Data-driven distributed optimization, markets, and control for an IBR-rich grid edge

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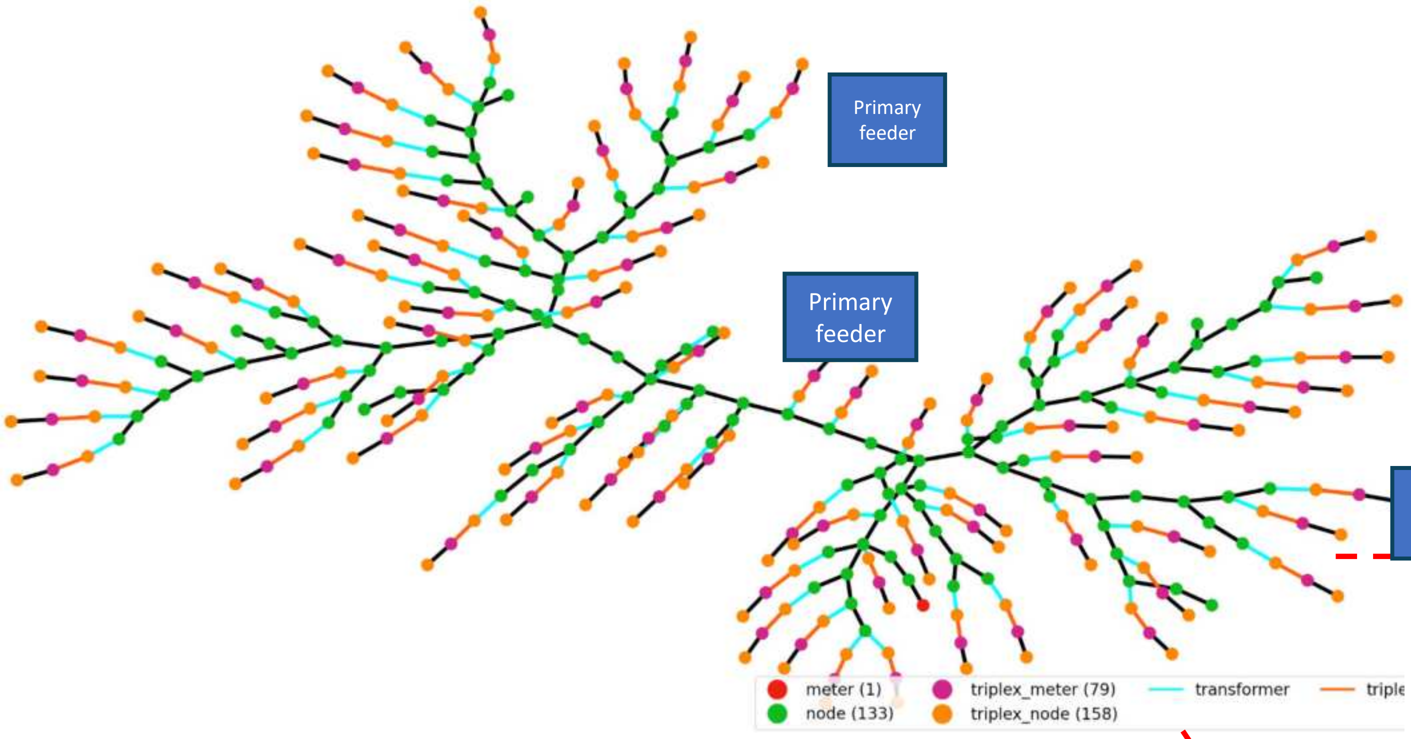
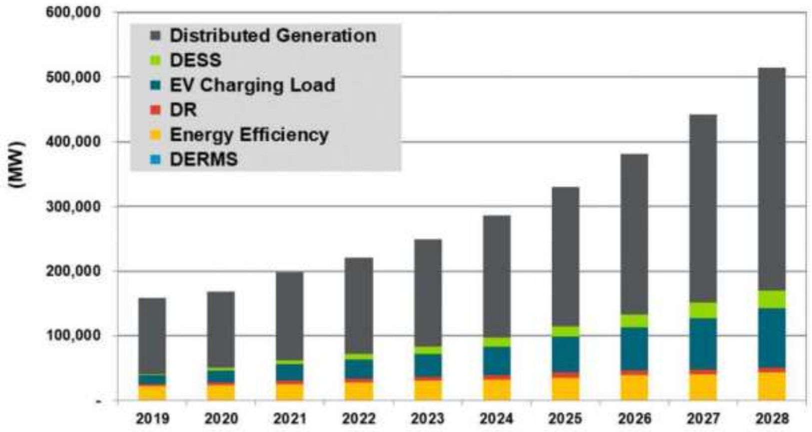
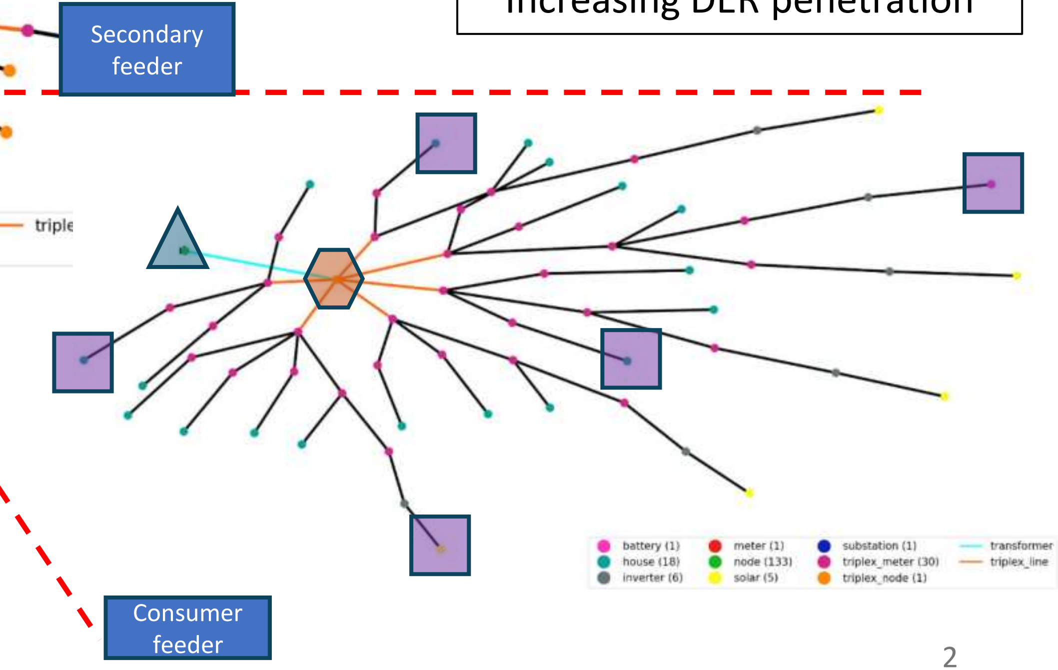
Grid edge becoming more complex, intelligent, capable





Increasing DER penetration



400 Secondary Feeders

1000 IoT devices
100 PVs (531.5 KW)
200 batteries

Typical distribution grid with many distributed energy resources (DERs) (modified IEEE-123 node feeder)

Source: PNNL Gridlab-D Modeling Team

A distributed paradigm

Urban distribution network: ~2 million nodes [1]

At grid's edge

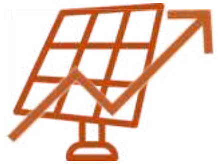
Intelligence + Control

119m smart meters in 2022 [2]

Communication

Internet of things

Renewables



Projected 6.7 GW solar in New England by 2028 [3]

Faster Timescales

Solar + Wind
Demand Response
milliseconds - minutes

- Resource Coordination: Distributed Optimization + Control
- Multiple stakeholders are present

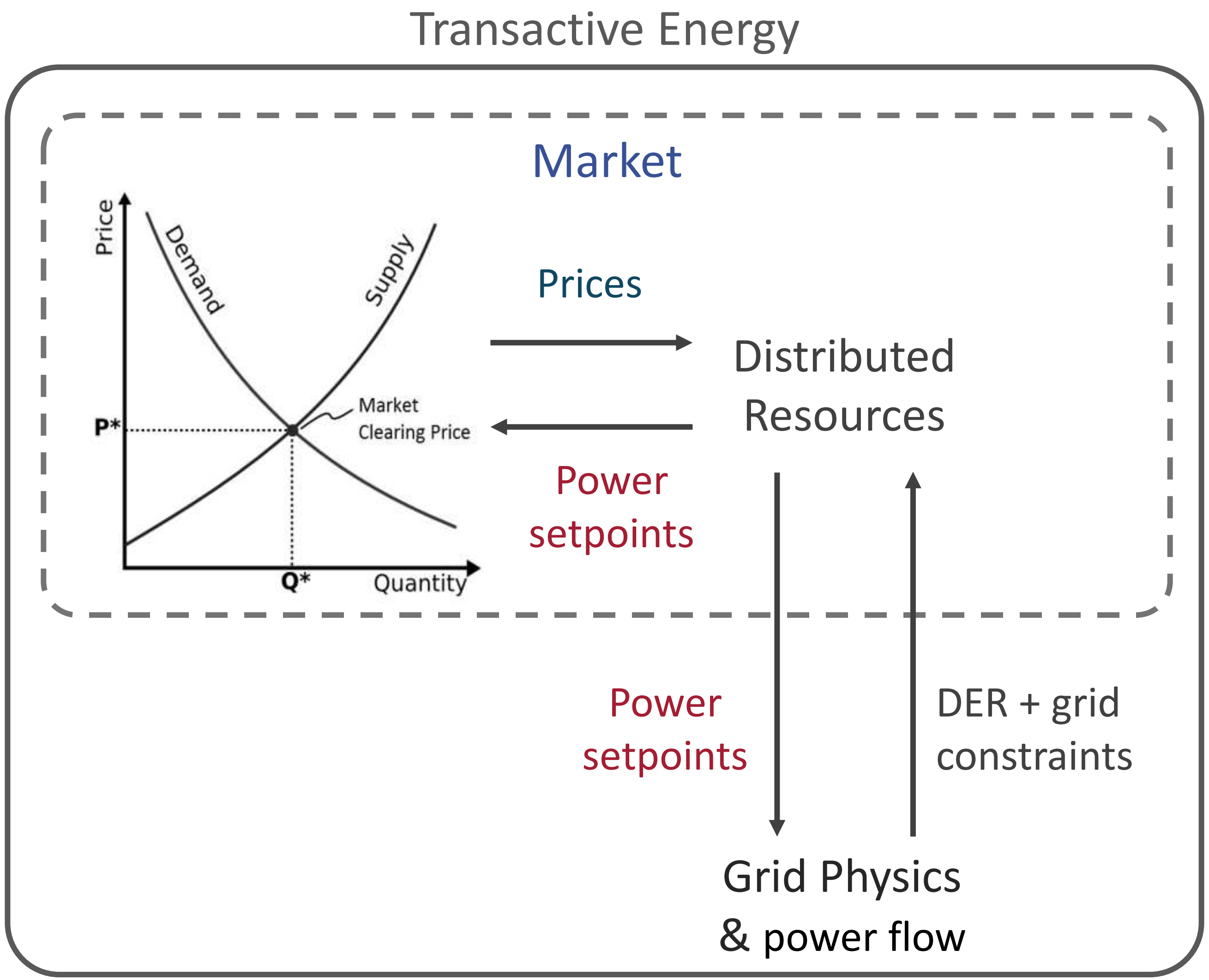
[1] M. Zhao et al. Trans. on Computer-Aided Design of Integrated Circuits and Systems, Feb. 2002
[2] EIA
[3] ISO-NE https://www.iso-ne.com/about/what-we-do/in-depth/solar-power-in-new-england-locations-and-impact.

Transactive Energy

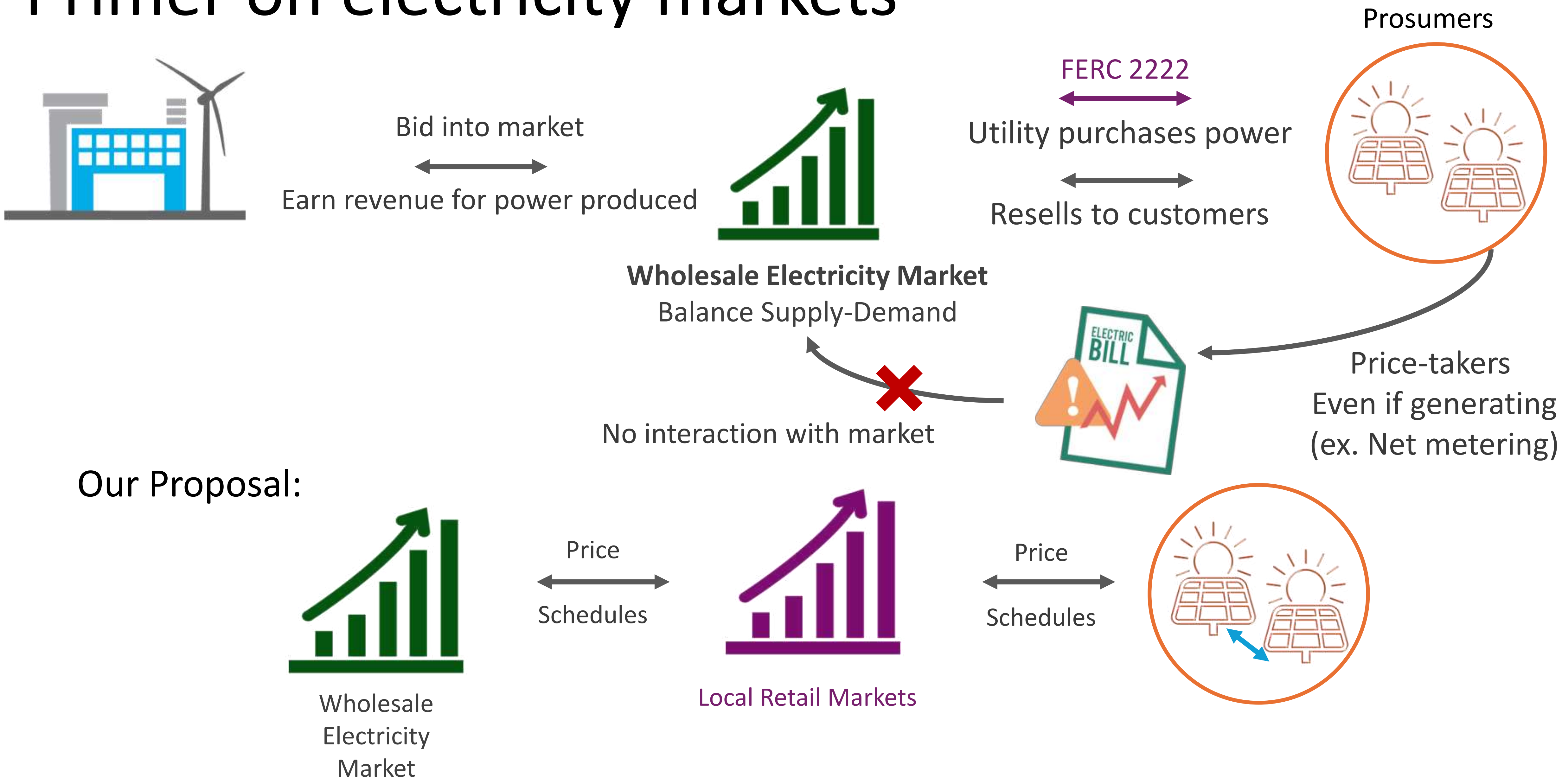
Use markets & prices to influence desired behaviours from various autonomous, independent agents at the grid edge, at fast timescales

Efficient integration of Distributed Energy Resources possible with a transactive design:

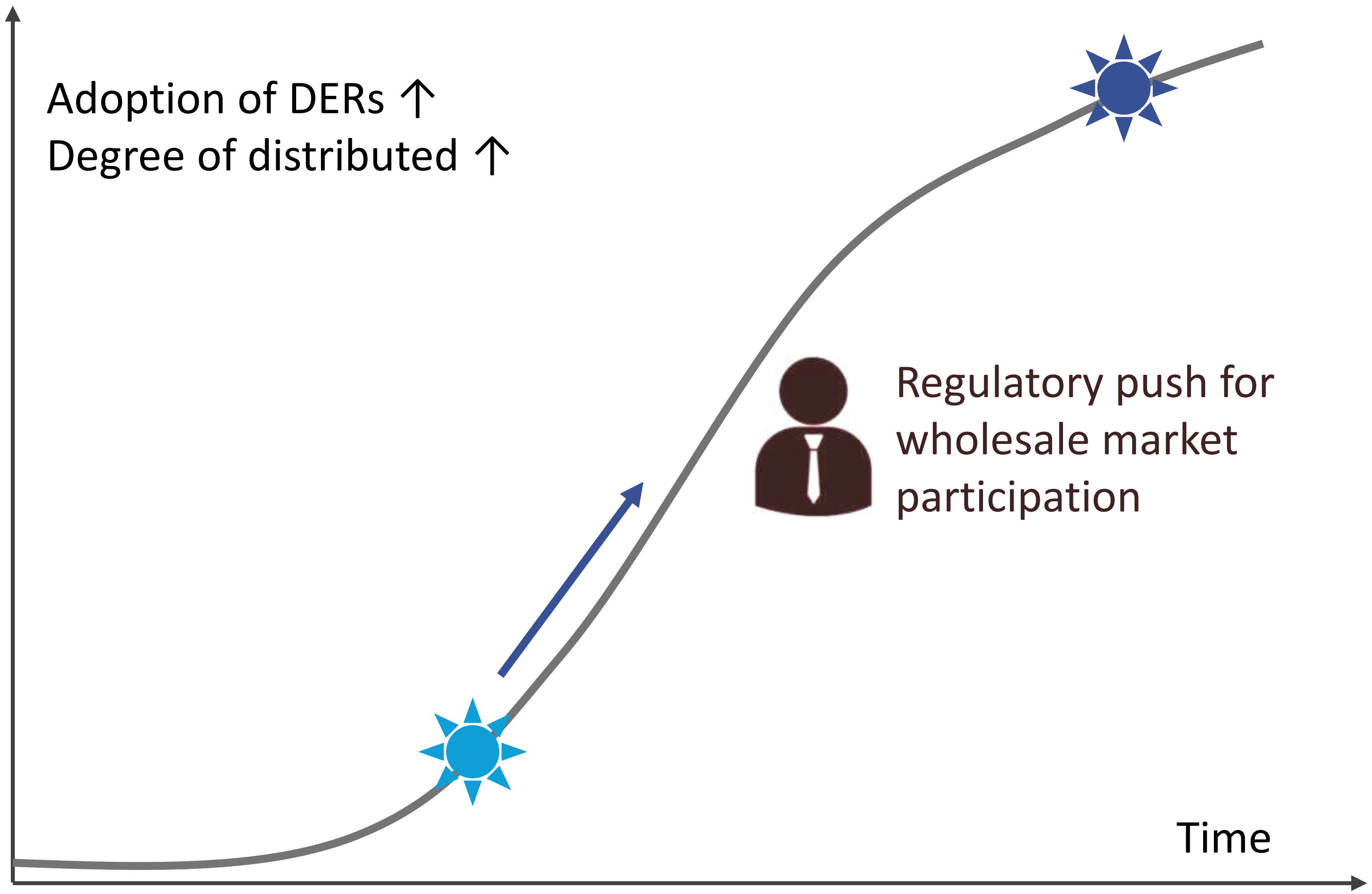
- **Flexible loads** (thermostats, water heaters)
- Distributed generation (rooftop **solar, wind**)
- Storage (**EVs, batteries**)



Primer on electricity markets



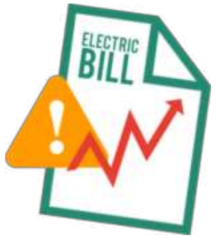
Why local retail electricity markets?



Gaps in Existing Programs

Wholesale

- Retail and wholesale differ
- Prohibitive costs for small resources
- Limiting participation requirements [1]



Retail

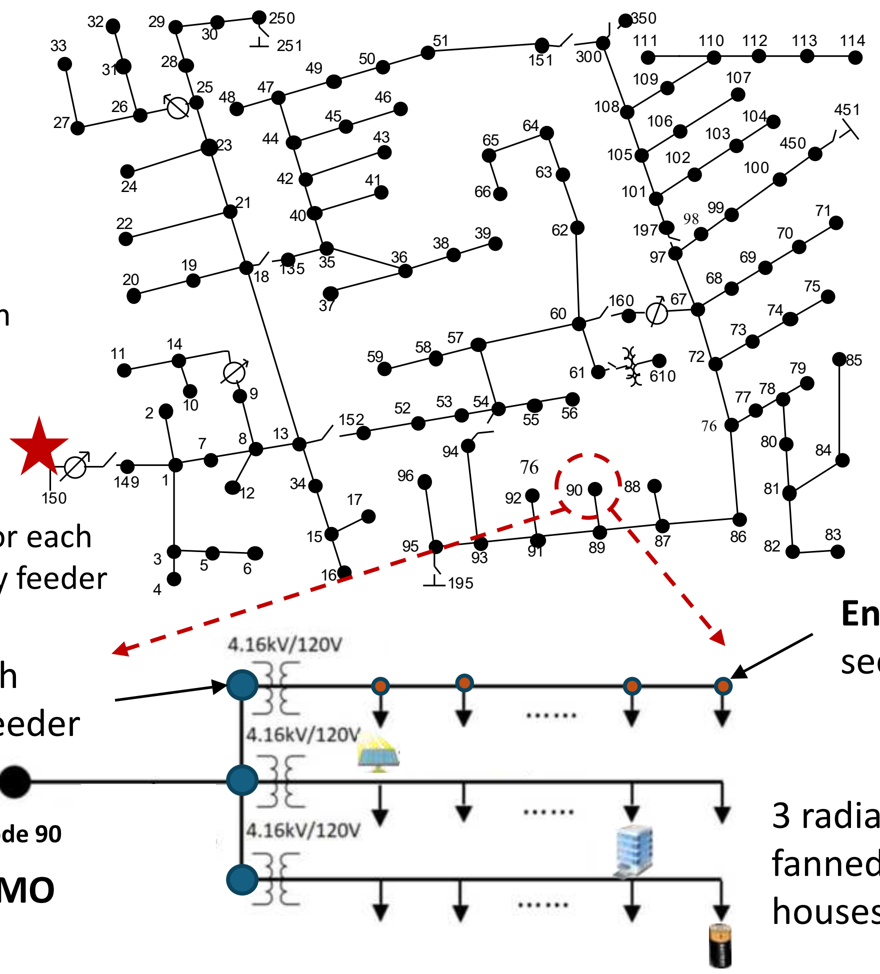
- Retail markets do not exist
- Fixed retail prices are inefficient
- Over- or under-compensation [2,3]

Vary spatially + temporally

Fully integrate DERs into the network
using **distributed & decentralized** local retail markets

[1] J. Gundlach and R. Webb. "Distributed energy resource participation in wholesale markets: Lessons from the California ISO", 2018
[2] Newell, S and Ahmad Fi "Dynamic Pricing: Potential Wholesale Market Benefits in New York" *The Brattle Group* (2009).
[3] L.V. Wood. "Why net energy metering results in a subsidy: The elephant in the room." 2016

Hierarchical local electricity markets (LEM)



Primary feeder distribution network (IEEE 123 taxonomy feeder system)

DSO at substation (Connection to transmission system)

SMO for each primary feeder node

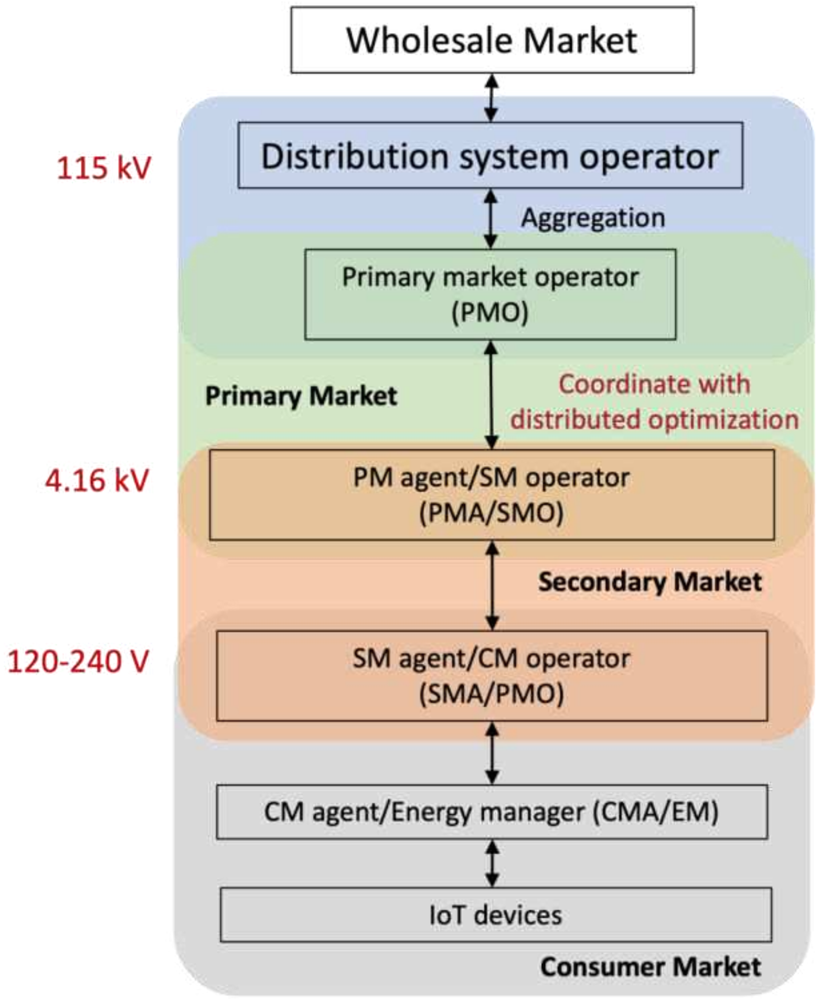
PMO for each primary feeder

Energy managers at each secondary feeder node

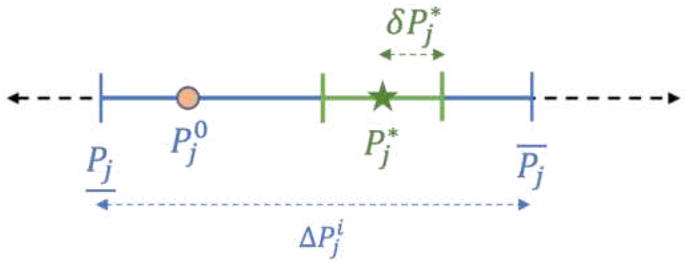
SMA for each secondary feeder

3 radial secondary feeders (SMAs) fanned out to each node with houses, PV, battery, EV etc.

IoT – EV/HVAC/Critical loads etc.



Secondary market (SM)



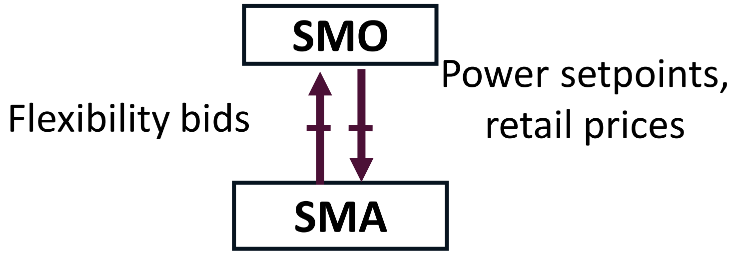
$$\min_{\vec{s_j}} \sum_j \begin{aligned} & w_1\left(\beta_j^P\left(P_j - P_j^0\right)^2 + \beta_j^Q\left(Q_j - Q_j^0\right)^2\right) \\ & + w_2\left(\mu_j^P P_j + \mu_j^Q Q_j\right) \\ & - w_3\left(\delta P_j + \delta Q_j\right) \\ & - w_4 \boxed{RS_j(t)} \left(\left(P_j\right)^2 + \left(Q_j\right)^2\right) \end{aligned}$$

Min: disutility to SMA_j

Min: net cost to SMO

Max: aggregate flexibility & reliability

Resilience score



Subject to:

- Device operating and flexibility limits (P and Q limits)
- Budget balance
- Price cap for retail prices
- Lossless power balance

- Multi-objective optimization via hierarchical approach
- Can also extend this to multiple phases

- **IoT trustability score (TS)**: Captures possibly of agents being compromised. Based on IoT network traffic patterns & cyber anomalies or vulnerabilities
- **Commitment score (CS)**: Measures how reliably agents will follow through & meet their contractual commitments
- **Resilience score (RS)** combines both to provide overall situational awareness

$$RS_j = CS_j + (1-\alpha)TS_j, 0 \leq \alpha \leq 1$$

$0 \leq RS \leq 1$ (RS closer to 1 = more resilient)

*Nair et al., TSG, 2022

Primary market: AC optimal power flow

- Branch flow (DistFlow) model
- Balanced, single-phase, radial network
- 2nd order cone convex relaxation

$$\min\ f(x)$$

Subject to:

$$v_j - v_i = (R_{ij}^2 + X_{ij}^2) l_{ij} - 2(R_{ij}P_{ij} + X_{ij}Q_{ij})$$

$$P_{ij} = R_{ij} l_{ij} - P_j + \sum_{k \in \{k_j\}} P_{jk}$$

$$Q_{ij} = X_{ij} l_{ij} - Q_j + \sum_{k \in \{k_j\}} Q_{jk}$$

$$P_{ij}^2 + Q_{ij}^2 \leq v_i l_{ij}$$

$$P_j \in [\underline{P_j}, \overline{P_j}],\ Q_j \in [\underline{Q_j}, \overline{Q_j}]$$

$$v_j \in [\underline{v_j}, \overline{v_j}]$$

where $l_{ij} = |I_{ij}|^2$ *and* $v_i = |V_i|^2$.

- Current injection model
- Unbalanced, 3-phase, radial/meshed network
- McCormick envelopes convex relaxation

$$\min_x f(x)$$

$$I^R = \mathrm{Re}(YV)$$

$$I^I = \mathrm{Im}(YV)$$

$$P_i^\phi = V_i^{\phi,R} I_i^{\phi,R} + V_i^{\phi,I} I_i^{\phi,I} \quad \forall i \in \mathcal{N}, \phi \in \mathcal{P}$$

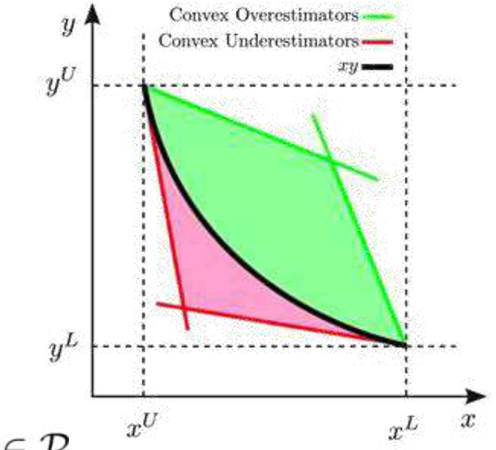
$$Q_i^\phi = -V_i^{\phi,R} I_i^{\phi,I} + V_i^{\phi,I} I_i^{\phi,R} \quad \forall i \in \mathcal{N}, \phi \in \mathcal{P}$$

$$\underline{V_i^\phi}^2 \leq \left(V_i^{\phi,R}\right)^2 + \left(V_i^{\phi,I}\right)^2 \leq \overline{V_i^\phi}^2 \quad \forall i \in \mathcal{N}, \phi \in \mathcal{P}$$

$$\underline{P_i^\phi} \leq P_i^\phi \leq \overline{P_i^\phi} \quad \forall i \in \mathcal{N}, \phi \in \mathcal{P}$$

$$\underline{Q_i^\phi} \leq Q_i^\phi \leq \overline{Q_i^\phi} \quad \forall i \in \mathcal{N}, \phi \in \mathcal{P}$$

$$(I_{ij}^R)^2 + (I_{ij}^I)^2 \leq \overline{I_{ij}}^2 \quad \forall i \in \mathcal{N}, \phi \in \mathcal{P}$$



Ferro et al., IFAC 2020; Nair et al., TSG, 2022; Nair et al., CCTA 2023

Distributed optimization: Proximal atomic coordination (PAC)

$$\min_{x \in \mathbb{R}^n} \sum_{i=1}^{n} f_i(x_i) \quad s.t. \quad Gx = b, \quad Hx \le d$$

Atomization

$$\min_{a_j} \sum_{j=1}^{k} f_j(a_j) \quad s.t. \quad G_j a_j = b_j, \quad H_j a_j \le d_j, \quad B_j a = 0 \qquad \forall j \in k$$

Lagrangian

$$\mathcal{L}(a, \eta, \nu) = \sum_{j \in K} \left[f_j(a_j) + \eta_j^T (G_j a_j - b_j) + \nu^T B^j a_j \right]$$

$$\triangleq \sum_{j \in K} \mathcal{L}_j(a_j, \eta_j, \nu)$$

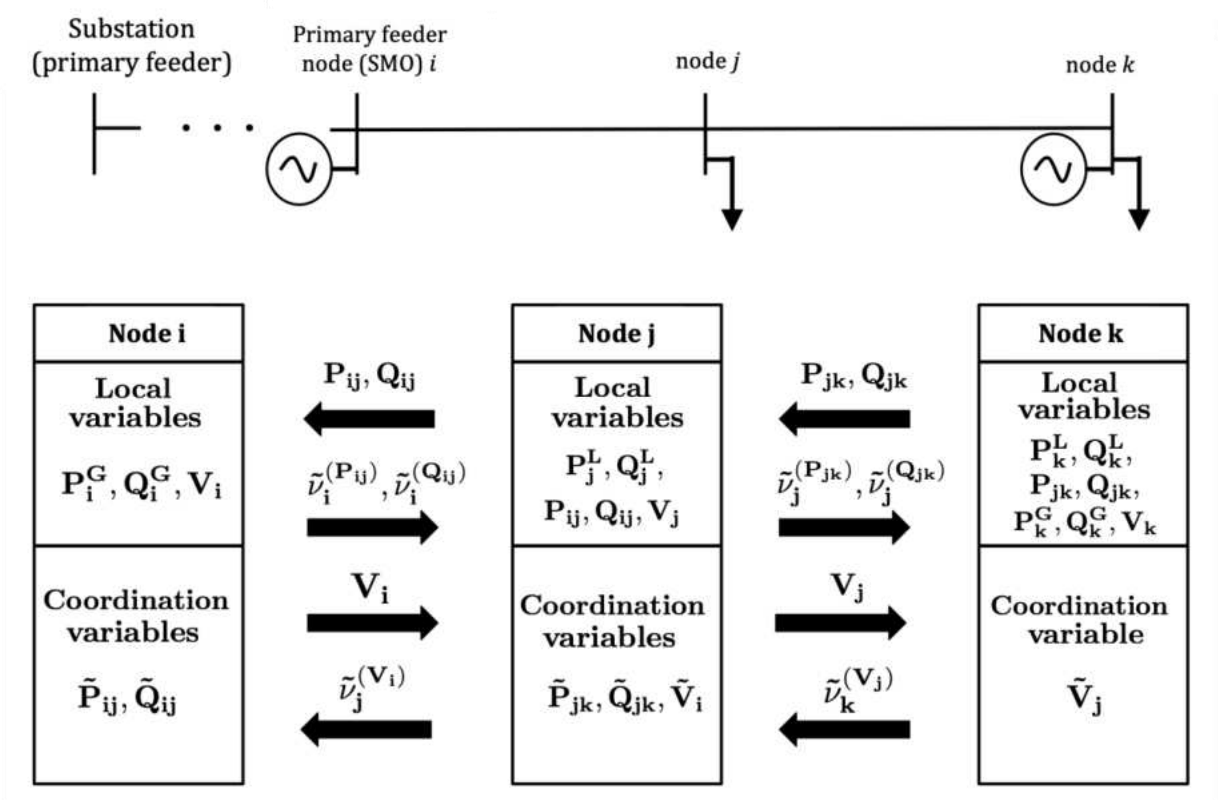
$$a_j[\tau+1] = \underset{a_j}{\operatorname{argmin}} \left\{ \mathcal{L}_j(a_j, \hat{\mu}_j[\tau], \hat{\nu}[\tau]) + \frac{1}{2\rho} \|a_j - a_j[\tau]\|_2^2 \right\}$$

$\mu_j[\tau+1] = \mu_j[\tau] + \rho\gamma_j \tilde{G}_j a_j[\tau+1]$ and $\hat{\mu}_j[\tau+1] = \mu_j[\tau+1] + \rho\hat{\gamma}_j[\tau+1]\tilde{G}_j a_j[\tau+1]$

Communicate $\{a_j[\tau+1]\}$ with neighbours, for all j

$\nu_j[\tau+1] = \nu_j[\tau] + \rho\gamma_j [B]_j a[\tau+1]$ and $\hat{\nu}_j[\tau+1] = \nu_j[\tau+1] + \rho\hat{\gamma}_j[\tau+1][B]_j a[\tau+1]$

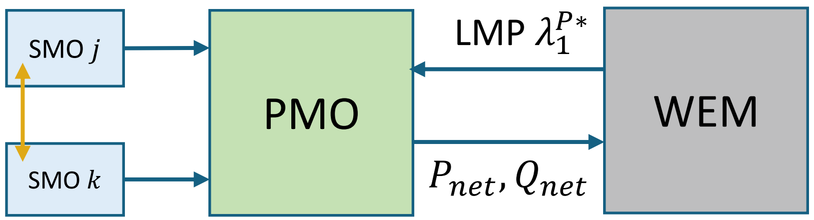
Communicate $\{\hat{\nu}_j[\tau+1]\}$ with neighbours, for all j



Romvary et al. IEEE TAC, 2021; Haider et al., TSG 2021

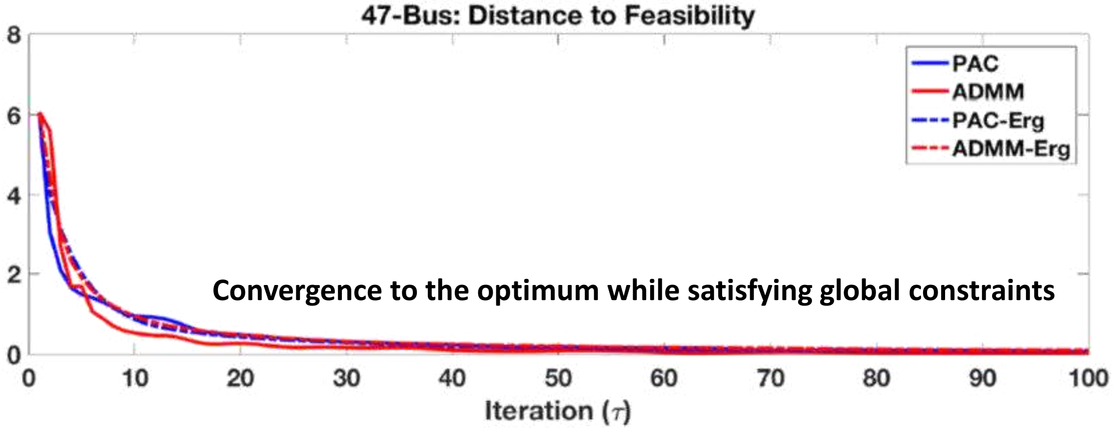
Primary retail market clearing using SMO bids & PAC

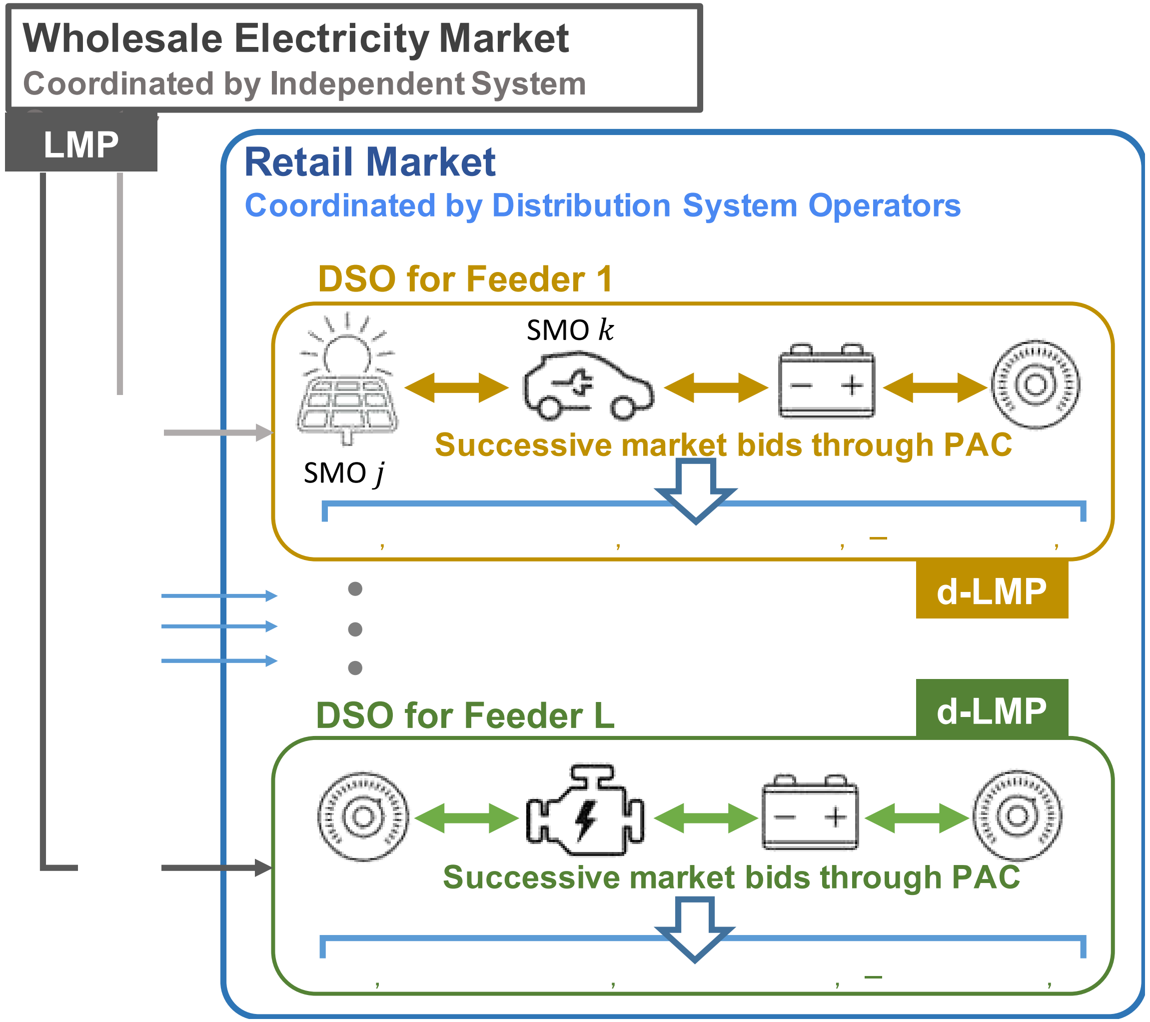
Every 1 min   average during 5min



$P_j^{G^*}, Q_j^{G^*}, P_j^{L^*}, Q_j^{L^*}, j \in \mathcal{B} = 1, \dots, 123$

d-LMPs $\mu_j^{P^{G^*}}, \mu_j^{Q^{G^*}}, \mu_j^{P^{L^*}}, \mu_j^{Q^{L^*}}, j \in \mathcal{B} = 1, \dots, 123$

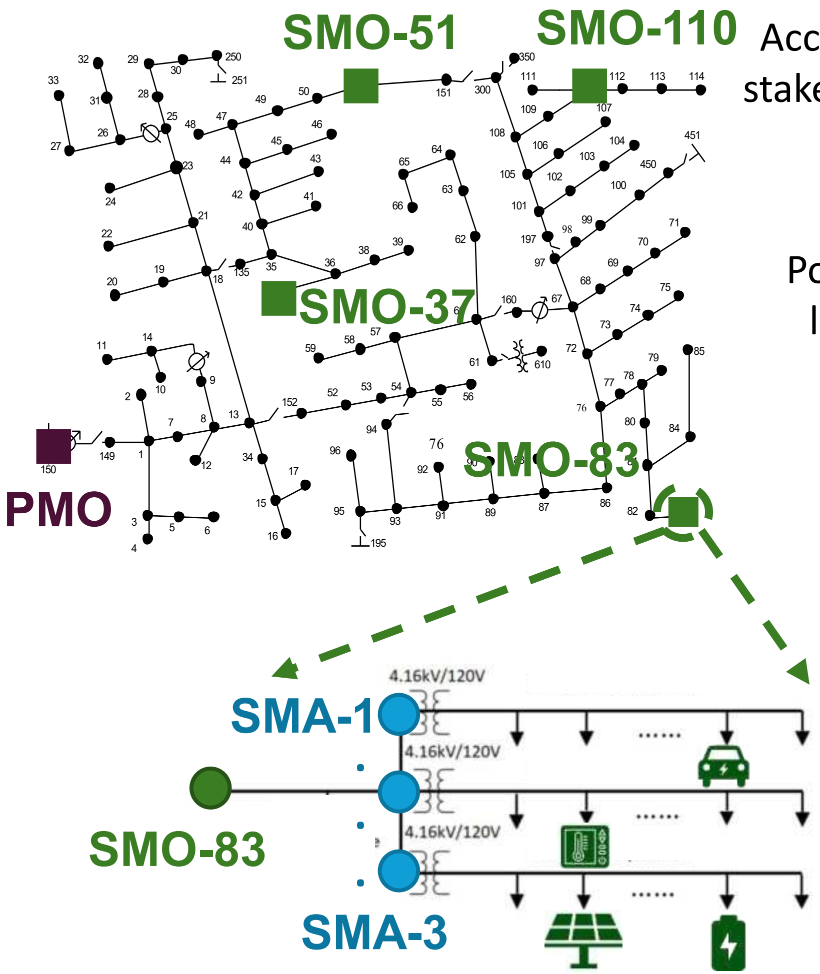




- Fully distributed
- Computationally tractable
- Reduced communication requirements
- Preserve data privacy (for dual variables)

* Haider et al., ADAPEN 2022; Romvary et al. IEEE TAC, 2021; Haider et al., TSG 2021

LEM summary

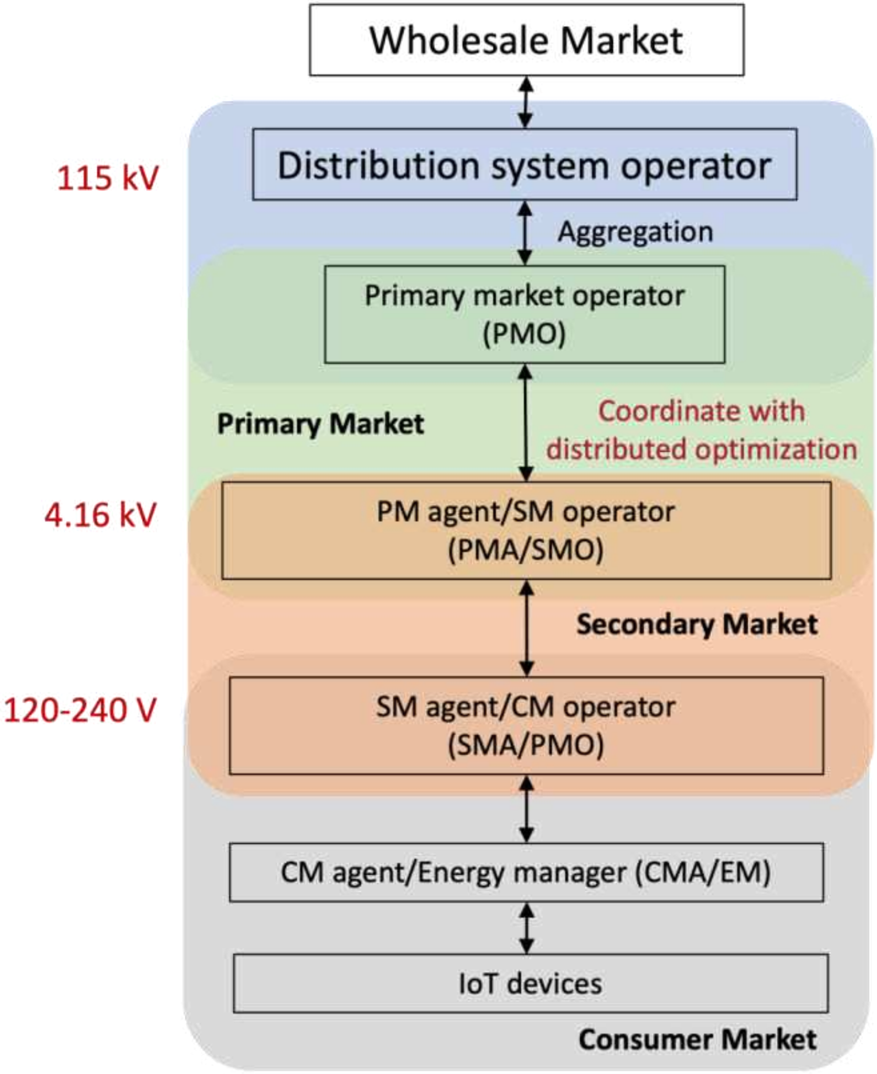


Hierarchical paradigm:
Accommodate concerns for market stakeholders and grid operators at all levels of the grid

Power physics and distribution-level constraints (Distributed optimization)

Commitment reliability, utility, flexibility & budget constraints (Decentralized optimization)

Prosumer preferences & end-user privacy (Game theory)

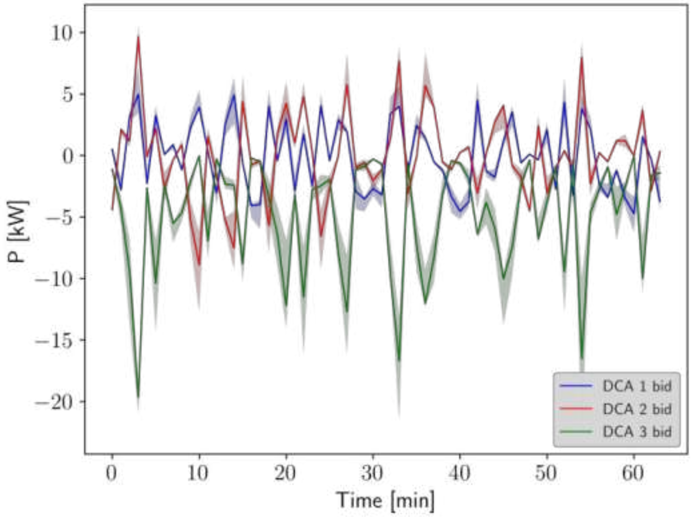


LEM provides situational awareness at both primary & secondary feeder levels

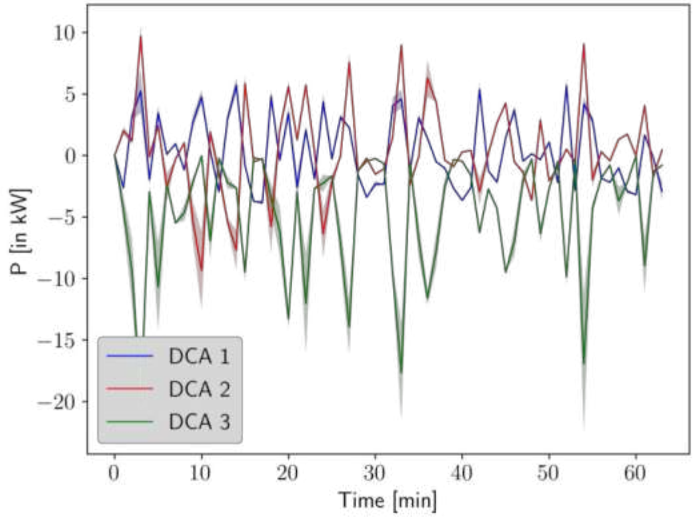
*Haider et al., TSG 2021; Nair et al., TSG 2022; Nair et al., CCTA 2023; Nair et al., ICCPS 2024.

Example secondary market results

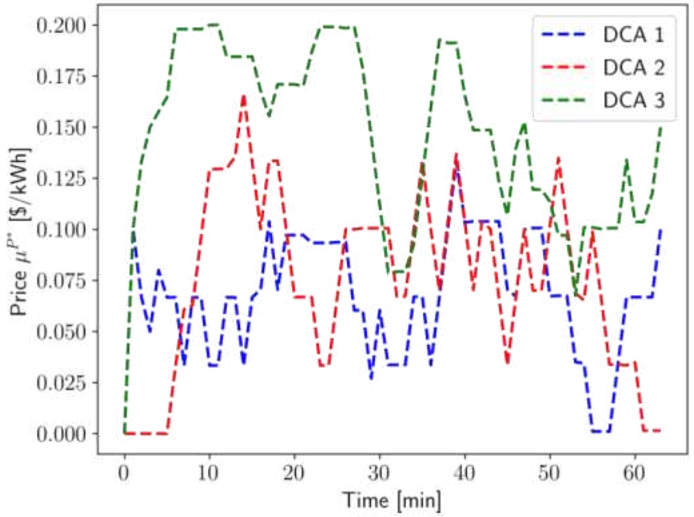
SMA bids into SM at node 7

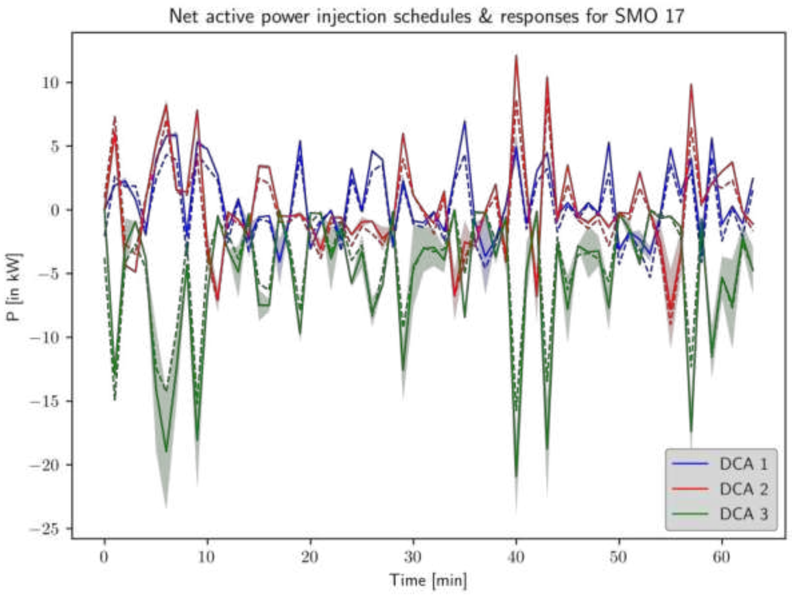


SMA schedules from SMO 7

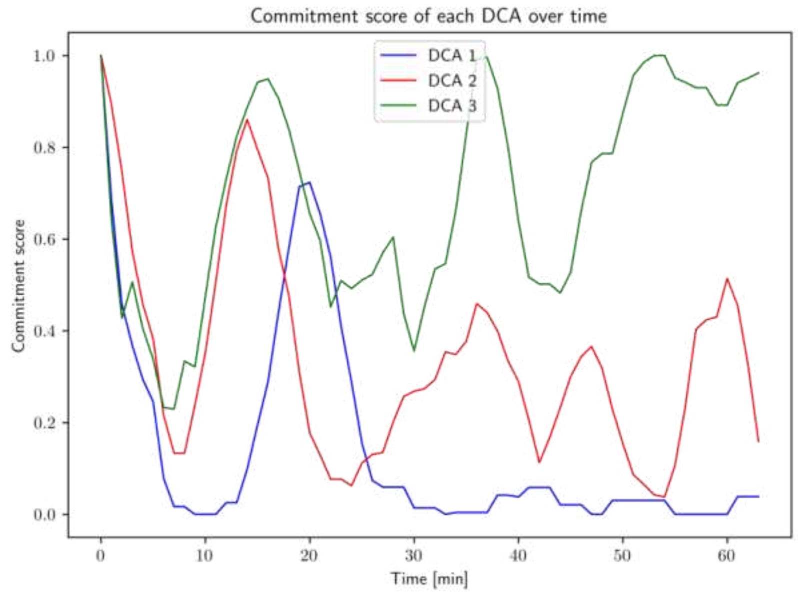


Local retail tariffs





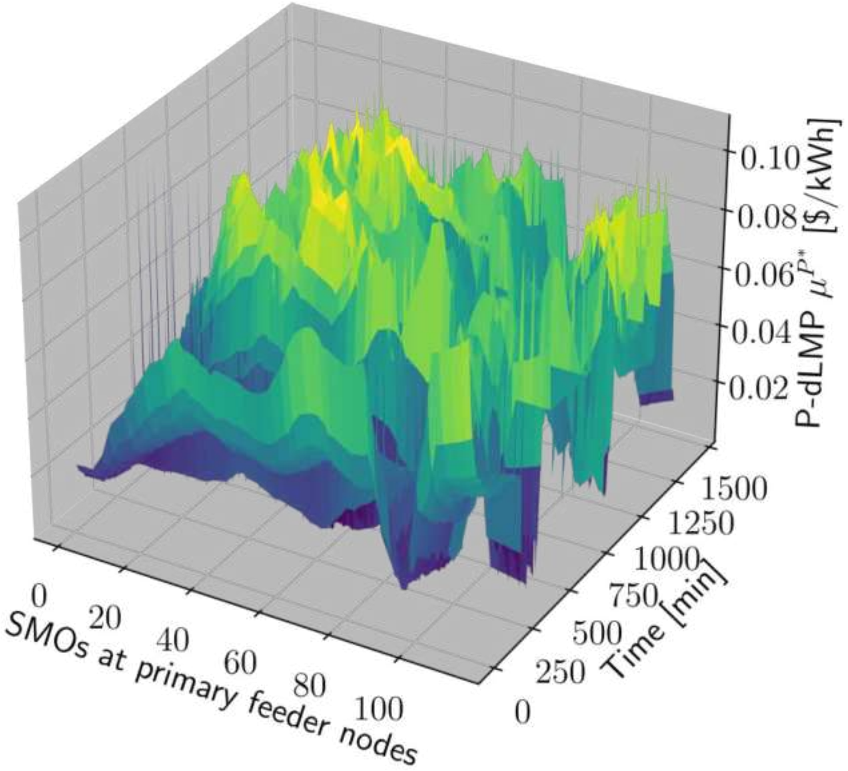
Use SMAs' actual responses to update commitment scores

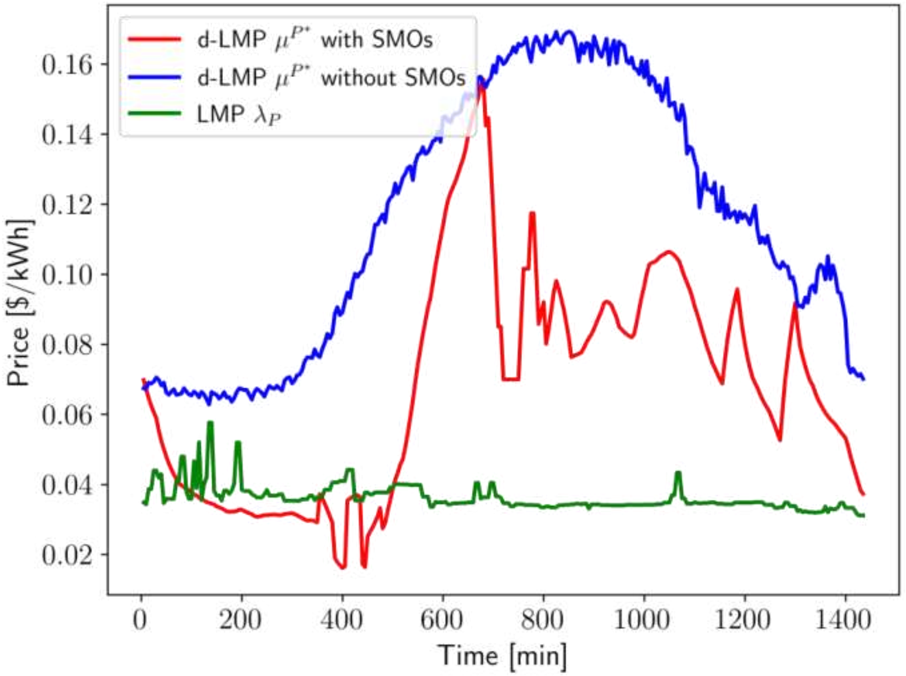


Retail prices across PM and SM

- PM and SM provide granular spatially and temporally varying prices

- Average dLMP across network better reflects real-time operational flexibility with SMO
  → Lower overall costs

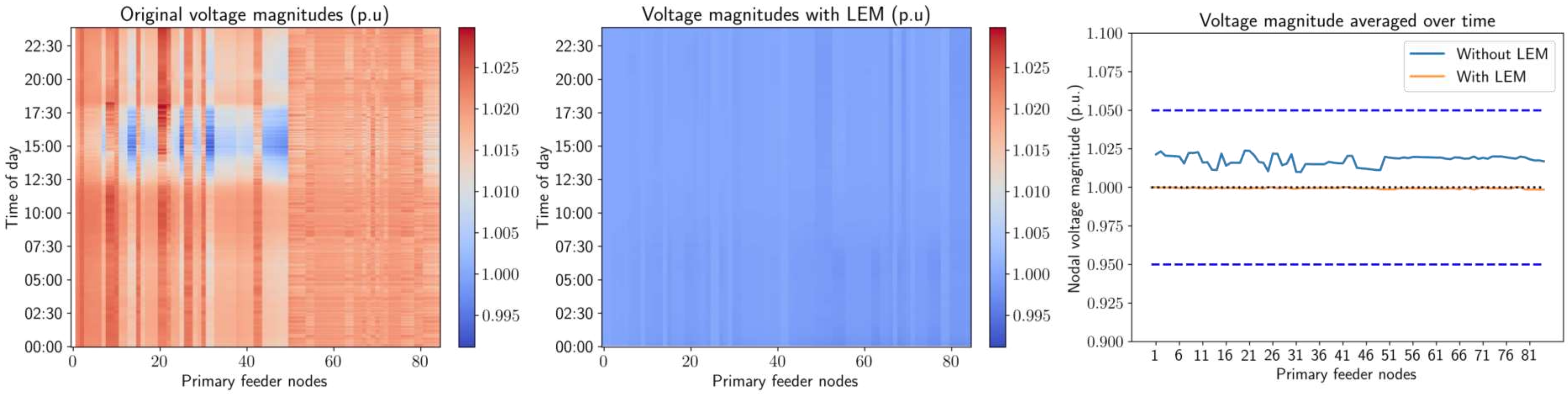




[$/kWh]	Hierarchical LEM	Primary LEM only	No LEM
Avg. dLMP	0.064	0.116	N/A
Avg. local tariff	0.082	0.116	0.129 [1]

[1] Eversource

LEM for voltage regulation



LEM (SM + PM) improves overall voltage profile → More uniform + closer to 1 p.u.

LEM enables accurate grid service pricing

KCL & KVL combined (Ohm's law)

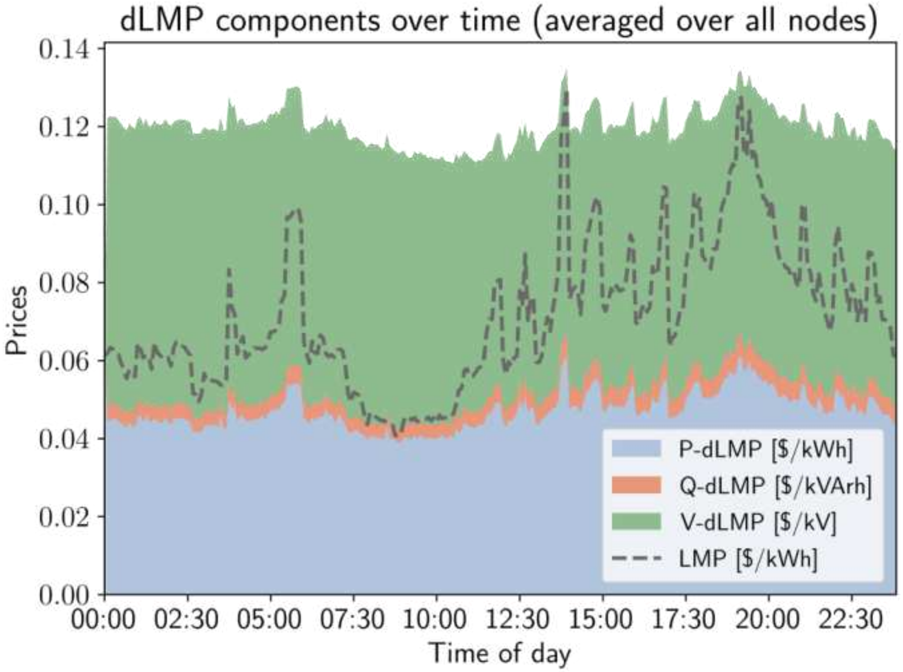
$$\left\{\begin{aligned} I^R &= \mathrm{Re}(YV) \\ I^I &= \mathrm{Im}(YV) \end{aligned}\right\}$$

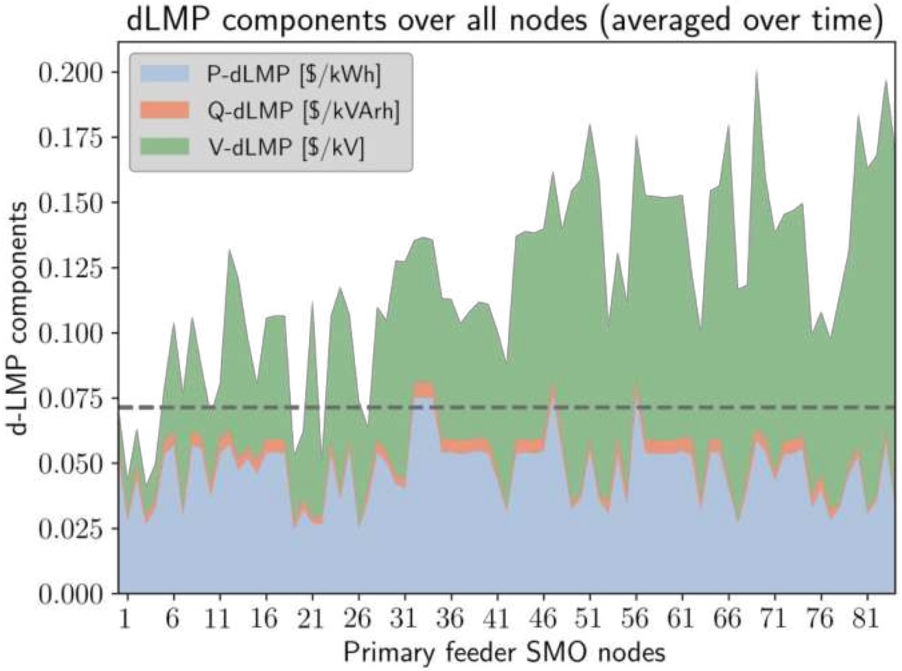
Value of voltage support $\mathrm{Re}(\lambda_V)$

Power balance

$$\left\{\begin{aligned} P_i^\phi &= V_i^{\phi,R} I_i^{\phi,R} + V_i^{\phi,I} I_i^{\phi,I} \quad \forall i \in \mathcal{N}, \phi \in \mathcal{P} \\ Q_i^\phi &= -V_i^{\phi,R} I_i^{\phi,I} + V_i^{\phi,I} I_i^{\phi,R} \quad \forall i \in \mathcal{N}, \phi \in \mathcal{P} \end{aligned}\right\}$$

P & Q "energy" prices λ_P, λ_Q





"Bundled" tariff

$$\lambda_{eq} = \left(\lambda_P^* P^* + \lambda_Q^* Q^* + \bar{\lambda}_V^* \Delta V^*\right) / P^*$$

$$\Delta V^* = \left|V^{R^*} - 1\right| + \left|V^{I^*}\right|$$

Nair et al., CCTA 2023

Distributed model predictive voltage control

- Primary control with passive grid circuit dynamics

$$\begin{bmatrix} \boldsymbol{L} & \boldsymbol{0} \\ \boldsymbol{0} & \boldsymbol{C} \end{bmatrix} \frac{d}{dt} \begin{bmatrix} \boldsymbol{i}(t) \\ \boldsymbol{V}(t) \end{bmatrix} = \begin{bmatrix} -\boldsymbol{Z} & \boldsymbol{B}^\top \\ -\bar{\boldsymbol{G}}\boldsymbol{B} & -\bar{\boldsymbol{G}}\boldsymbol{Y}_{\text{load}} \end{bmatrix} \begin{bmatrix} \boldsymbol{i}(t) \\ \boldsymbol{V}(t) \end{bmatrix} + \begin{bmatrix} 0 \\ -\boldsymbol{C}\boldsymbol{K}_q \Delta \boldsymbol{q}(t) \end{bmatrix}$$

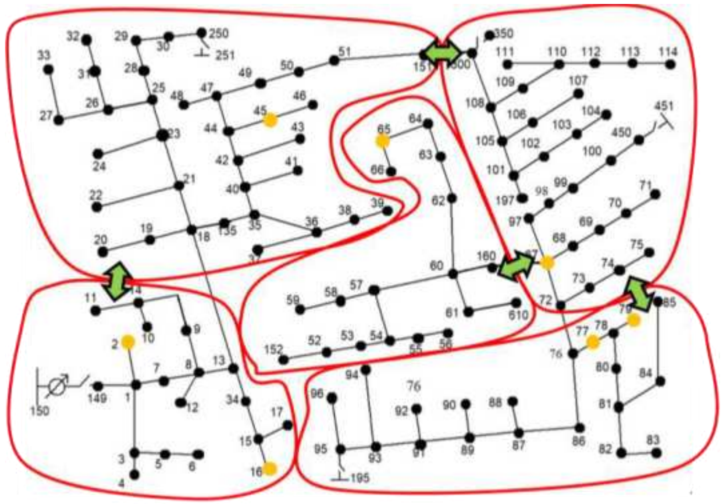
- Derive coupled cluster dynamics
- Define DMPC optimization problem
- Bring distributed optimization into standard separable form for solver

$$\min_{\boldsymbol{U}_c(k) \,\in\, \mathcal{U}_c} \sum_{c \in \mathcal{C}} f_c(\boldsymbol{U}_c(k))$$

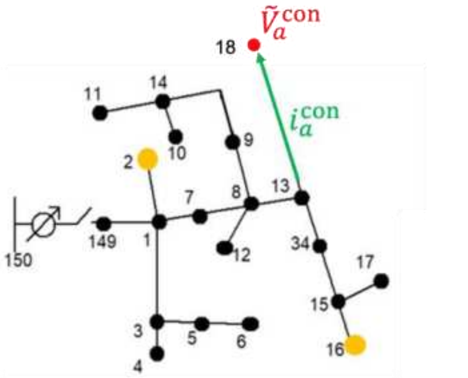
$$\text{s.t.} \quad \sum_{c \in \mathcal{C}} \boldsymbol{A}_c \boldsymbol{U}_c(k) = \boldsymbol{d}$$

$$\boxed{\begin{aligned} &\boldsymbol{x}_c(\ell+1) = \boldsymbol{A}_c \boldsymbol{x}_c(\ell) + \boldsymbol{M}_c \boldsymbol{u}_c(\ell) + \boldsymbol{c}_c \forall \ell, \ \forall c \in \mathcal{C}, && \text{Cluster dynamics} \\ &\tilde{\boldsymbol{v}}_{c_i}^{\text{con}}(\ell) = \tilde{\boldsymbol{B}}_{c_j,c_i}^{\text{con}} \tilde{\boldsymbol{x}}_{c_j}(\ell), \ \forall (c_i, c_j) \in \mathcal{E}_c, \ \forall \ell, && \text{Consensus constraints} \\ &\tilde{\boldsymbol{v}}_{c_j}^{\text{con}}(\ell) = \tilde{\boldsymbol{B}}_{c_i,c_j}^{\text{con}} \tilde{\boldsymbol{x}}_{c_i}(\ell), \ \forall (c_i, c_j) \in \mathcal{E}_c, \ \forall \ell, && \text{for voltage copies} \end{aligned}}$$

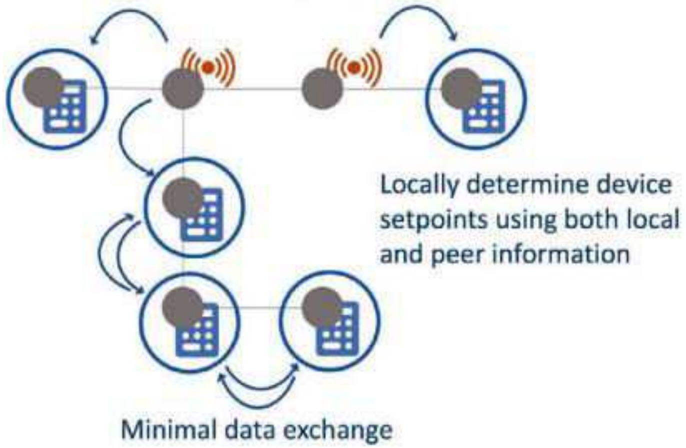
- Solve using algorithm based on alternating direction method of multipliers [1]



IBRs



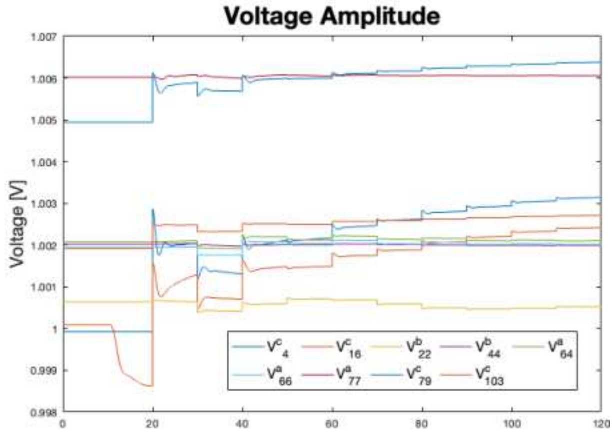
Maintain variable copies + exchange subset of variables

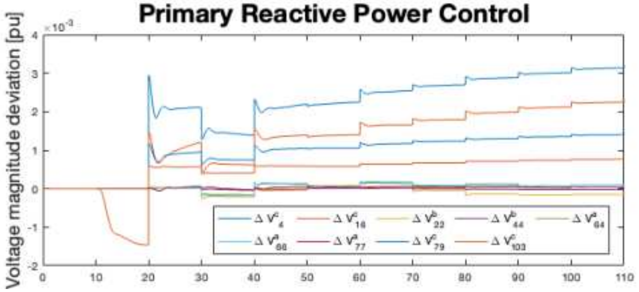


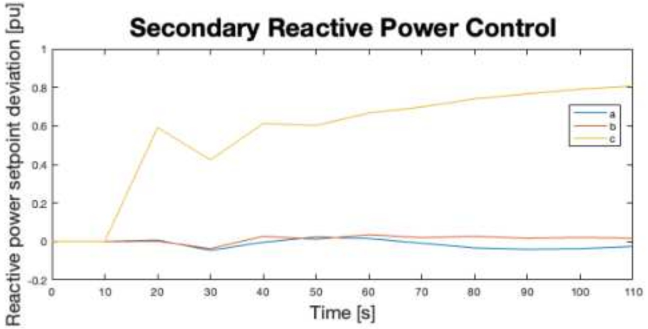
[1] A. Falsone, et al., "Tracking-ADMM for distributed constraint-coupled optimization," Automatica, Volume 117, 2020.
Hartmann et al., MITAB 2024; Srivastava et al., 2023

DMPC outperforms averaging PI control

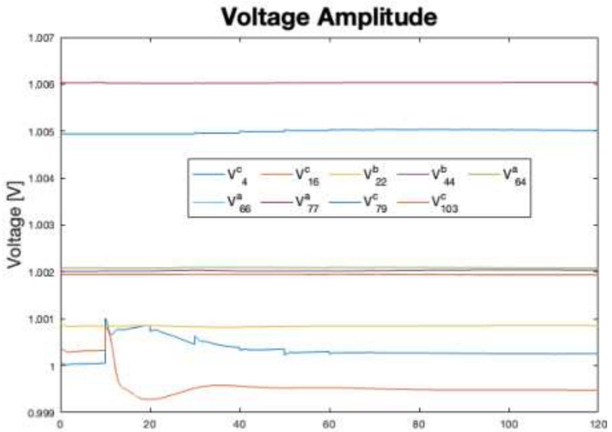
PI

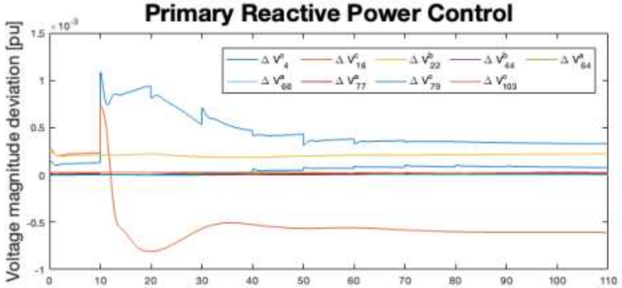


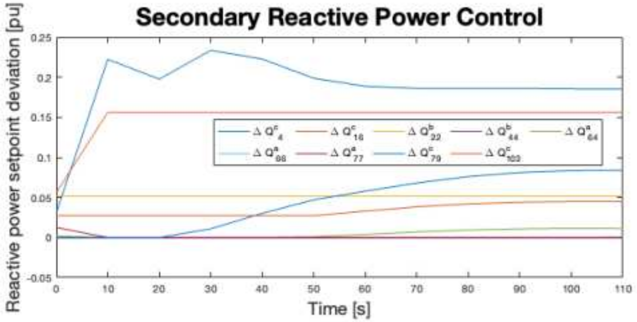




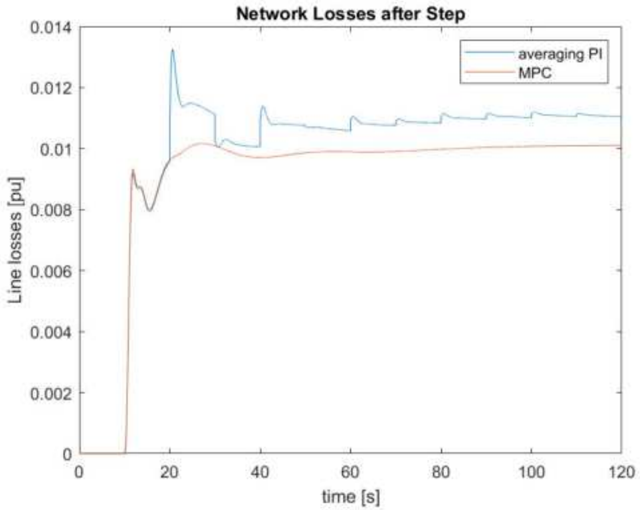
DMPC







- Simulate large load step disturbance
- Stable response without parameter tuning
- Reduces oscillations
- Relies more on on IBRs closer to load step
- More efficient dispatch → Lower losses



Hartmann et al., MITAB 2024

Conclusions

- Hierarchical local electricity markets allowing handling of grid constraints & agent preferences @ different levels
  - Improve grid reliability & avoid ‘tier-bypassing’ issues
  - Provide grid services like flexibility & voltage control
  - Spatial-temporal prices → Accurately charge/compensate prosumers
- Markets can be used to implement distributed optimization & control algorithms
- Questions for discussion:
  - How can we extend our methods to cases with limited observability?
  - How can we use our algorithms for reforming electricity markets & policy?
  - How do we redesign utility business models for IBR-rich grids?
  - How do we redistribute costs & ensure fair tariffs?

Enhanced version: NST-PAC

$$
\begin{aligned}
a_j[\tau+1] &= \underset{a_j}{\operatorname{argmin}}\Big\{\mathcal{L}_j\left(a_j, \hat{\eta}_j[\tau], \hat{\nu}[\tau]\right) \\
&\quad + \frac{\rho_j\gamma_j}{2}\left\|G_j a_j - b_j\right\|_2^2 + \frac{\rho_j\gamma_j}{2}\left\|B_j a_j\right\|_2^2 \\
&\quad + \frac{1}{2\rho_j}\left\|a_j - a_j[\tau]\right\|_2^2\Big\} \\
\hat{a}_j[\tau+1] &= a_j[\tau+1] + \alpha_j[\tau+1]\left(a_j[\tau+1] - a_j[\tau]\right) \\
\eta_j[\tau+1] &= \hat{\eta}_j[\tau] + \rho_j\gamma_j\left(G_j\hat{a}_j[\tau+1] - b_j\right) \\
\hat{\eta}_j[\tau+1] &= \eta_j[\tau+1] + \phi_j[\tau+1]\left(\eta_j[\tau+1] - \eta_j[\tau]\right)
\end{aligned}
$$

Communicate $\hat{a}_j$ for all $j \in [K]$ with neighbors

$$
\begin{aligned}
\nu_j[\tau+1] &= \hat{\nu}_j[\tau] + \rho_j\gamma_j B_j\hat{a}_j[\tau+1] \\
\hat{\nu}_j[\tau+1] &= \nu_j[\tau+1] + \theta_j[\tau+1]\left(\nu_j[\tau+1] - \nu_j[\tau]\right)
\end{aligned}
$$

Communicate $\hat{\nu}_j$ for all $j \in [K]$ with neighbors

- Use nonlinear regularization terms instead of linearized (PAC)
- Both primal & dual variable updates use Nesterov acceleration
- Privacy for both primals/duals
  - Use time-varying & atom-specific step-sizes

Ferro et al., TCNS 2022