Panel Session: Pushing Distribution Grid Analytics to the Edge: Opportunities, Challenges and Best Practices

Federated Learning and Edge Computing Enabled Local Energy Markets

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Market Transition: From Centralized to Localized

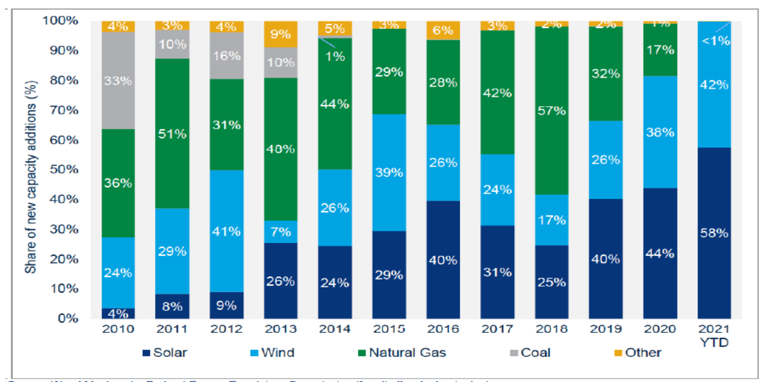
How is the market developing?

Distributed Photovoltaic (PV)

Fast capacity expansion

New U.S. electricity-generating capacity additions, 2010-2021YTD

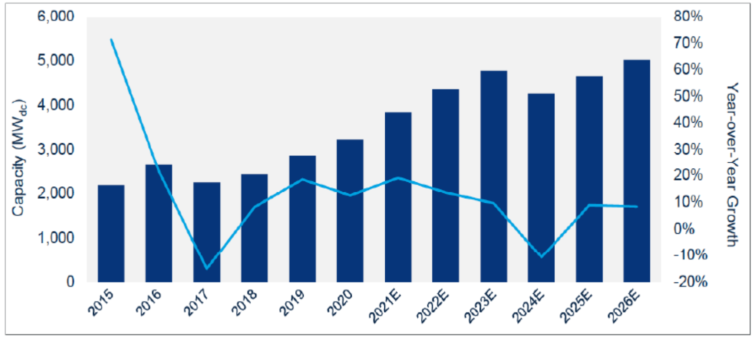
1



Source: Wood Mackenzie, Federal Energy Regulatory Commission (for all other technologies)

Residential installations and forecast, 2015-2026E

2



Source: Wood Mackenzie; note that Wood Mackenzie's forecasts do not assume any extension of the ITC

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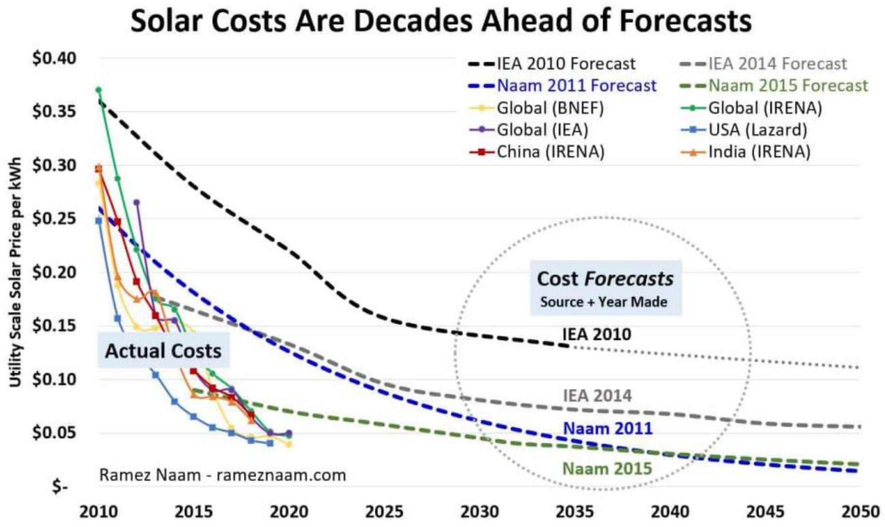


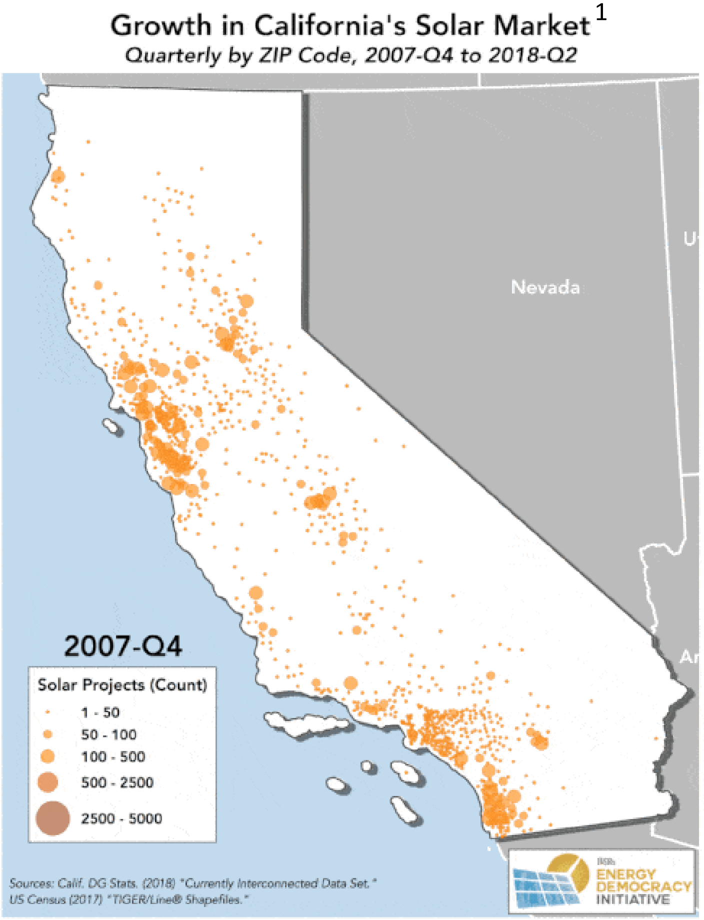
By 2035, solar energy has the potential to power 40% of the nation's electricity[4]

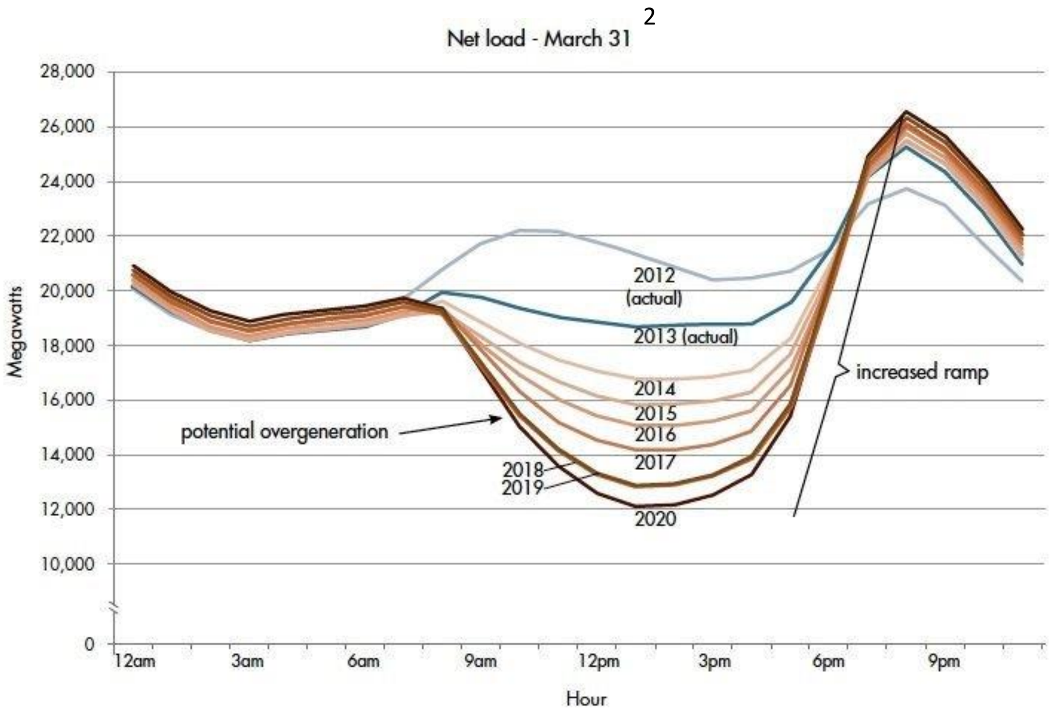
1. 2. https://www.seia.org/research-resources/solar-market-insight-report-2021-q2

3. https://rameznaam.com/2020/05/14/solars-future-is-insanely-cheap-2020/
4. https://www.energy.gov/articles/doe-releases-solar-futures-study-providing-blueprint-zero-carbon-grid

Distributed Photovoltaic (PV)

Challenging with excess capacity



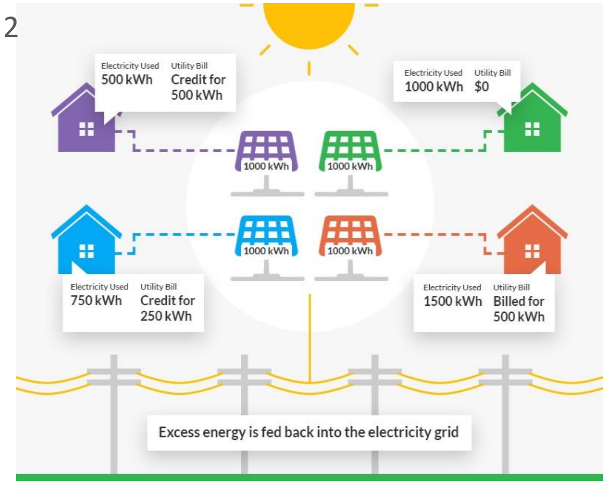


- Negative prices and PV curtailment
- Quickly increased ramp after sunset
- Reverse power flow fed back to the grid

1. https://ilsr.org/visualizing-calif-booming-solar-market/
2. https://www.energy.gov/eere/articles/confronting-duck-curve-how-address-over-generation-solar-energy

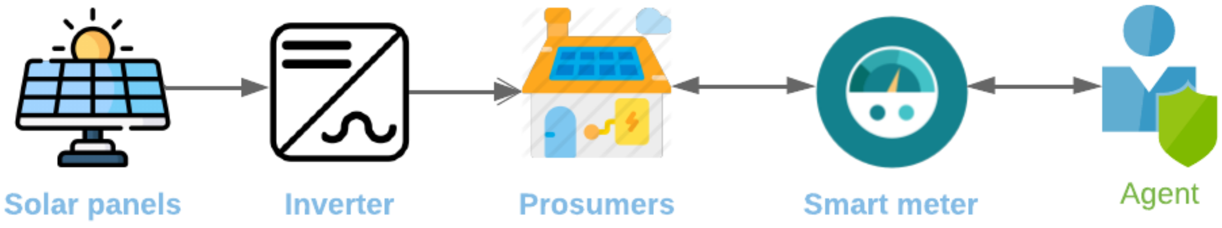
Energy Sharing and Storage

1


2


Net-metering is proposed to pay solar panels owners of sending energy back

❖ Net-metering



PV generation *P*

Load consumption *L*

Netload = *L* - *P*

❖ Energy Storage & PV

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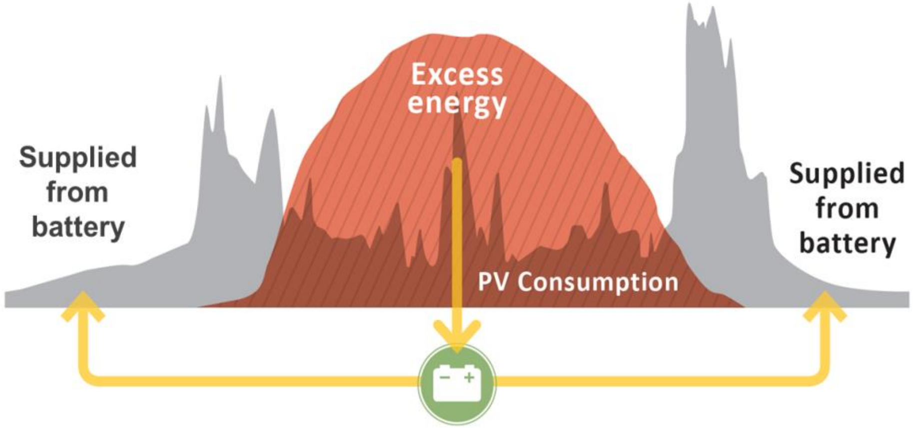

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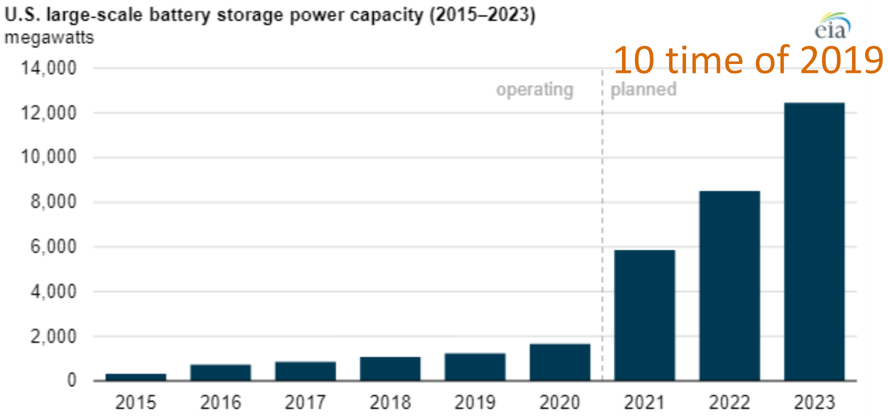
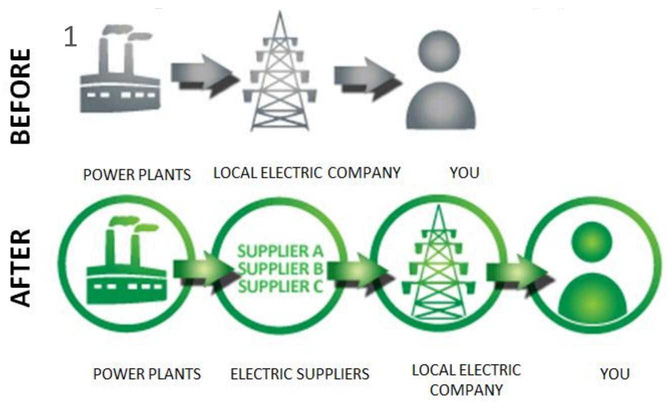


10 time of 2019

1. https://www.energy.gov/eere/articles/no-roof-no-problem-shared-solar-programs-make-solar-possible-you
2. https://www.letsgosolar.com/consumer-education/community-solar/
3. https://solairgen.com/alternative-to-pv-system-net-energy-metering-improving-grid-stability/
4. https://www.eia.gov/todayinenergy/detail.php?id=49236

Local Electricity Market (LEM)

❖ Deregulated and transactive market



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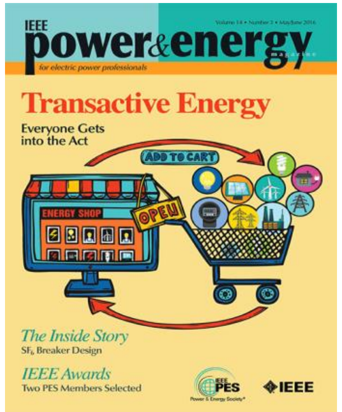
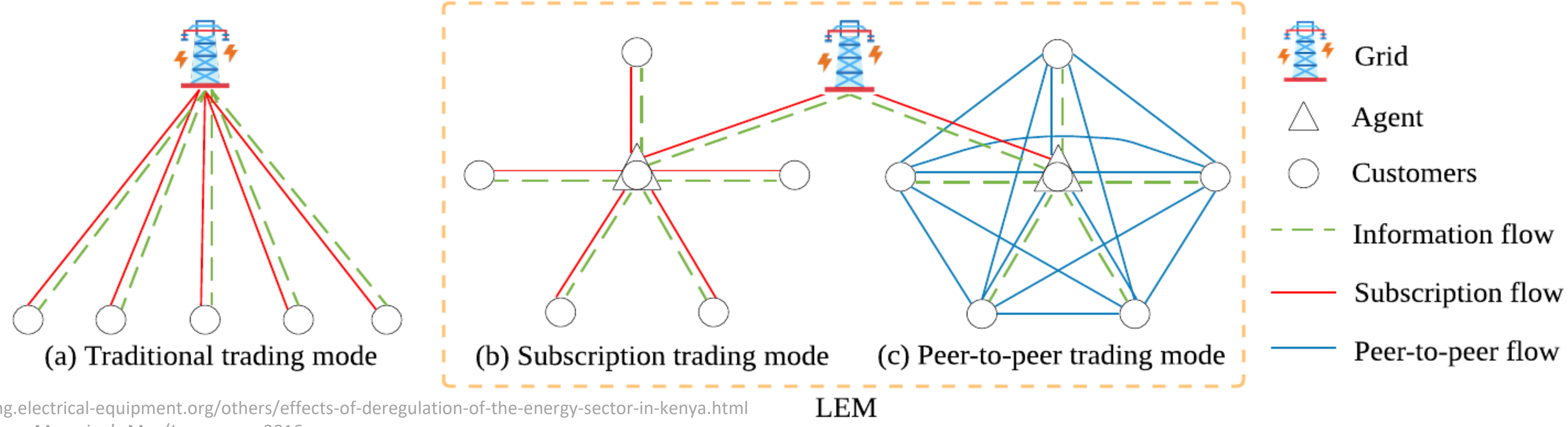


❖ Market structure



❖ Market structure: pros & cons

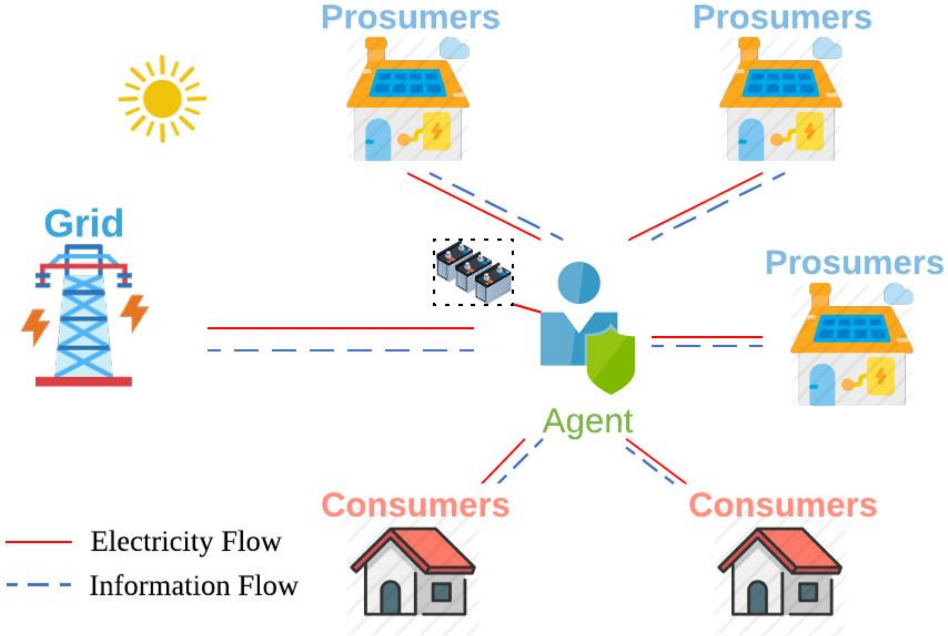
(a) Pros: simple structure, centralized-control, existing lines
Cons: low flexibility and reliability

(b) Pros: centralized-control, high flexibility, reliability, and efficiency
Cons: extra lines and entities

(c) Pros: decentralized-control, high flexibility, reliability, and efficiency
Cons: extra lines and entities, information security

1. http://engineering.electrical-equipment.org/others/effects-of-deregulation-of-the-energy-sector-in-kenya.html
2. IEEE Power & Energy Magazine's May/June cover, 2016

Agent-based LEM



❖ **Energy flow**

Direct sharing	• Prosumers-agent-consumers • Agent acts as a middleman
Buffered sharing	• Prosumers-agent-ES-consumers • ES acts as a buffer, stores excess PV
Arbitraging from the grid	• Grid-agent-ES-customers • ES stores energy during off-peak hours

❖ **Agent's objective function**

- **Stage 1**: Minimize the trading cost with external grid

$$C^{h\sim H} = \sum_{t=h}^{H}\left[\pi_s^t \cdot \max\left(\boxed{NL^t} + \boxed{x^t}, 0\right) + \pi_f^t \cdot \min\left(NL^t + x^t, 0\right) + \boxed{c \cdot |x^t|}\right]$$

Aggregated netload   ES schedule   ES cost

s.t. $-\Lambda/C_{rate} \le x^t \le \Lambda/C_{rate}$

$$SoC_{min} \le SoC^t \le SoC_{max}$$

$$SoC^t = \begin{cases} SoC^{t-1} + x^t \cdot \eta, & x_i^t > 0 \\ SoC^{t-1} + x^t/\eta, & x_i^t < 0 \end{cases}$$

- **Stage 2**: Maximize profit through internal pricing

$$P = \begin{cases} \sum \boldsymbol{\lambda}_s \odot \boldsymbol{E}_b - \sum \boldsymbol{\lambda}_b \odot \boldsymbol{E}_s - \pi_s \Delta E - c \cdot |x|, & \Delta E \ge 0 \\ \sum \boldsymbol{\lambda}_s \odot \boldsymbol{E}_b - \sum \boldsymbol{\lambda}_b \odot \boldsymbol{E}_s - \pi_f \Delta E - c \cdot |x|, & \Delta E < 0 \end{cases}$$

s.t. $(\lambda_b, \lambda_s) \in [\pi_f, \pi_s]$

$$E_b = \sum_{i=1}^{\mathcal{N}_b}(l_i - pv_i)$$

$$E_s = \sum_{i=1}^{\mathcal{N}_s}(pv_i - l_i)$$

$$\Delta E = E_b - E_s + x$$

- *Price constraints – ToU/FiT*
- *Total demand from buyers*
- *Total supply from sellers*
- *Balancing with the utility grid*

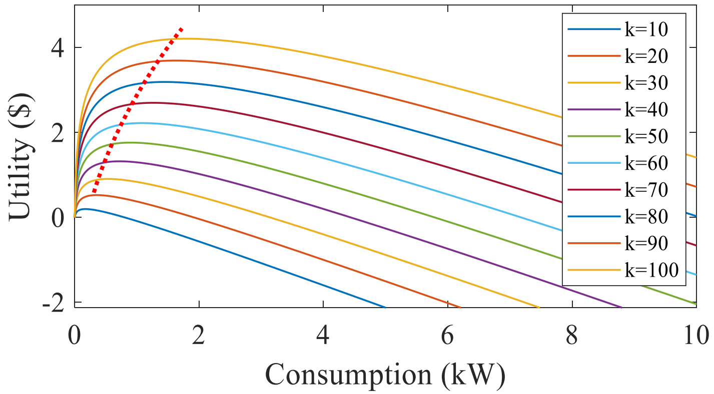
He, L. and Zhang, J. Customized Prices Design for Agent-based Local Energy Market with PV and Energy Storage. NAPS 2021

Agent-based LEM

❖ Customers' utility function

$$U_i = \begin{cases} k_i \ln(1 + l_i) - \lambda_s(l_i - pv_i), & l_i \geq pv_i \\ k_i \ln(1 + l_i) - \lambda_b(l_i - pv_i), & l_i < pv_i \end{cases}$$

- Net Consumer
- Net Producer



- *Utility from consumption*
- *Cost of trading*
- *K_i: consumption preferences*
- *Strictly concave function*

s.t. $l_i \in [l_{min}, l_{max}]$

- *Load shifting constraints*

$$l_i^* = \arg\max \quad U_i(k_i, l_i, pv_i, \lambda_b, \lambda_s)$$

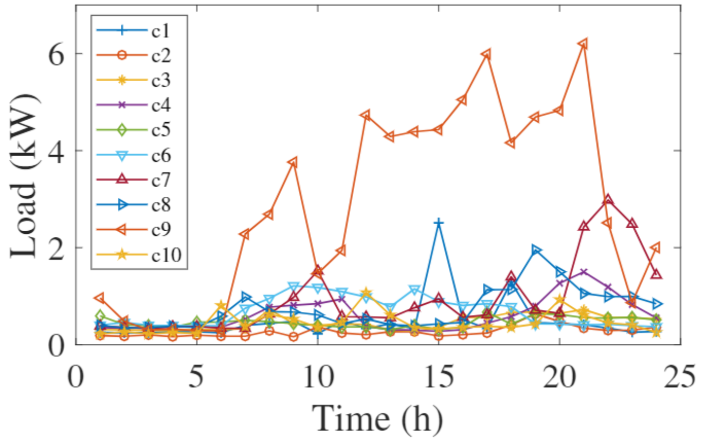
Optimal strategy

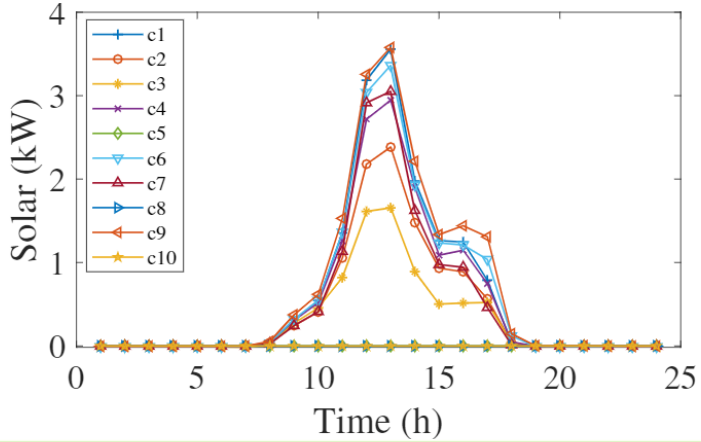
$$l_i^* = \begin{cases} k_i/\lambda_s - 1, & l_i \geq pv_i \\ k_i/\lambda_b - 1, & l_i < pv_i \end{cases}$$

- *Best response*

❖ Customers' load and PV profiles

Source: PecanStreet Dataport Date: Nov. 6, 2018
c5, c8, and c10 are consumers, others are prosumers





LEM: Preliminary Results

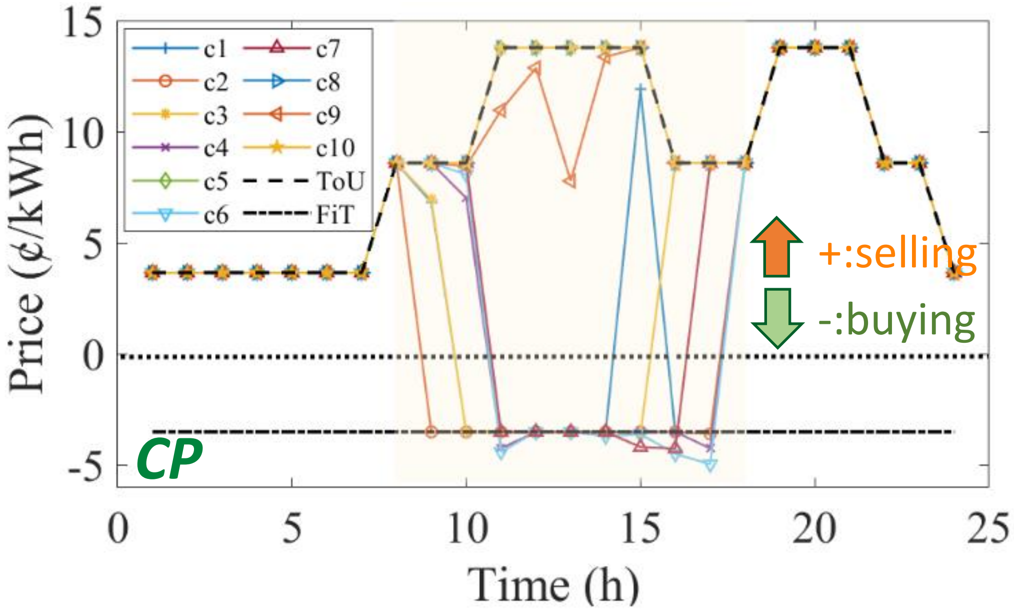
***Baseline:** Time-of-use (ToU) price & Feed-in-tariff (FiT) price*

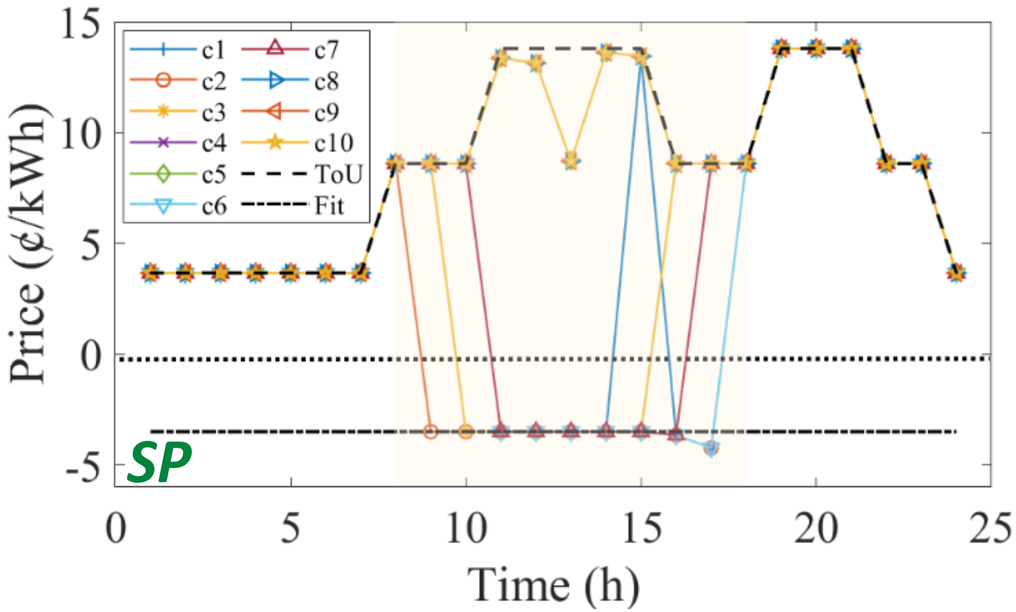
***Customized Pricing (CP):** Price discrimination between customers*

***Single uniform Pricing (SP):** No price discrimination*

ToU: ¢13.8/kWh 7:00-9:00; 18:00-21:00
¢ 3.7/kWh 23:00-7:00
¢ 8.6/kWh in other hours

FiT: ¢ 3.5/kWh in all hours





- C9 is offered the lowest selling price during 11:00-14:00
- C6 is offered the highest buying price during 11:00-17:00
- C3 and C5 are offered lower selling price at 9:00
- C4 and C6 are offered lower selling price at 10:00

- Uniform selling prices apply to all buyers
- Uniform buying prices apply to all sellers
- Internal prices are same with utility prices when no energy sharing occurs

Agent-based LEM

Current limitations:

1. **Perfect foresight of load and PV**
2. **Behind-the-meter PV generation is available**
3. **Privacy is not considered**

Forecasting + BTM disaggregation

Federated learning

LEM → Customized pricing LEM → Privacy-preserving LEM

Cyber-security and privacy challenges: concerns of data sharing

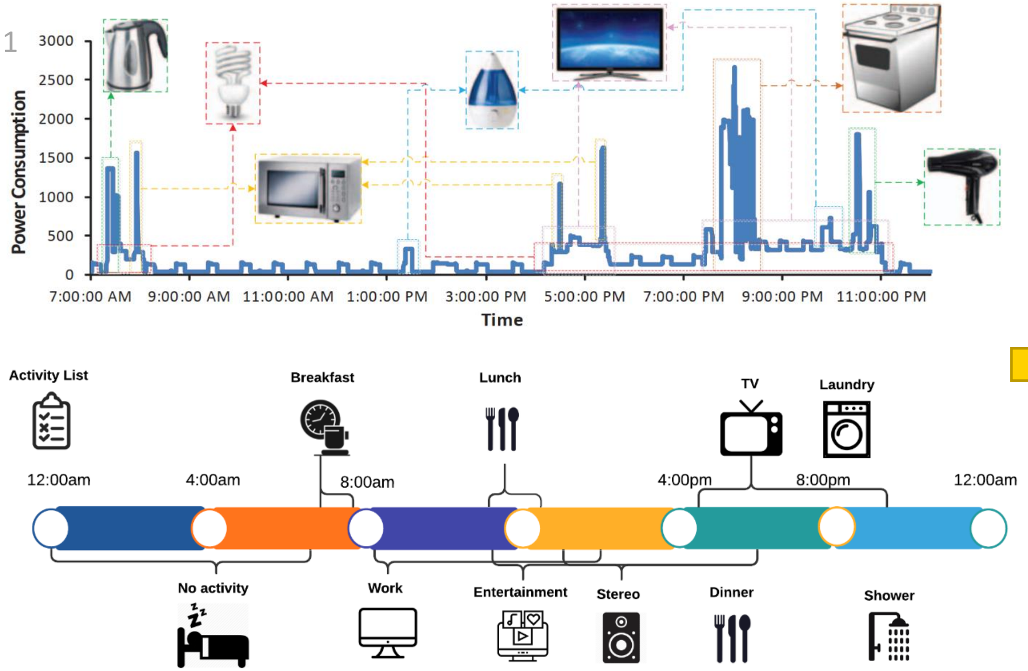
How could the private data be used?

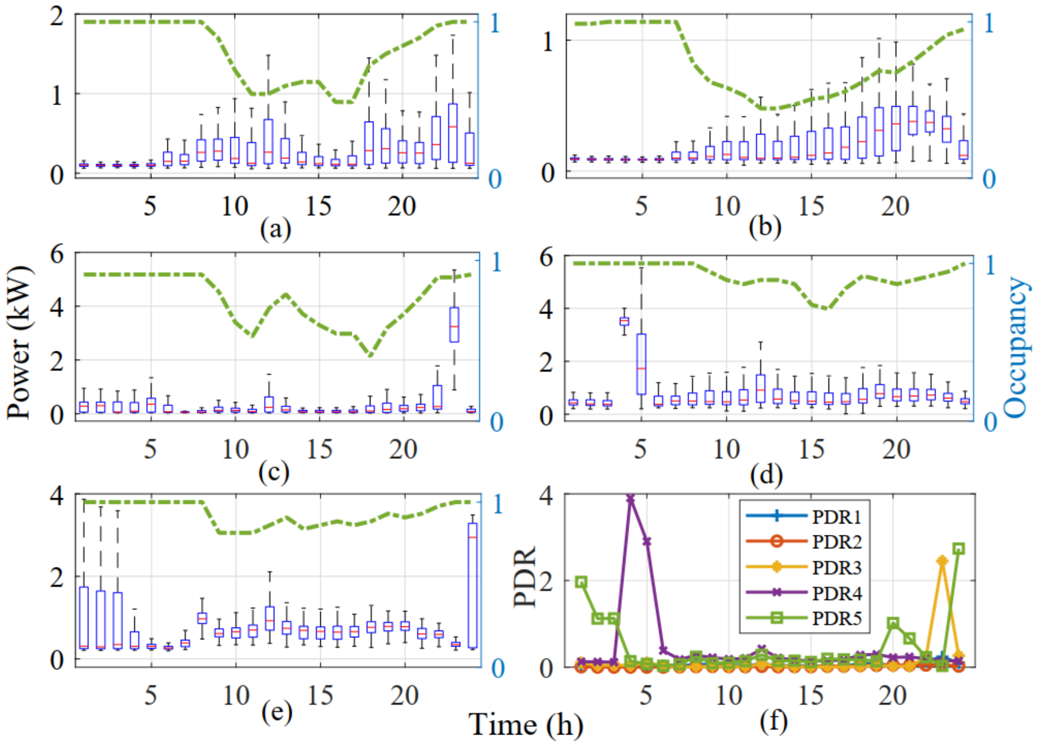
What information your data can reveal:

- Appliances (flexibilities)
- Activities (preferences)

- Occupancy (routines)
- Probability of demand response (PDR)

1

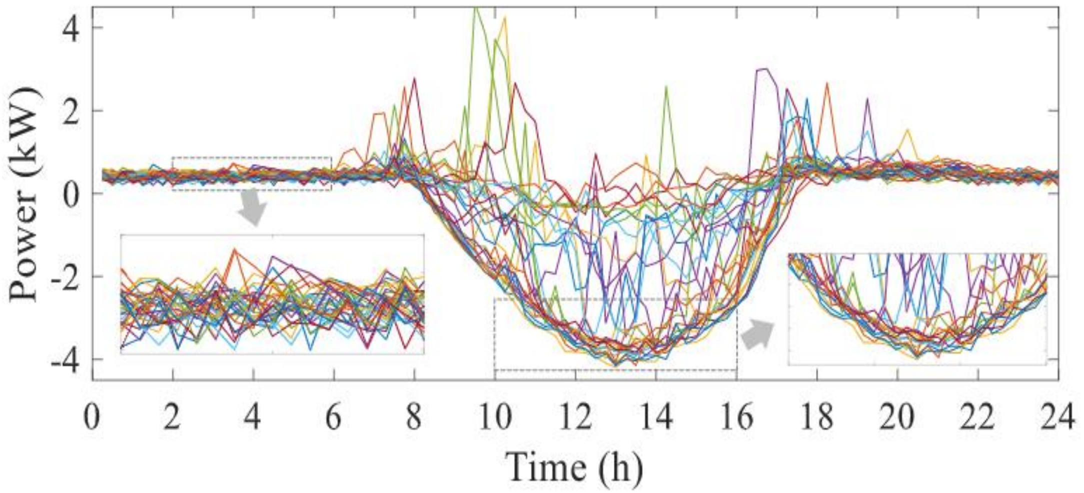




1. Tang, G, et al. The meter tells you are at home! non-intrusive occupancy detection via load curve data. In 2015 IEEE International Conference on Smart Grid Communications.
2. He, L, et al. An Occupancy-Informed Customized Price Design for Consumers: A Stackelberg Game Approach. in IEEE Transactions on Smart Grid.

What information your data can reveal:

Behind-the-meter estimations



Netload curves of one prosumer in one month

Netload data:

a) Consumption noises
b) Gross load > 0
c) Minimal netload < clear-sky generation

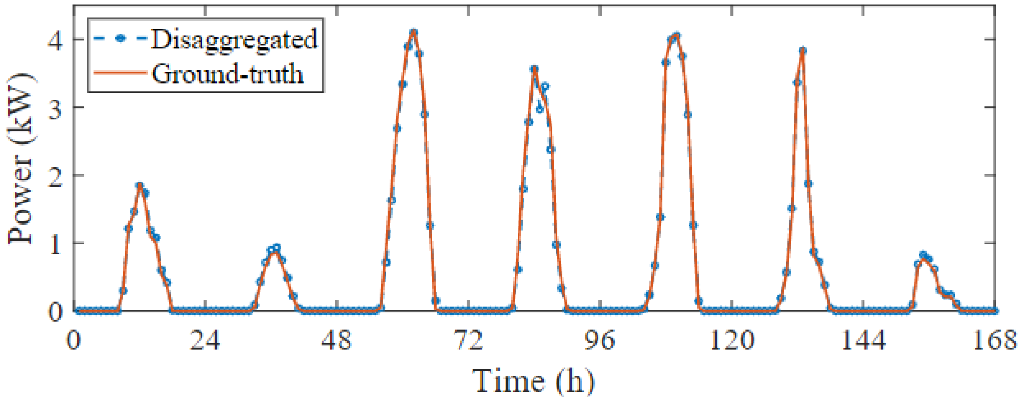
Minimal netload extracting
- Denoise
- Smooth

Clear-sky day identification
- Maximum generation

Estimate the BTM capacity
- Local output are highly correlated

Table 1: Accuracy of BTM Disaggregation, MAPE [%]

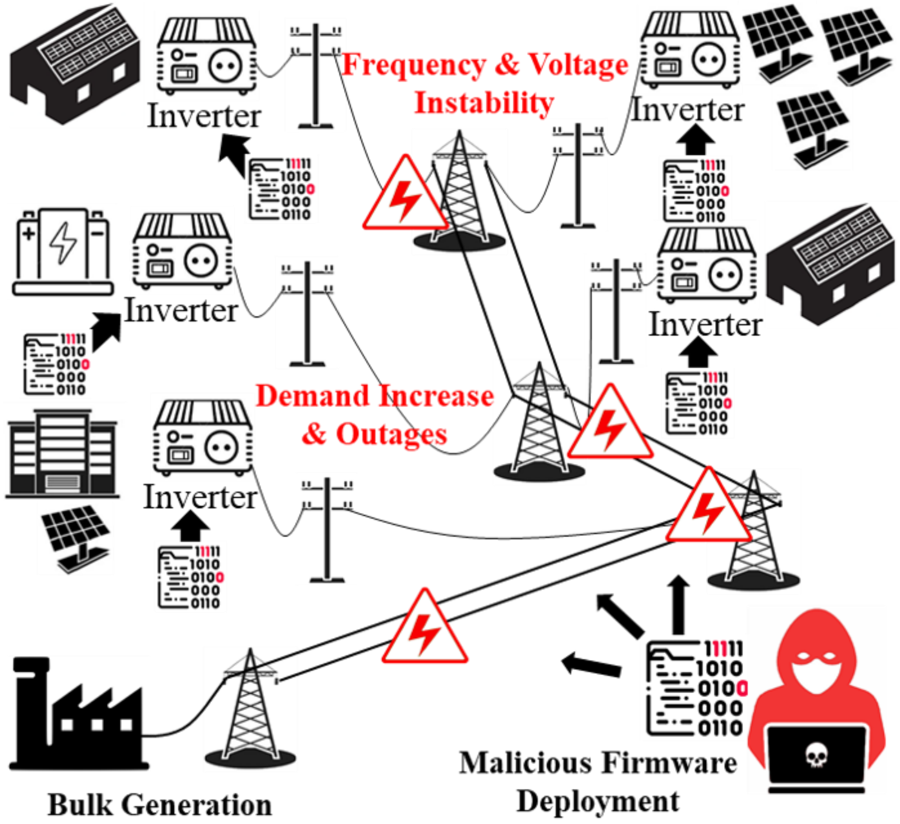
c1	c2	c3	c4	c6	c7	c9	Agg
10.12	13.76	19.32	6.38	10.71	12.44	9.53	1.31



He, L. and Zhang, J. Customized Price Design for Energy Sharing in Agent-Based Local Electricity Markets with Behind-The-Meter Solar and Energy Storage. (under review)

How could your data be used?

Cyber attack



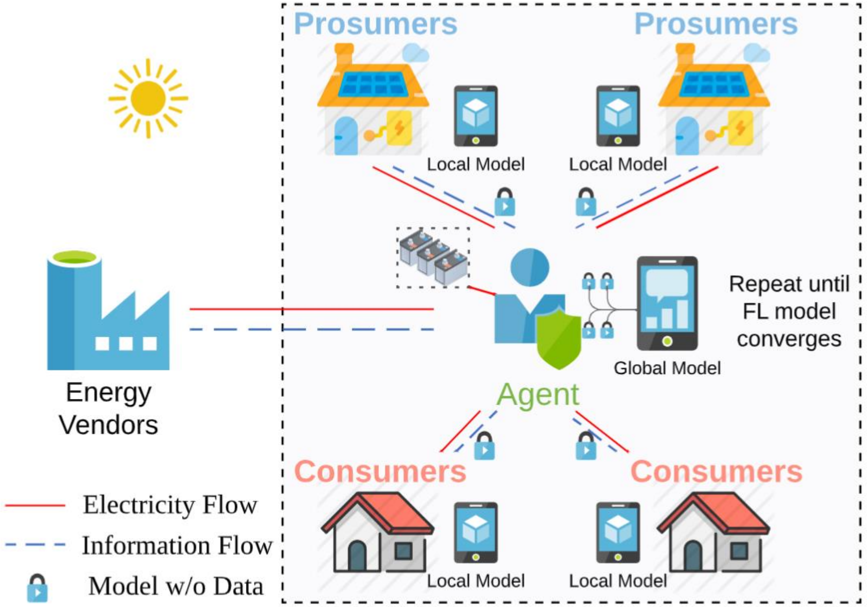
Burglary

Federated Learning and Edge Computing

How could the privacy be protected?

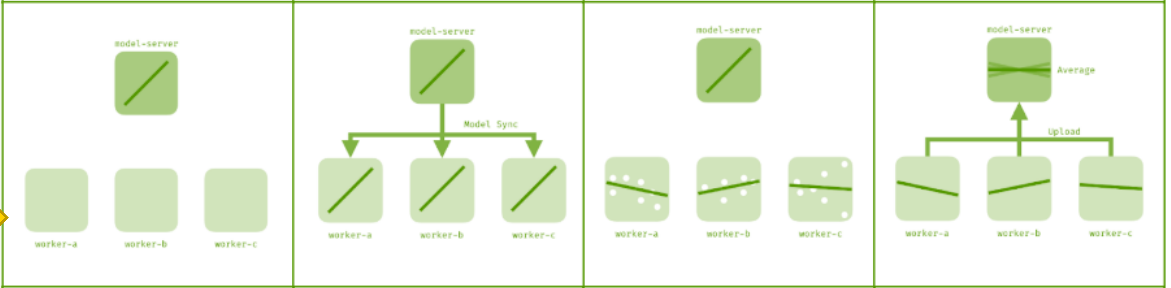
Federated Learning-based LEM

❖ Extension of previous LEM structure



❖ Federated Learning

[1]



Step 1	Step 2	Step 3	Step 4
Central server chooses a statistical model to be trained	Central server transmits the initial model to several nodes	Nodes train the model locally with their own data	Central server pools model results and generate one global mode without accessing any data

- Agent generates the global forecasts without obtaining local datasets
- Agent designs incentives for customers with potential additional datasets
- Clients receive prices and determine load response on the edge of the network

1. https://en.wikipedia.org/wiki/Federated_learning

Federated Learning-based LEM

❖ **Non independent and identically distributed (Non-IID) dataset**

- Members selection: choose the most correlated members (preliminary)
- Robust learning rate: dynamically modify the learning rate (future work)

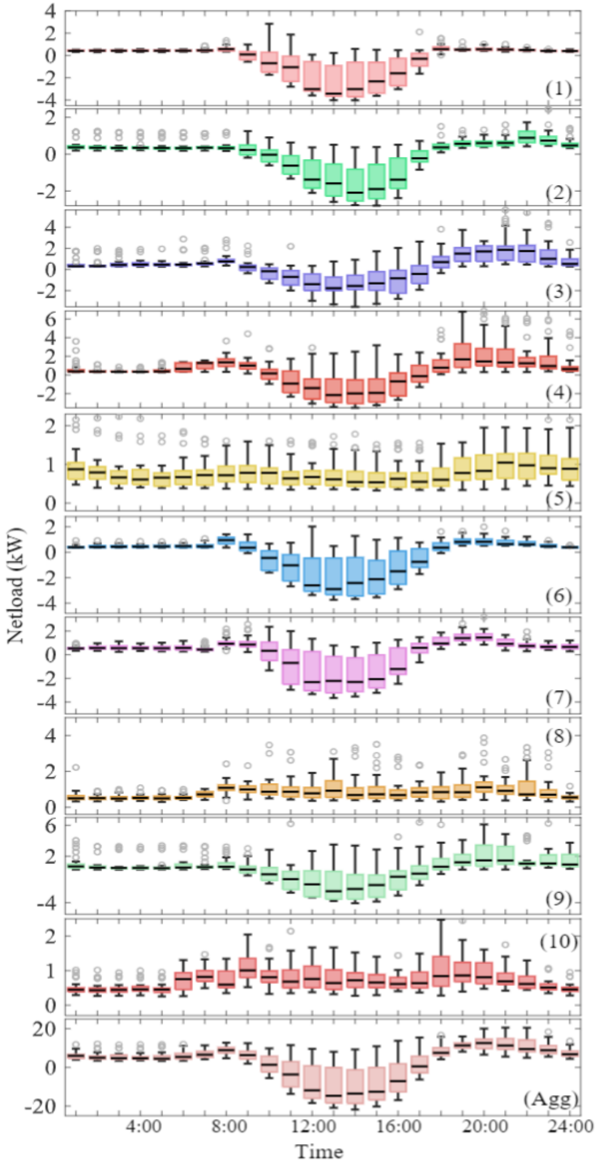
Identify the best combination of FL members

TABLE I
CORRELATION COEFFICIENT BETWEEN THE AGGREGATED AND INDIVIDUAL NETLOAD

Agg	c1	c2	c3	c4	c5	c6	c7	c8	c9	c10
1	0.9189	0.9230	0.8521	0.8803	0.5067	0.9491	0.9159	0.1029	0.8609	0.2947

TABLE II
GLOBAL FORECASTING PERFORMANCE (NRMSE) UNDER DIFFERENT MEMBERS SELECTION

	c1	c2	c3	c4	c5	c6	c7	c8	c9	c10
M1	47.21%	47.07%	62.71%	45.08%	63.77%	**24.09%**	35.97%	37.59%	41.60%	30.27%
M2	22.59%	20.66%	19.93%	39.67%	**16.03%**		28.54%	24.00%	23.89%	44.95%
M3	24.81%		22.02%	31.86%	23.29%		26.05%	**15.80%**	27.75%	51.44%
M4			22.49%	**19.92%**	24.95%		23.90%	20.15%	25.29%	36.14%
M5			22.68%	21.36%	25.20%			**20.36%**	24.82%	29.31%



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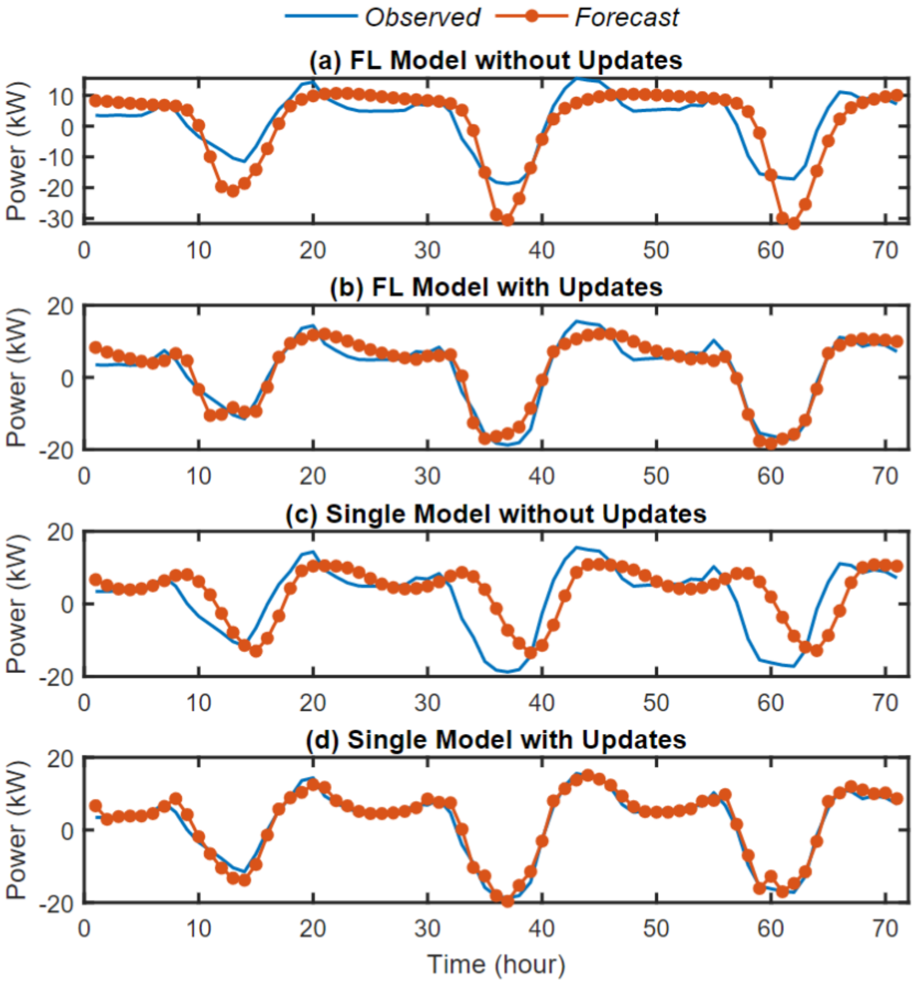
Federated Learning-based LEM

Global forecasting performance using best combination

(a) FL (b) FL + updates
(c) Single LSTM (d) Single LSTM + updates

	A	B	C	D
RMSE (kW)	6.4189	2.6962	7.8635	1.8263

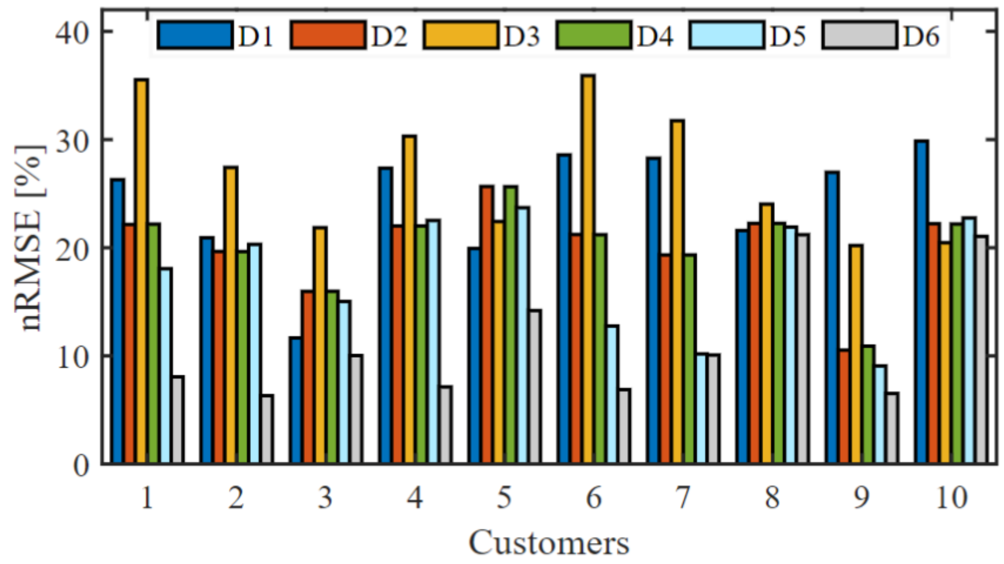
Scenarios	(a)	(b)	(c)	(d)	Actual
Profits ($)	10.48	11.13	10.05	11.41	11.75
Increase [%]	12.19	5.57	16.92	2.98	-



- (a) *vs.* (c): FL has better performance using jointly trained mode when there is no available data
- (b) *vs.* (d): Extra data helps in improving the single model
- Better forecasting accuracy yields higher profit in LEM

Federated Learning-based LEM

Individual forecasting performance with extra data (privacy leakage)



(D1) No extra data
(D3) 1st half data
(D5) 1DA data

(D2) All historical data
(D4) 2nd half data
(D6) Full data with updates

TABLE III
COST SAVINGS OF PV PROSUMERS [%] UNDER FL MODEL (A)

Cases	c1	c2	c3	c4	c6	c7	c9
D1	17.04	11.39	2.13	11.02	15.13	4.54	4.49
D5	4.71	4.87	2.11	1.34	8.01	4.53	4.45
D6	0.04	0.12	0.03	0.05	0.06	0.12	0.02

- Extra data helps in improving the accuracy
- False data injection misleads the agent (D4 *vs.* D3)
- Limited data is enough to improve the accuracy (D5)
- Less leakage yields higher cost savings (D1>D5>D6)

Federated Learning-based LEM

Ongoing research:

- Robustness to Non-IID dataset
- Accountable FL Frameworks
- False data injection attack in FL

Q & A

Thanks!