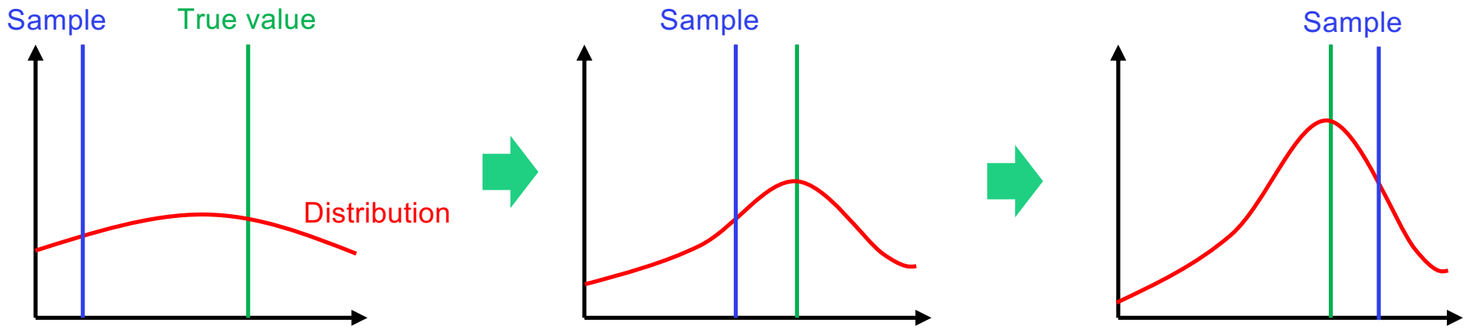

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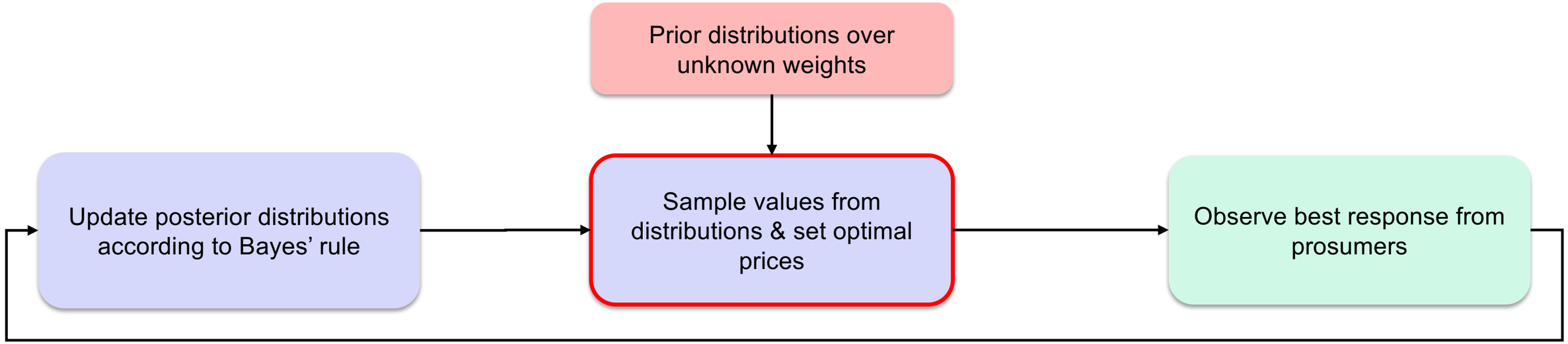

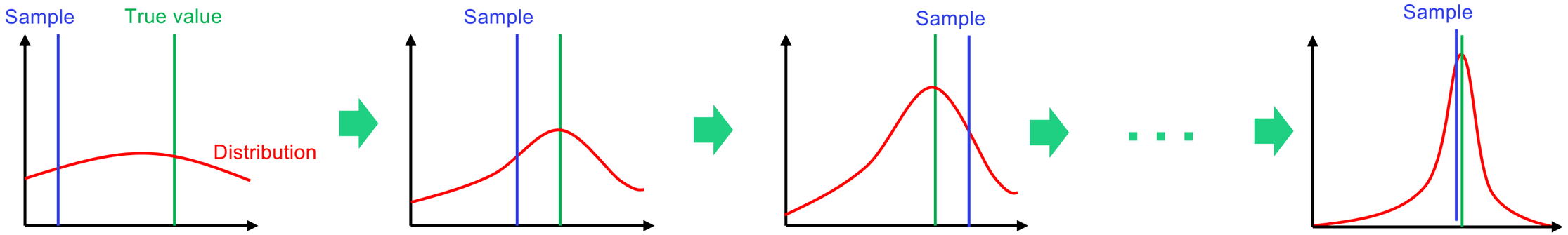

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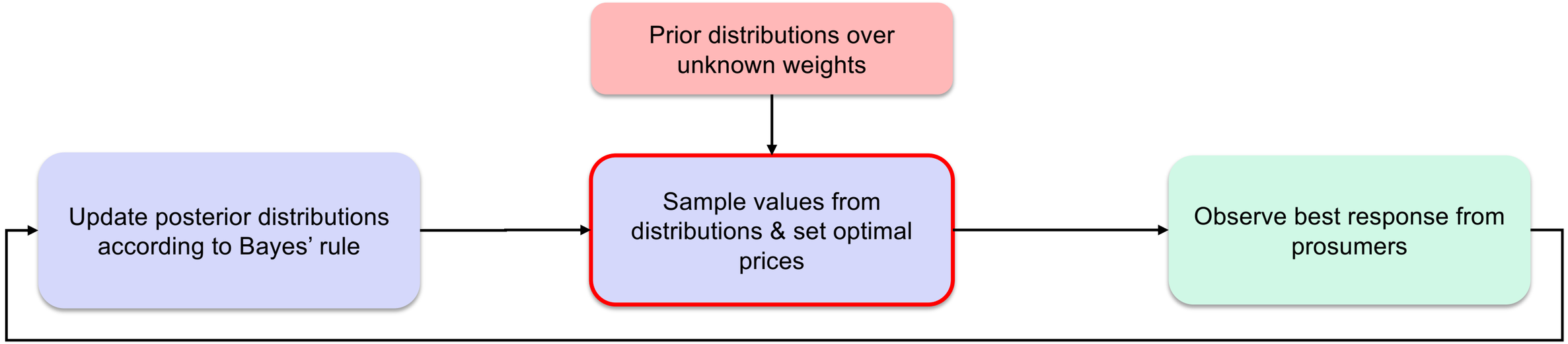

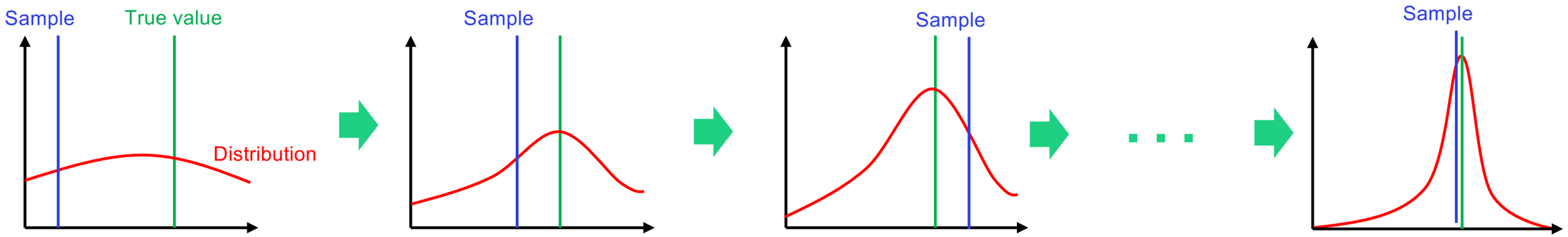

Posterior distributions converge to true weights → **Samples get closer to true weights** → **Price signals converge to optimal ones** → **Community's aggregate response is optimized**

Reformulation of Bilevel Prise-Setting Problem

Bilevel problem without signatures

Objective: Minimize community cost

Subject to: Grid service constraints

Individual rationality constraints

Budget balance constraint

Objective: Minimize prosumer cost

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Weighted signature aggregation

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$\theta_{1,1}$

$\theta_{1,2}$

$\theta_{1,3}$

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$\theta_{2,1}$

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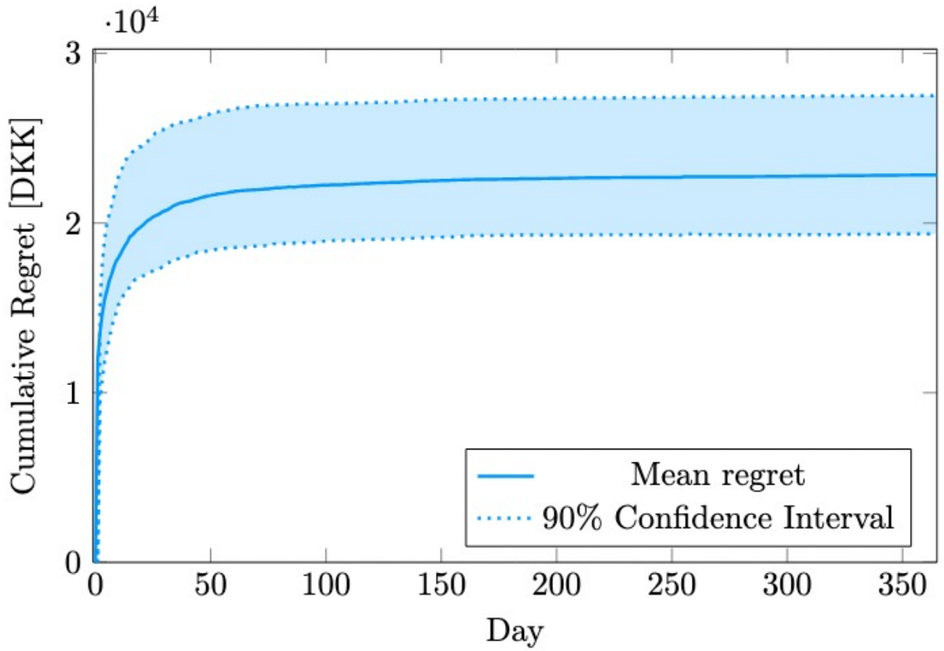
Near Zero Regret Achieved

Regret compares the daily community cost from the learning algorithm to the daily community costs of a clairvoyant price-setter.

- After **100 days**, we reach **near-zero regret**.
- All independent runs achieve near-zero regret



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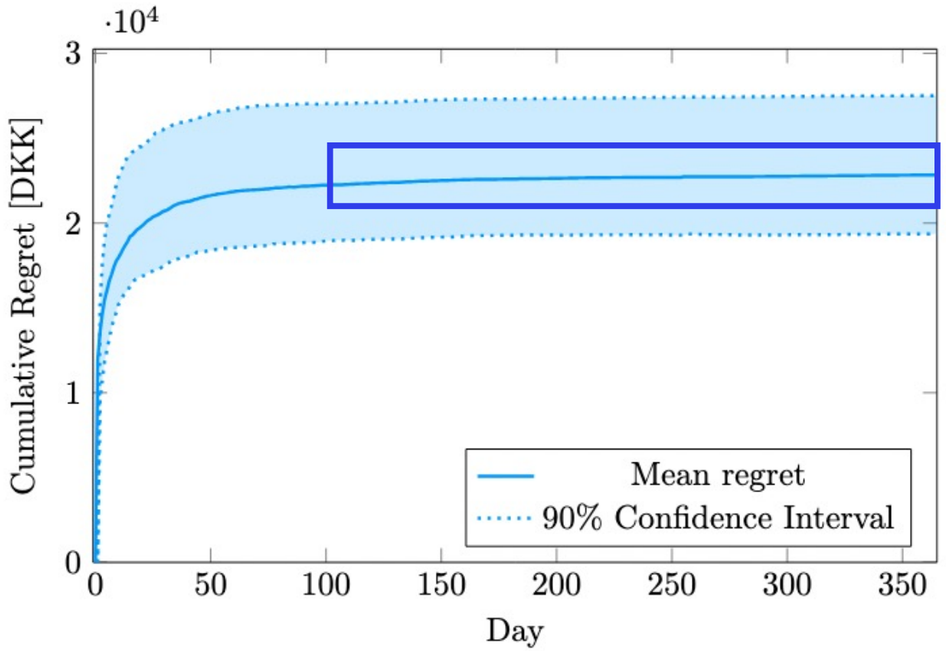

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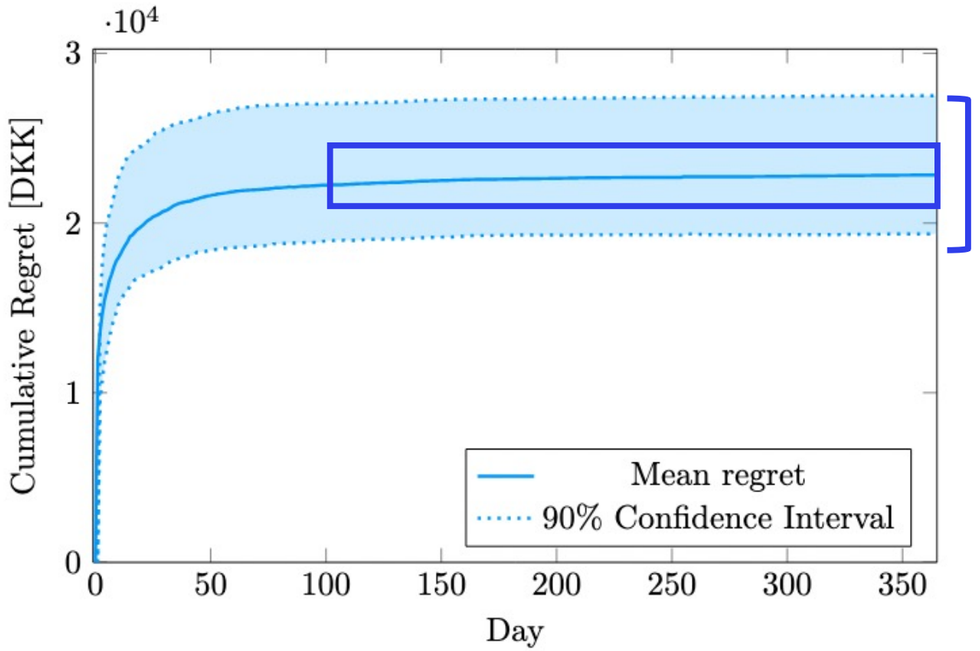
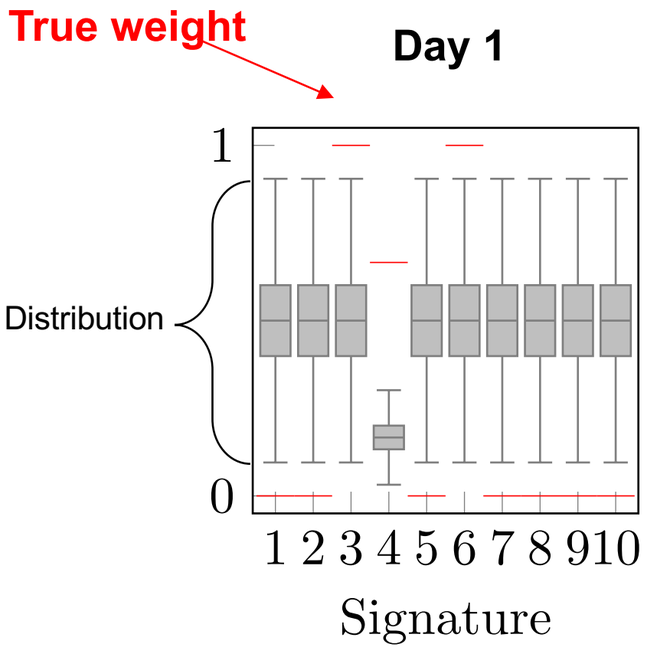


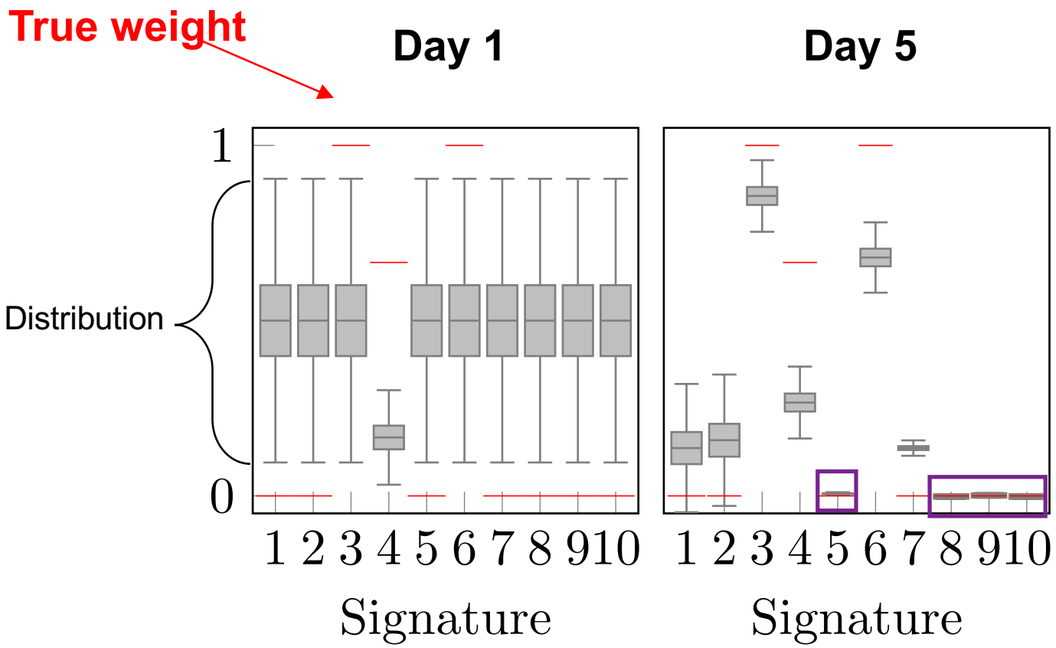
Range of regret

Convergence top true weights



- The distributions **converge at different rates** for all signatures.

Convergence top true weights



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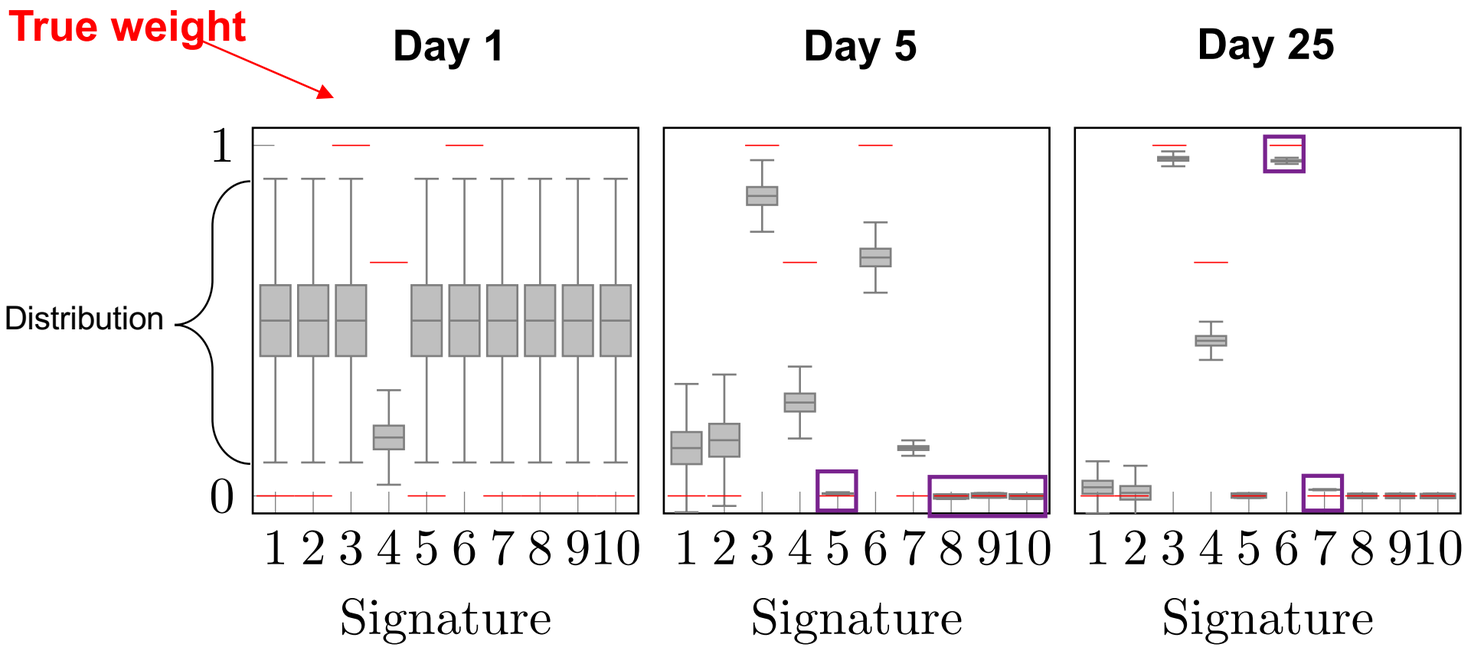

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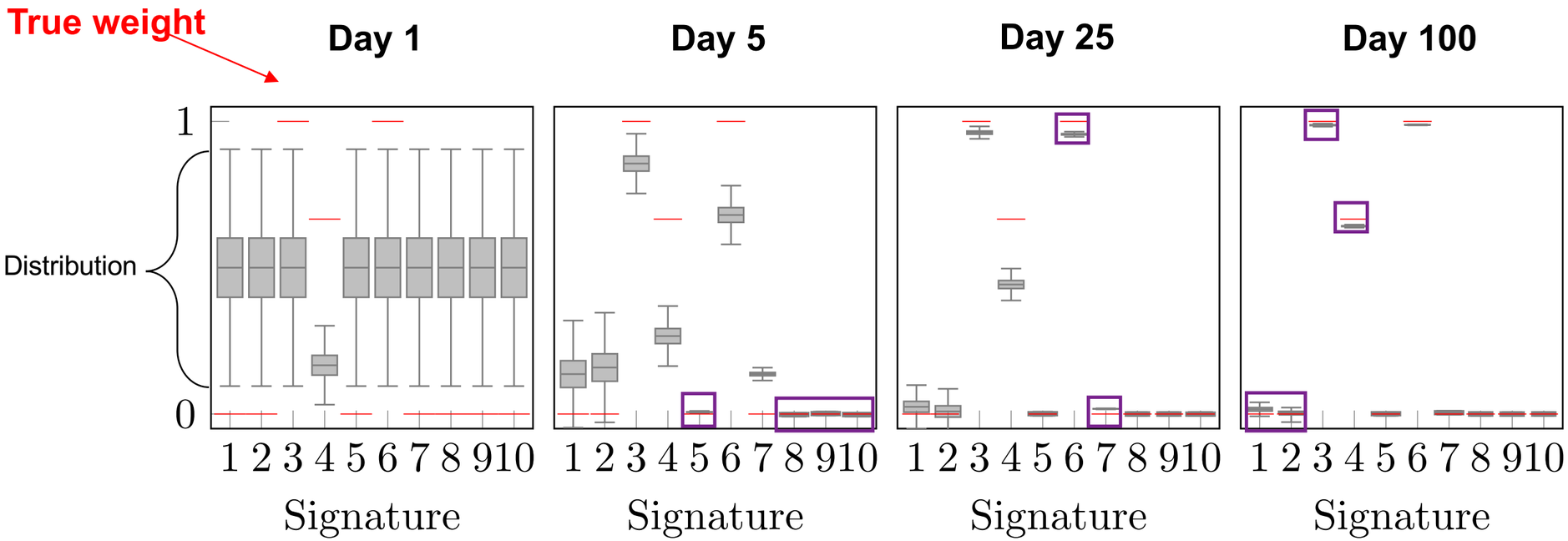
- The **high power** signatures (HPs, Evs) converge **fastest (day 25)**.

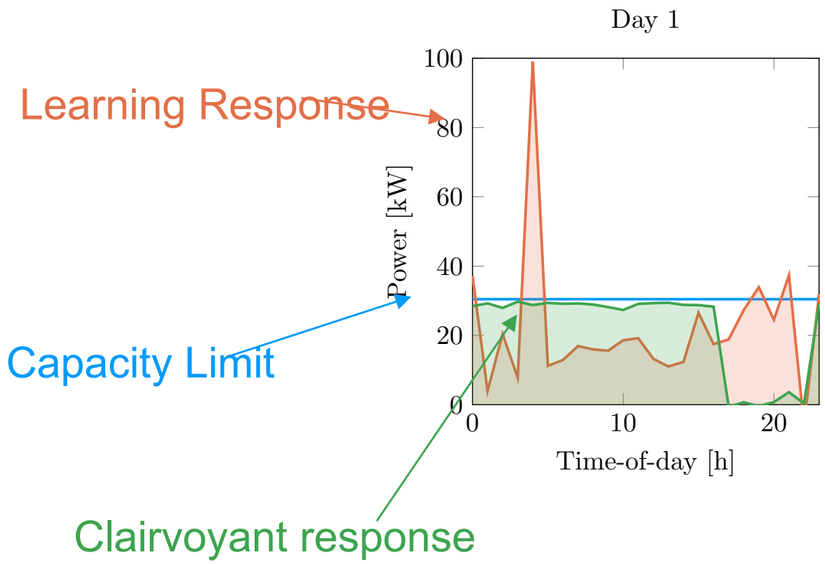
Convergence top true weights



- The distributions **converge at different rates** for all signatures.
- The **high power** signatures (HPs, Evs) converge **fastest (day 25)**.
- All distributions have **converged correctly** by **day 100**.

Community learns to follow capacity limits

- On **day 1** the community does a **poor job** of maintaining the capacity limitation.



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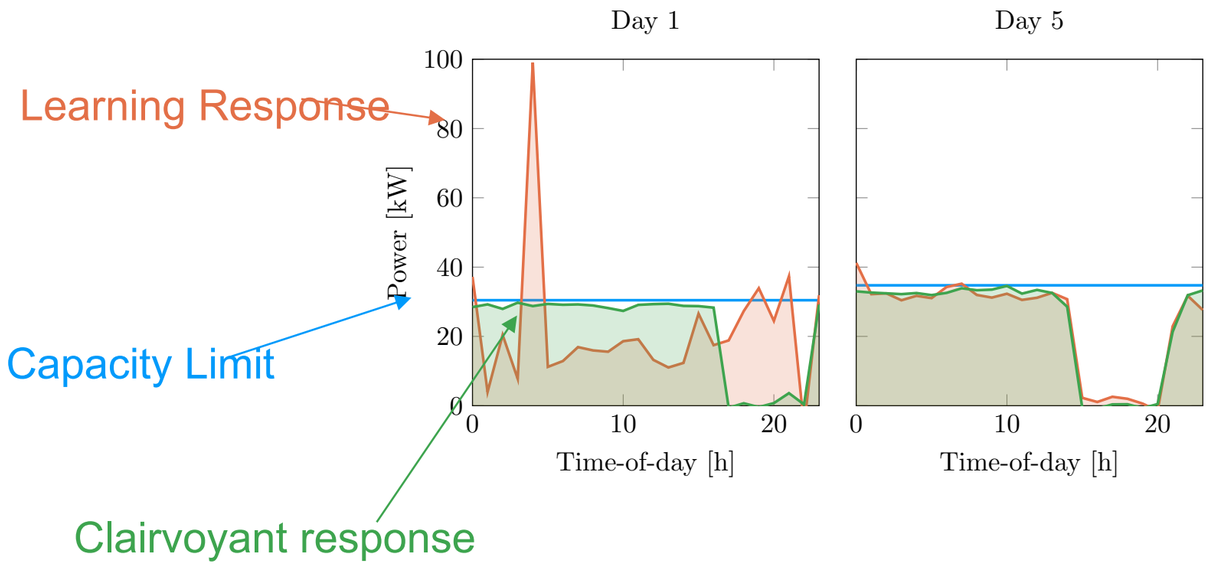

Community learns to follow capacity limits

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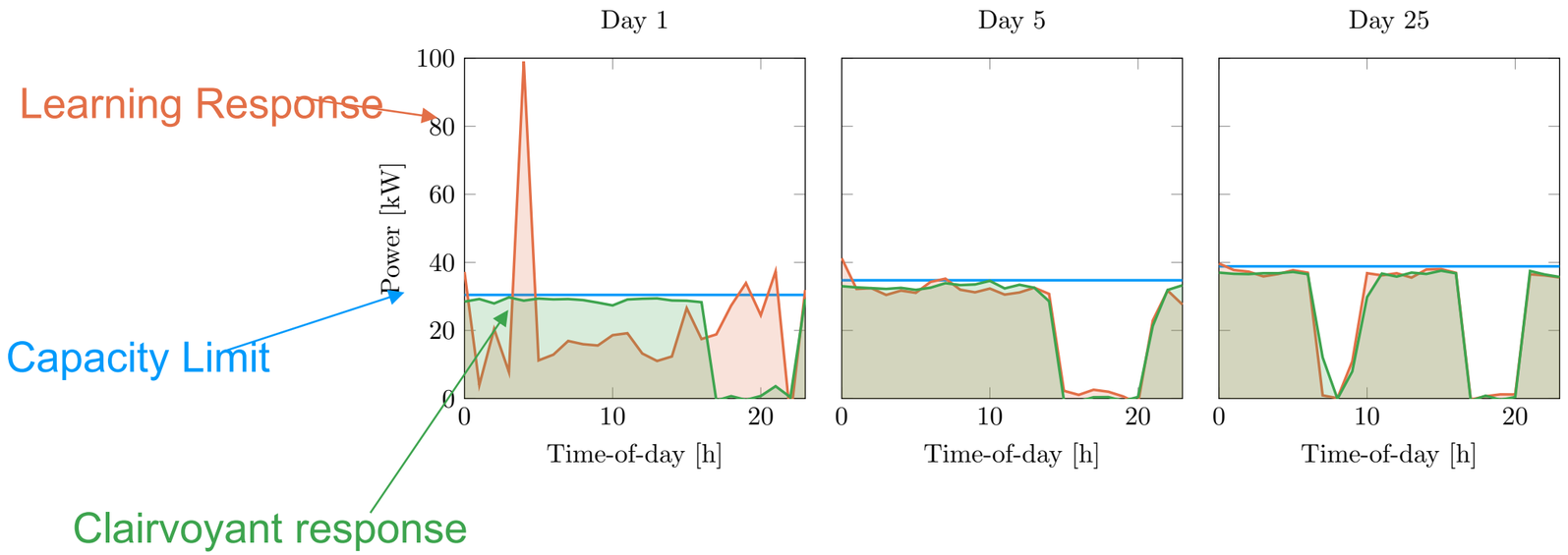
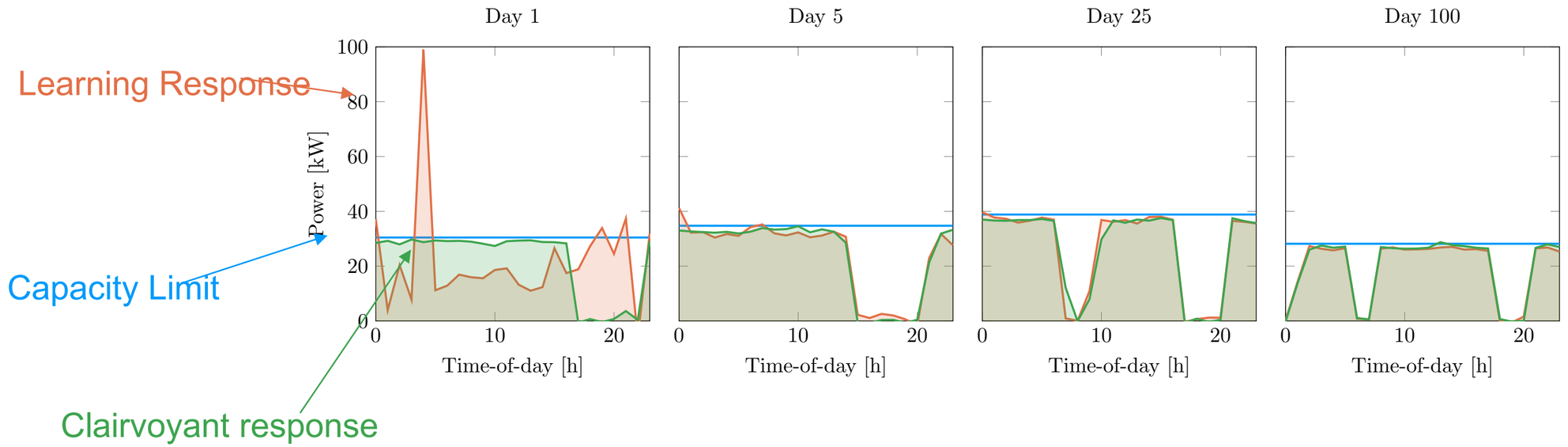
- By **day 5**, the major spikes and deviations are gone, but **we still exceed the limit**.
- From **day 25 onwards** we follow the capacity limit with minor violations



Community learns to follow capacity limits

- On **day 1** the community does a **poor job** of maintaining the capacity limitation.
- By **day 5**, the major spikes and deviations are gone, but **we still exceed the limit**.
- From **day 25 onwards** we follow the capacity limit with minor violations
- By **day 100** we match the clairvoyant response closely without violations



Key Takeaways

Learning algorithm that integrates bilevel programming and Thompson sampling to learn prosumer preferences while setting optimal prices.

Demonstrated that the algorithm **can achieve near-zero regret** and learn to reliably deliver a capacity limitation service.

References

How can energy communities provide grid services? A dynamic pricing mechanism with budget balance, individual rationality, and fair allocation

Bennevis Crowley, JK, and Lesia Mitridati

Applied Energy, vol. 382, Article no. 125154, March 2025

[link | arXiv | GitHub]

Learning prosumer behavior in energy communities: Integrating bilevel programming and online learning

Bennevis Crowley, JK, Lesia Mitridati, and Mahnoosh Alizadeh

Applied Energy, vol. 392, Article no. 125932, August 2025

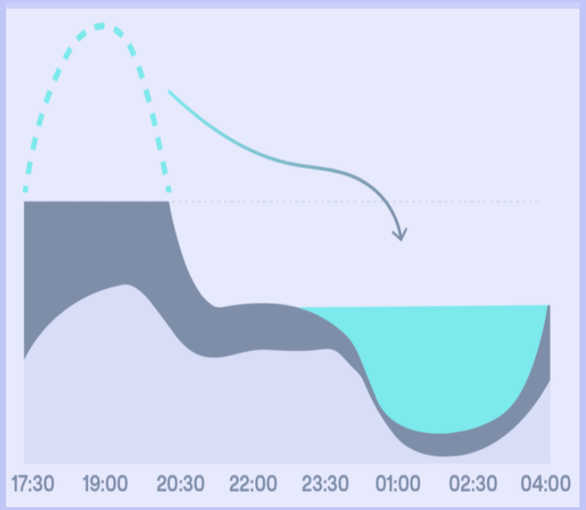
[link | arXiv | GitHub]

Thank you

Future Perspectives

Research direction 1

Quantify the benefits and viability of energy communities



Source: Ohme

Research direction 2

Efficiently coordinate prosumers in energy communities, under uncertainty on their preferences

Source: Wikipedia

(not in this talk)

Research direction 3

Ensure balance between prosumers' privacy and efficient & safe grid operations

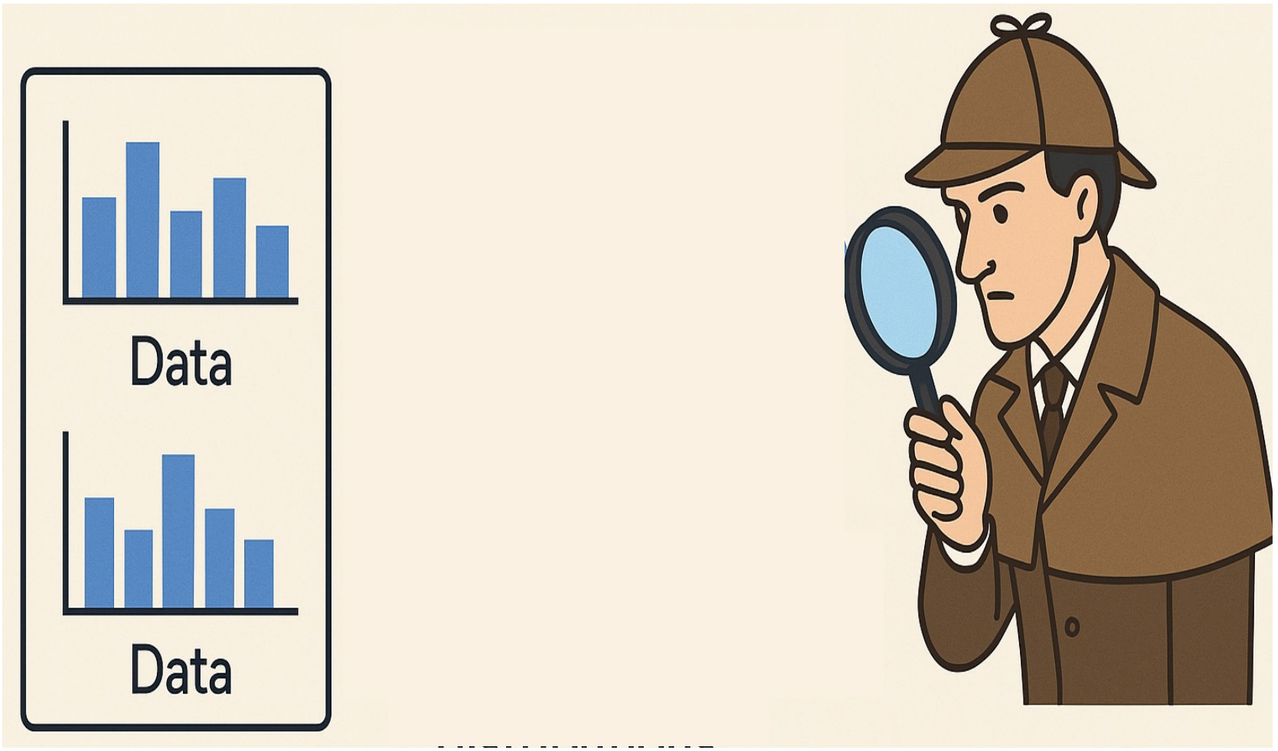
Source: ChatGPT

Motivation: Privacy and Cybersecurity

- **Joint community-based LEM** for energy and reserves provides a practical framework for harnessing CECs' flexibility
- **BUT they raise security and privacy concerns**

Standard LEMs (P2P and community-based markets)

- 👎 Centralized approaches require knowledge of sensitive prosumers information
- 👎 Unsafe communication & exchanges among members and community manager
- 👎 Sensitive information can be inferred even in decentralized markets

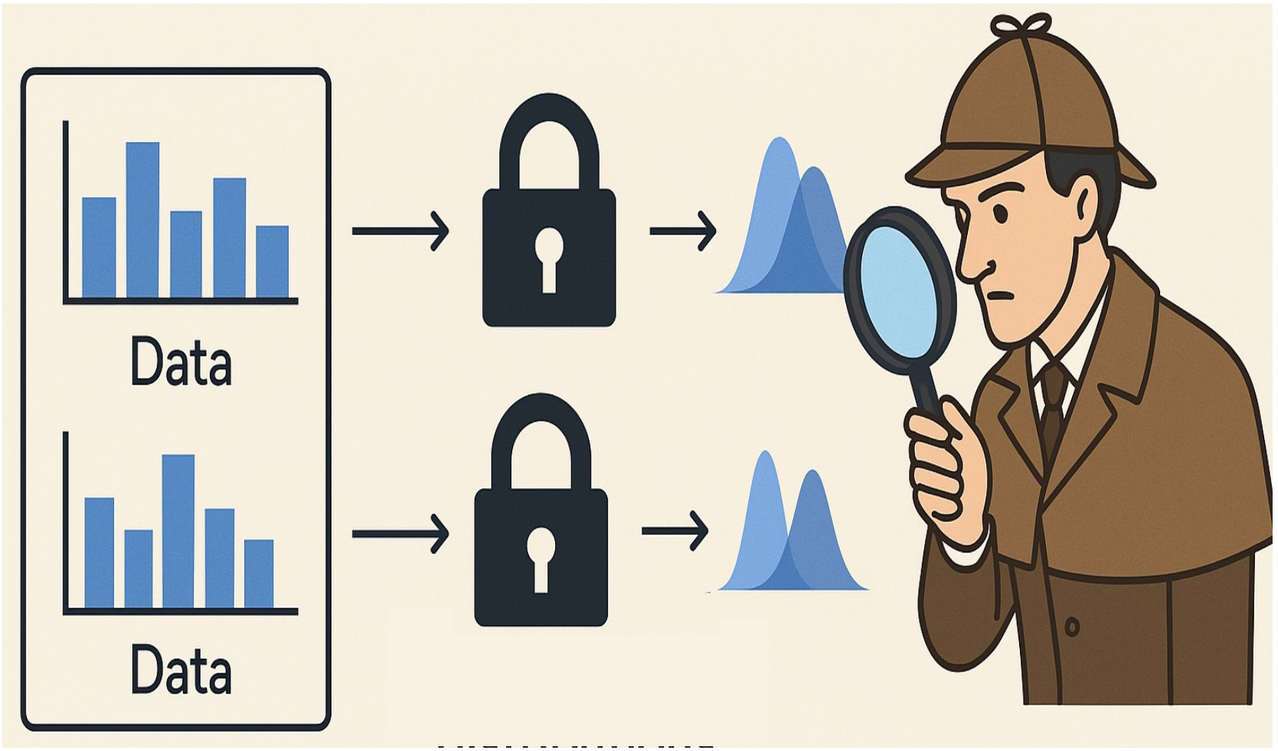


Motivation: Privacy and Cybersecurity

- **Joint community-based LEM** for energy and reserves provides a practical framework for harnessing CECs' flexibility
- **BUT they raise security and privacy concerns**

Privacy-Preserving and Secure LEM

- 👍 Privacy-preserving decentralized operation which convergences to centralized solutions
- 👍 Secure communication & exchanges



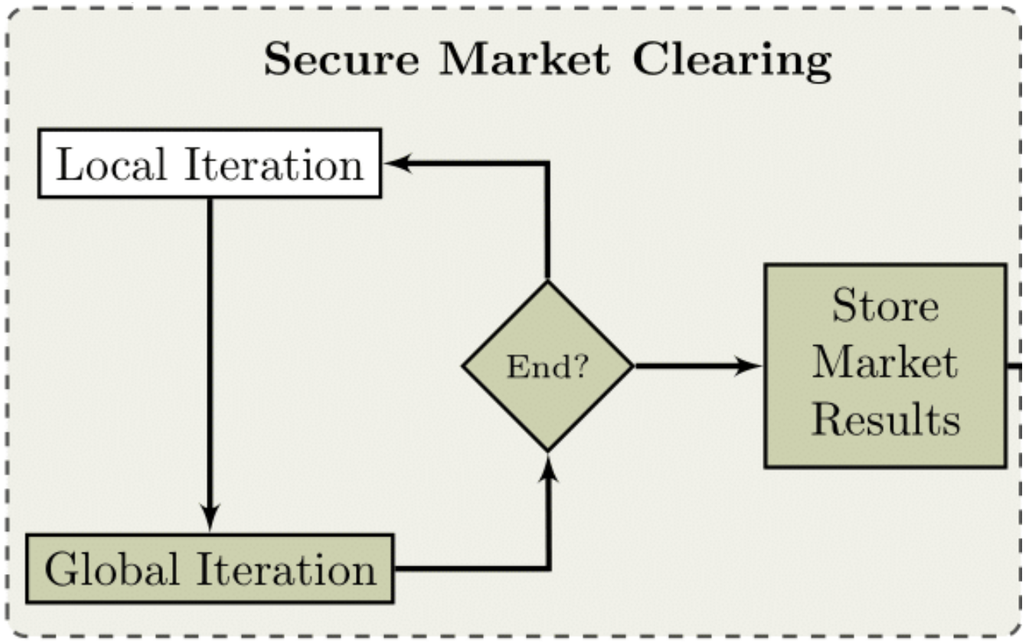
PPDMM Core Idea

Decentralized Market Clearing using **ADMM**, secured by **SMPC**

Consensus Alternating Direction Method of Multipliers (**ADMM**), iteratively solves:

1. Local optimisation of prosumers and DERs' dispatch
2. Global coordination to achieve consensus on the flows within the community
3. Convergence check

Risks of reconstructing the sensitive information of prosumers!

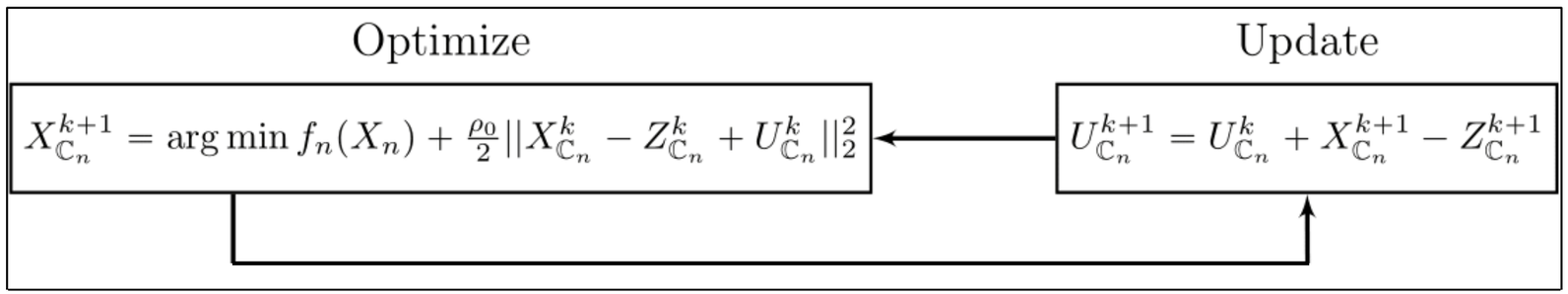


PPDMM Core Idea

Decentralized Market Clearing using **ADMM**, secured by **SMPC**

Secure Multi-Party Computation (**SMPC**) to secure ADMM updates:

ADMM update without SMPC:



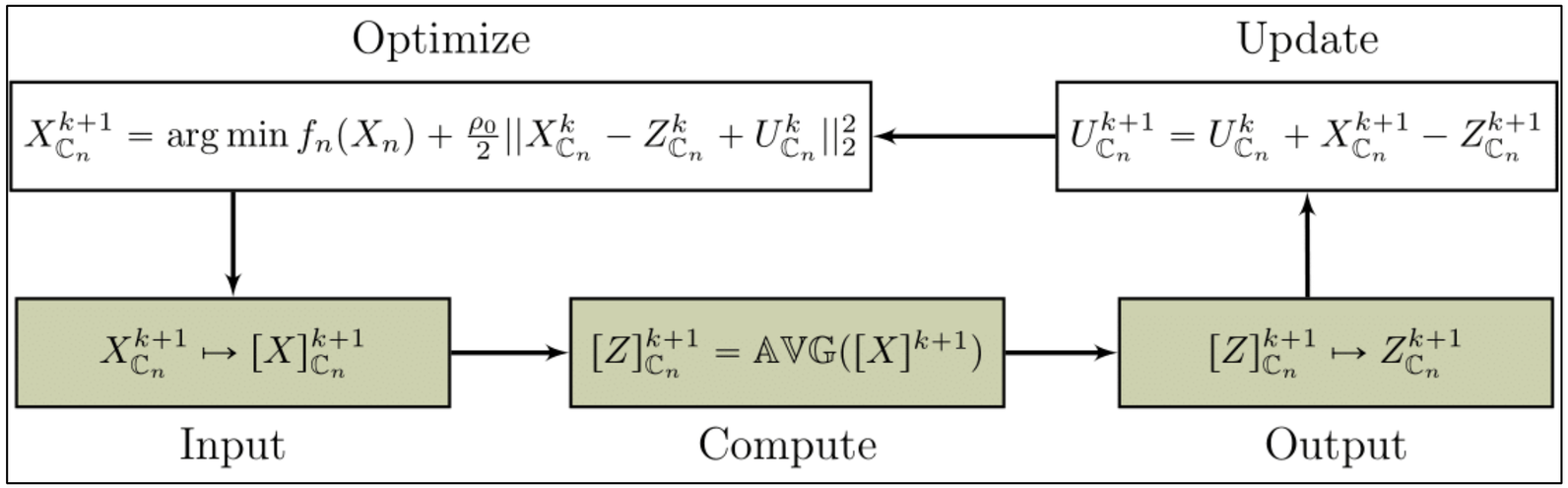
PPDMM Core Idea

Decentralized Market Clearing using **ADMM**, secured by **SMPC**

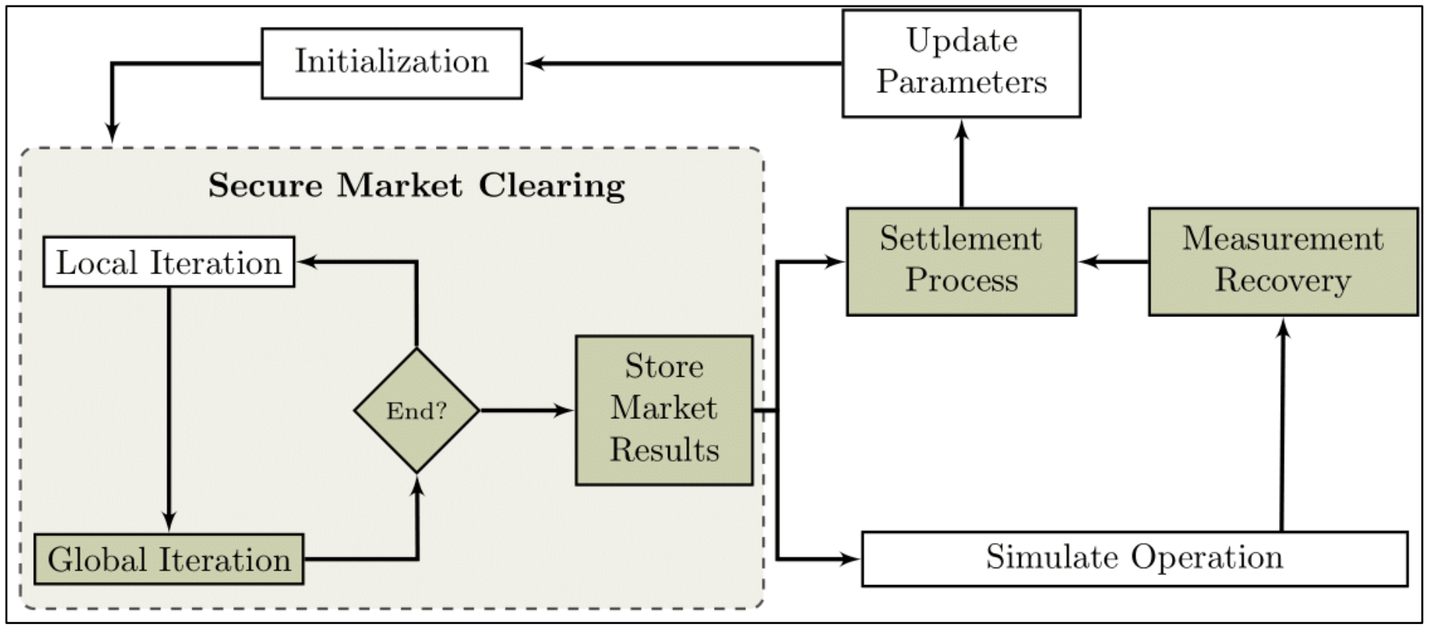
Secure Multi-Party Computation (**SMPC**) to secure ADMM updates:

1. Input Phase: **Shamir Secret-Sharing** with random polynomials
2. Compute Phase: **Algebraic Circuit** with Shares
3. Output Phase: Reconstruct results via **Lagrangian Interpolation**

ADMM update with SMPC:



Security Guarantees of PPDMM



Adversary Capabilities:

- **Passive (honest but curious)**: Follows protocol, trying to information
- **Static**: Corruption stays fixed throughout protocol
- **Threshold**: Only one unknown set of **t** corrupted participants (**n** total participants)

Threshold Security Guarantee of SMPC for considered passive adversary (Ben-Or, et al. 1988):

We can “securely evaluate any specification with perfect security” **if and only if t < n/2**

- With an **Honest Majority**, the PPDMM is **secure** against adversary!

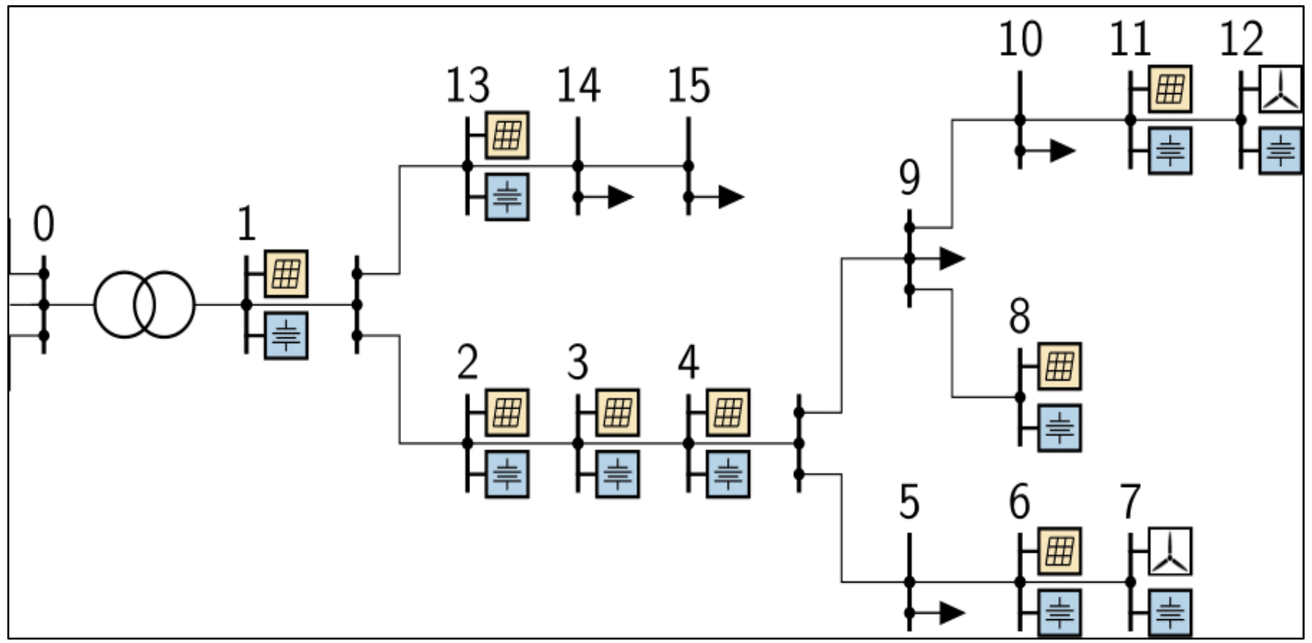
Case Study and Testing Methodology

Case Study:

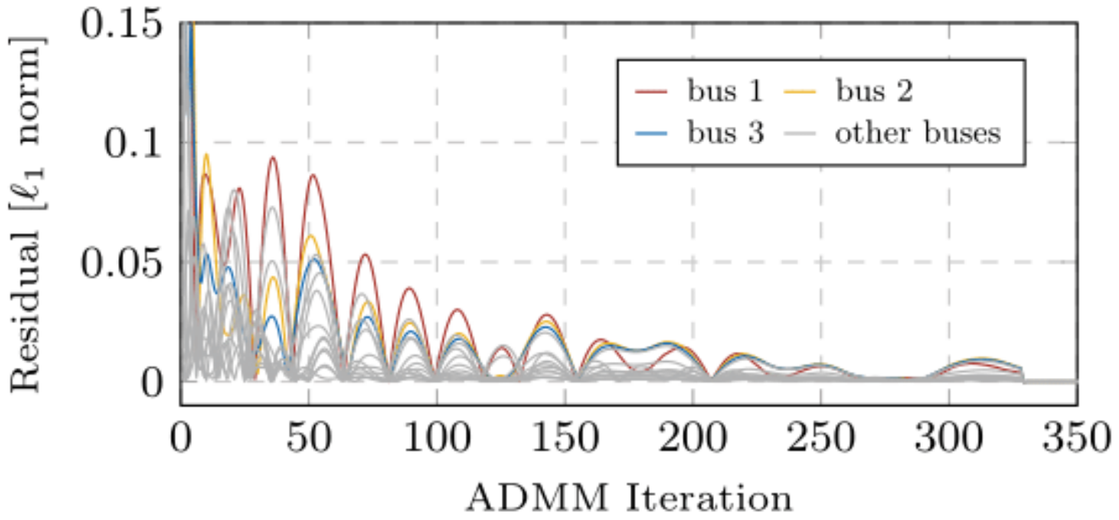
- CEC in 15-bus distribution network
- Flexible loads, solar, wind power, batteries
- Synthetic data sources for generation and demand

Compare 3 different solvers (centralised, ADMM, SMPC-basesed ADMM) in terms of:

- Computational complexity
- Quality of solutions.



Key Results of the PPDMM



	Centralized	ADMM	Secure ADMM
Time (min)	**0.49**	66.76	119.8
# iterations	1	595	593
Rel. accuracy (%)	0	1.8	4.21

Convergence behavior of Secure ADMM

- **Dampening** oscillatory behaviour typical for ADMM
- **Larger** oscillations closer to slack bus
- In-built trade-off between line flows and voltages **delay** eventual convergence

Computational Complexity & accuracy:

- **Centralized** solution is **fastest**, as it is single-shot
- **Secure** ADMM takes **twice** as long as insecure ADMM for **similar iterations and accuracy**