Towards energy sustainability: a system point of view

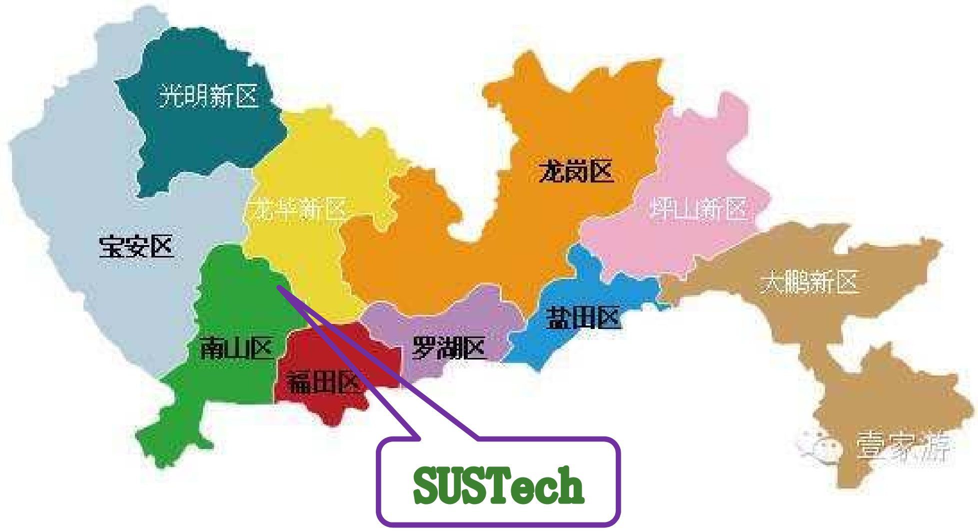
Zaiyue Yang 楊再躍

Ph.D, Professor,

Southern U. of Sci. & Tech.

Southern U. of Sci. and Tech. (SUSTech)

- Quick facts
  - Est. **2011**, **1.9** km^2
  - 1000 UG, 450 MS and 250 PhD per year
  - Faculty members: 330 (800)
  - 20 academicians, 48 (74) recipients of 1000-program (youth)
  - 14 schools/departments
  - 26 academic programs



- Goal
  - World-class research university

Science

Engineering

Life science

Business

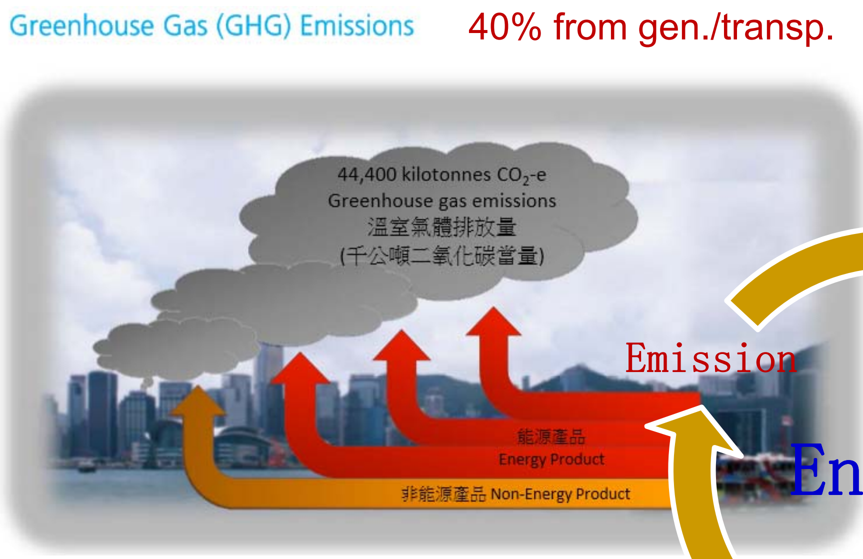
Med. School

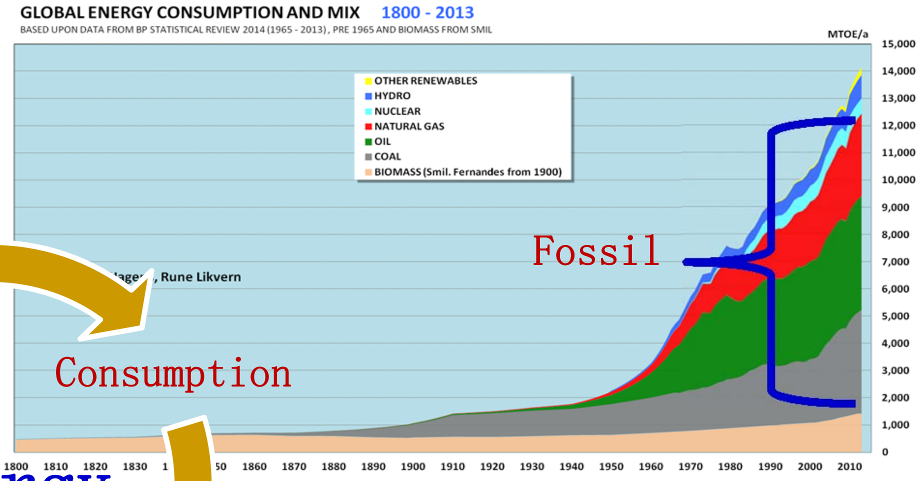
Arts and social sci.

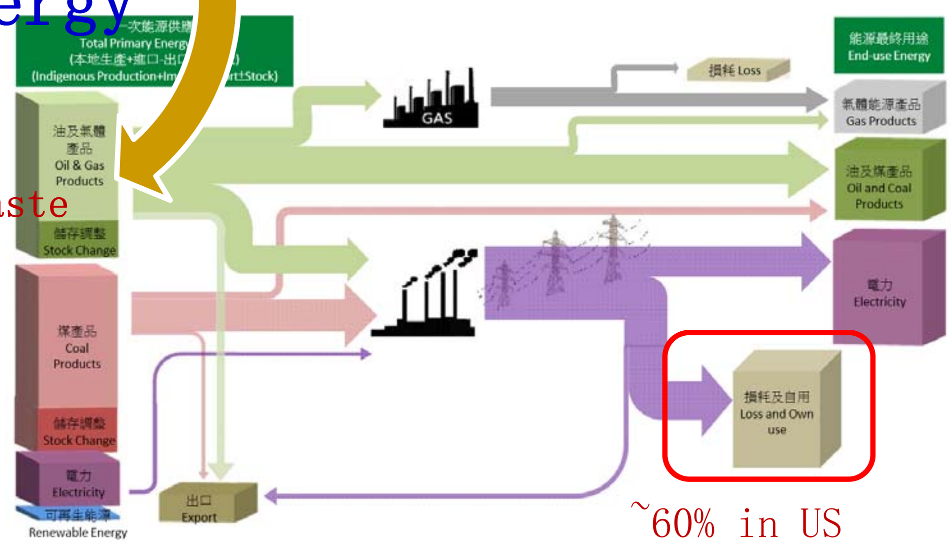
Innovation college

We are recruiting!

Energy sustainability and smart grid



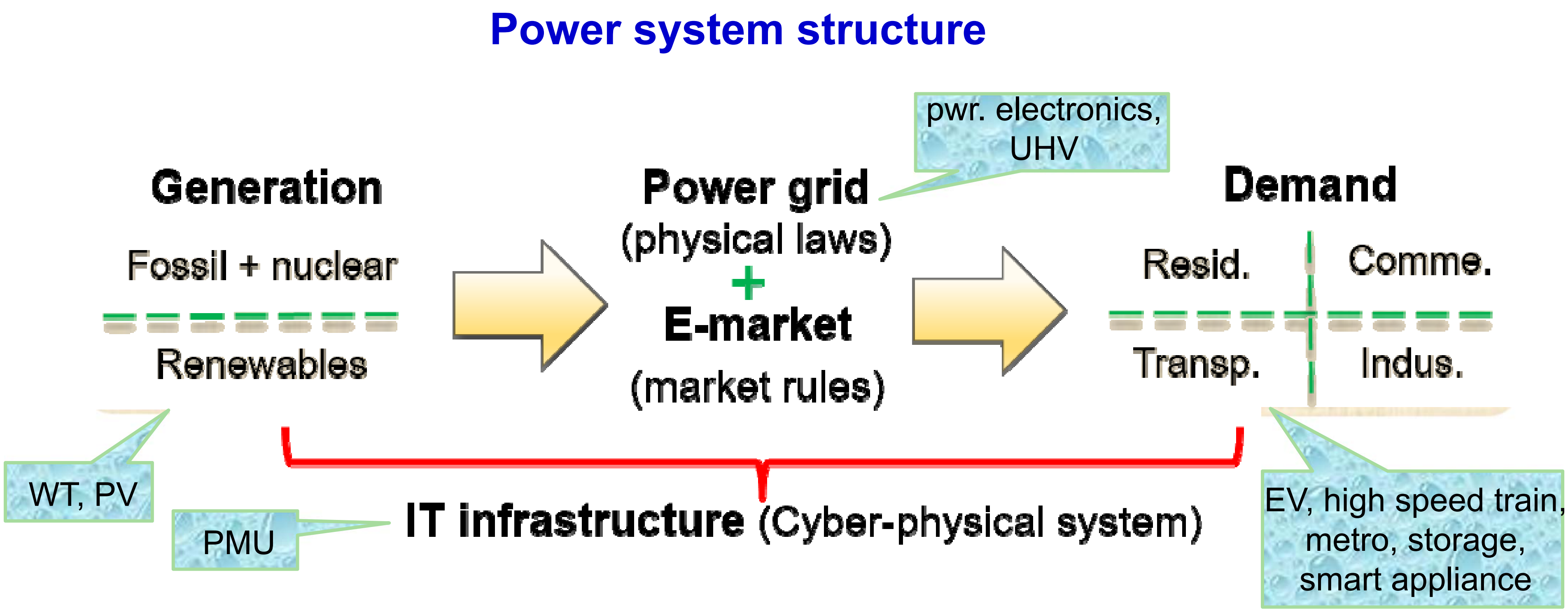




- Promising solutions
  - Renewable generation
  - Energy efficiency
  - E-transportation

All related to **smart grid technologies**

SG technologies: component level

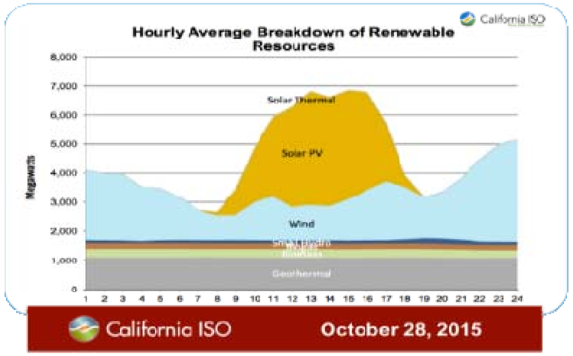


Are they enough?

SG technologies: system level

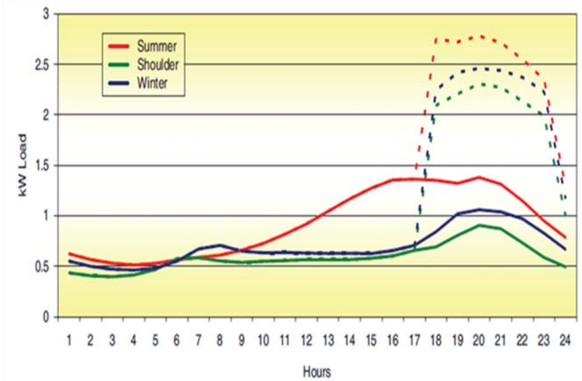
An example:
deep penetration of renewables and EV

Renewable gen.



+

EV charging load



=

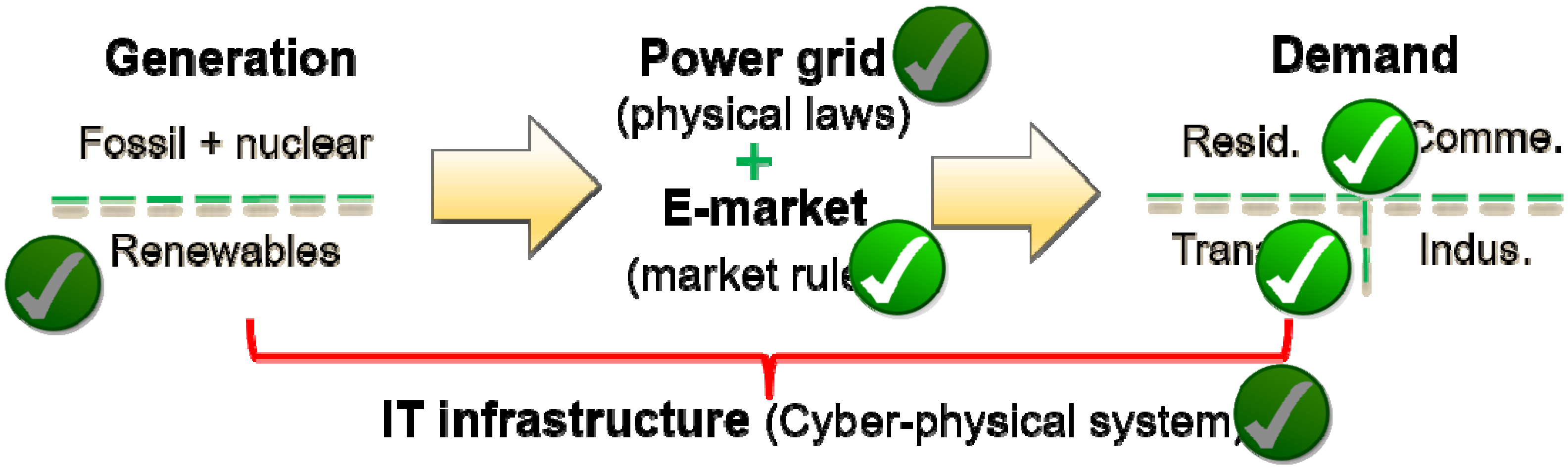
Mismatch,
large peak load

Unstable, inefficient

System level challenge: how to make components work together, and make full advantages of them?

- **System level tech**: DSR, market design, PS operation, cyber security, resilience, etc

My current research



- System level research
  - Demand side response
  - E-transportation
  - Electricity market
  - WT control[1]
  - Microgrid operation[2]
  - Cyber security[3]

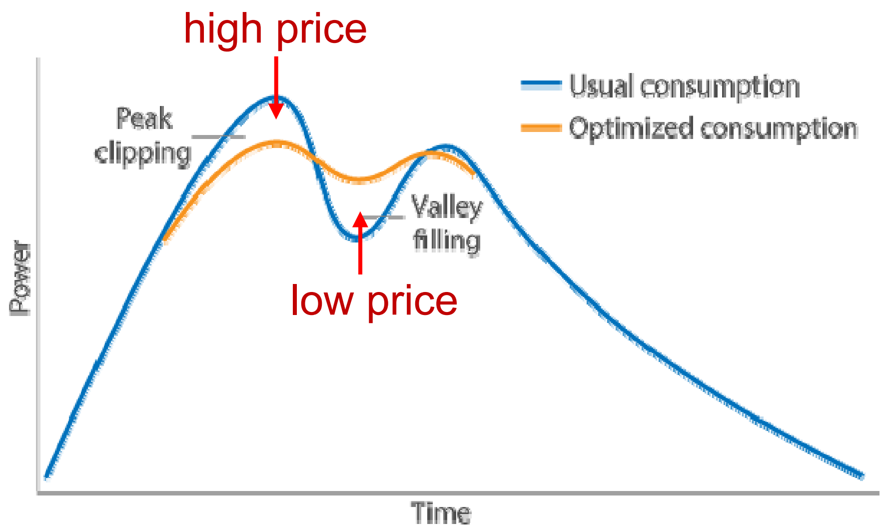
[1] Meng, WC, Yang, ZY, et al., Adaptive power capture control of variable-speed wind energy conversion systems with guaranteed transient and steady state performance, IEEE TEC, 28(3), 716-725, 2013;
[2] Yang, ZY, et al., Economical Operation of Microgrid with Various Devices via Distributed Optimization, IEEE TSG, 7(2), 857-867, 2016;
[3] Chai, B. and Yang, ZY. Impacts of unreliable communication and modified regret matching based anti-jamming approach in smart microgrid, AHN, 22, 69-82, 2014;

Demand Side Response

Concept and benefit

- According to **electricity price**, users change **load profile** by **operating controllable components**[4]

Dynamic price:
G > D, low price
G < D, high price



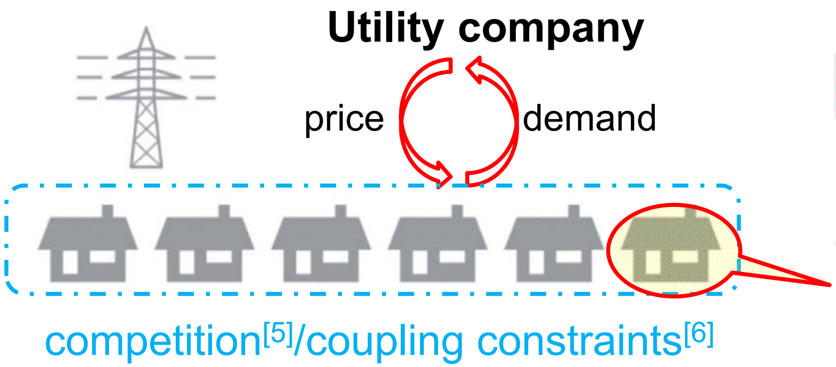
- Projects and benefits
  - PJM, CAISO, NYISO, Ecogrid EU, etc.
  - Peak load reduction: 0.9M kW in TX, 1.5M kW in CA
  - Annual cost saving: $0.8B in MA, $2.5B in IL*

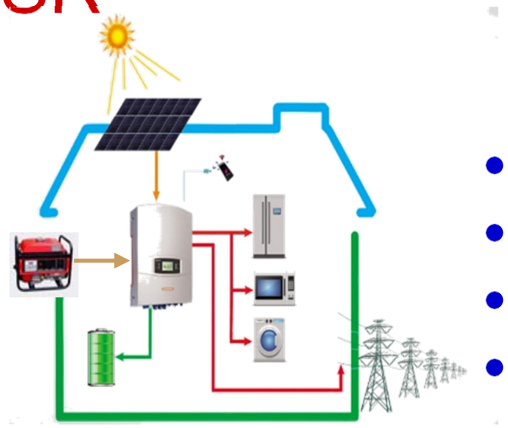
[4] Deng, RL, Yang, ZY, et al., A Survey on Demand Response in Smart Grids: Mathematical Models and Approaches, IEEE TII, 11(3), 570-582, 2015;

*Advanced energy economy, 2014

The building block in DSR

- Structure





Building block

- Renewables
- Storages
- Appliances
- Small generators

How to work together in response to dynamic price?

- **An optimization perspective**: min cost/max welfare
- Challenges
  - Uncertain renewable gen., 0/1 decision of storage, large scale of system
  - Receding horizon control: predict/update, **re-optimize**, execute
  - Efficient/distributed algorithm

[5] Deng, RL, Yang, ZY, et al., Residential Energy Consumption Scheduling: A Coupled-Constraint Game Approach, IEEE TSG, 5(3), 1340-1350, 2014;
[6] Deng, RL, Yang, ZY, et al., Load Scheduling with Price Uncertainty and Temporally-Coupled Constraints in Smart Grids, IEEE TPWRS, 29(6), 2823-2834, 2014;

Mathematical formulation

- Objective[7] (MILP, mixed integer linear program)

$$\min_{p,u,s} \mathcal{P} = \sum_{h\in\mathcal{H}} \sum_{g\in\mathcal{G}} \left[f_g\left(p_g^h\right) + R_g^h\left(1 - u_g^{h-1}\right)\right] u_g^h + \sum_{h\in\mathcal{H}} c^h s^h + \sum_{h\in\mathcal{H}} \sum_{a\in\mathcal{A}} V_a^h\left(p_a^h\right) + \sum_{h\in\mathcal{H}} \sum_{b\in\mathcal{B}} r_b^h\left(p_{b,c}^h + p_{b,d}^h\right)$$

$$\boxed{\text{Total cost = gen. + purchase + user dissatisfaction + batt. loss}}$$

- Constraints: individual + balance

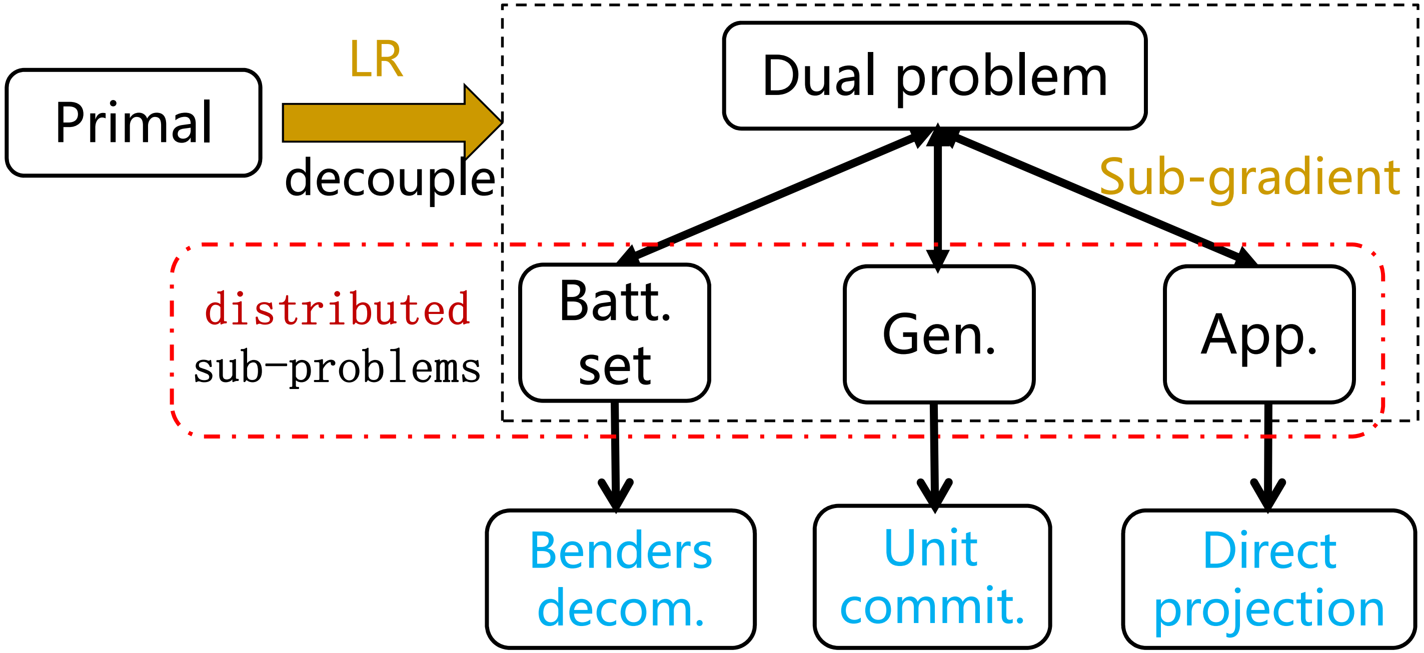
$$\underbrace{\sum_{g\in\mathcal{G}} u_g^h p_g^h + s^h + \sum_{b\in\mathcal{B}} p_{b,d}^h}_{\text{Supply}} + \omega^h p_{\text{rate}} = \underbrace{\sum_{a\in\mathcal{A}} p_a^h + p_0^h + \sum_{b\in\mathcal{B}} p_{b,c}^h}_{\text{Demand}}$$

Spatially coupled over all components

[7] Yang, ZY, et al., Joint Scheduling of Large-Scale Appliances and Batteries via Distributed Mixed Optimization, IEEE TPWRS, 30(4), 2031-2040, 2015;

Distributed algorithm

- Problem transformation



Direct projection

- Convex problem (find H-d vector p_a):

$$L_1 = \min_{p_a} \sum_{h \in \mathcal{H}} \left[\alpha^h p_a^h + V_a^h \left(p_a^h \right) \right]$$

$$\text{s.t.} \;\; p_a^{\min} \le p_a^h \le p_a^{\max} \qquad \sum_{h \in \mathcal{H}} p_a^h = D_a$$

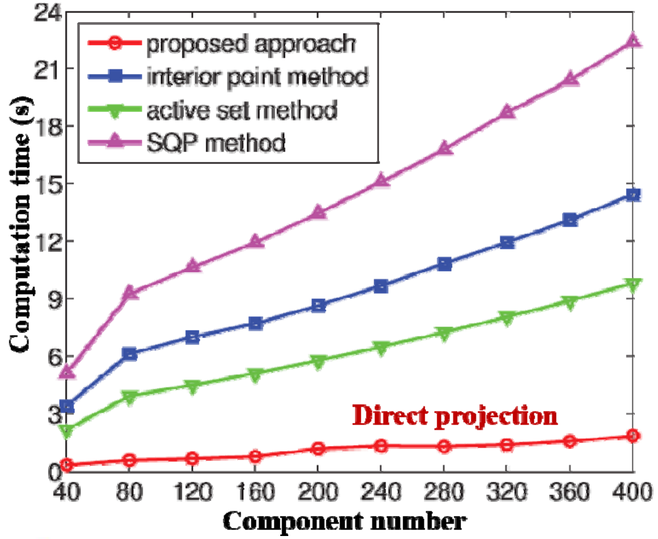
- Based on KKT conditions, transform **H-d implicit** problem into **1-d explicit**

$$\begin{cases} 2o_a^h p_a^h + \alpha^h - \tau_a + \psi_a^h - \xi_a^h = 0 \\ \tau_a \left(D_a - \sum_{h \in \mathcal{H}} p_a^h \right) = 0 \\ \psi_a^h \left(p_a^h - p_a^{\max} \right) = 0 \\ \xi_a^h \left(p_a^{\min} - p_a^h \right) = 0 \end{cases} \xrightarrow[\text{Comp. reduced from H-d to 1-d}]{p_a^h \text{ as a func. of } \tau_a} \begin{cases} \boxed{p_a^h(\tau_a) = \max\left\{ \min\left\{ \dfrac{\tau_a - \alpha_a}{2o_a^h}, p_a^{\max} \right\}, p_a^{\min} \right\}} \\ \psi_a^h(\tau_a) = \max\left\{ \tau_a - \alpha_a - 2o_a^h p_a^{\max}, 0 \right\} \\ \xi_a^h(\tau_a) = \max\left\{ 2o_a^h p_a^{\min} + \alpha_a - \tau_a, 0 \right\}. \end{cases}$$

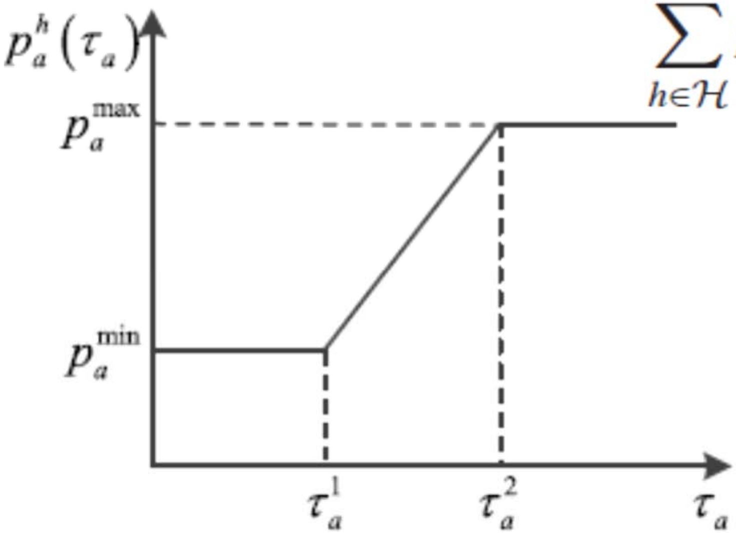
Direct projection

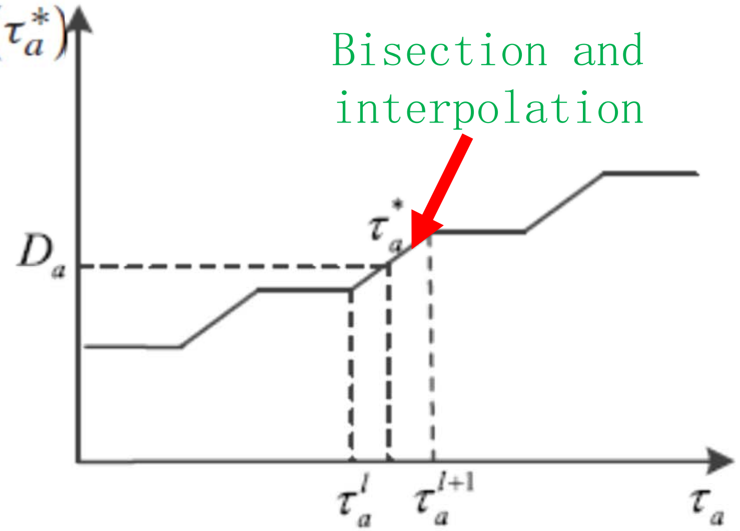
- How to find τ_a

$$\tau_a\left(D_a - \sum_{h\in\mathcal{H}} p_a^h\right) = 0$$



  - Tow possibilities: either $\tau_a^* = 0$, or $\sum_{h\in\mathcal{H}} p_a^h(\tau_a^*) = D_a$





Results

- Distributed computation
- Computational efficiency and scalability
- Schedule of each component

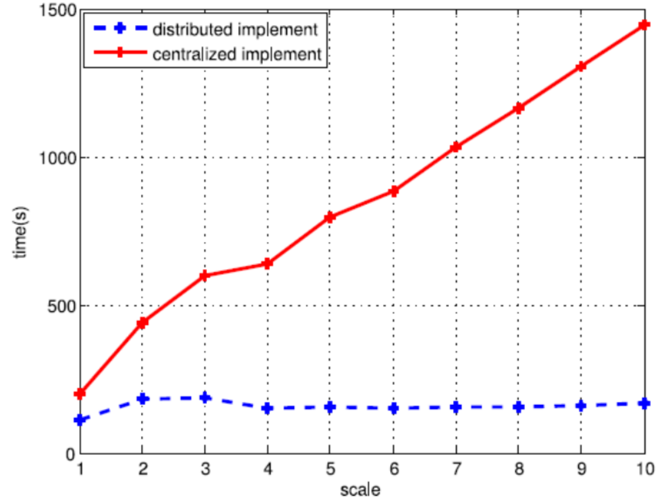


Fig. 8. Computation time of centralized and distributed implementation.

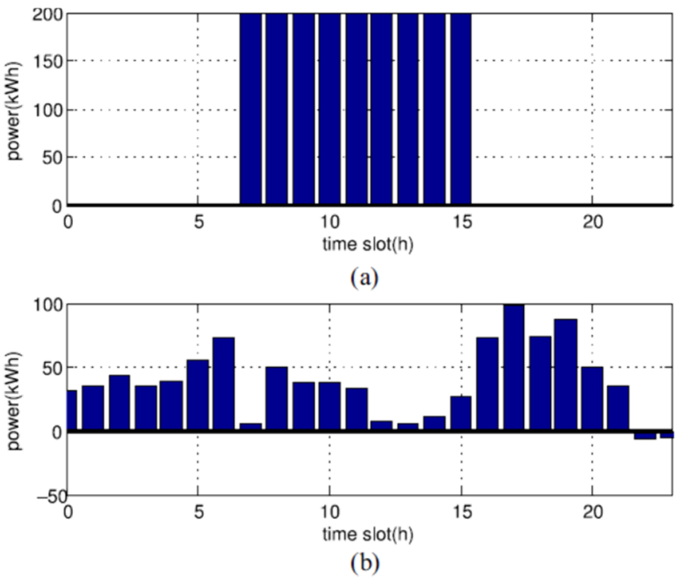


Fig. 5. Power of supply side. (a) Generating power of generator set. (b) Purchased power from grid.

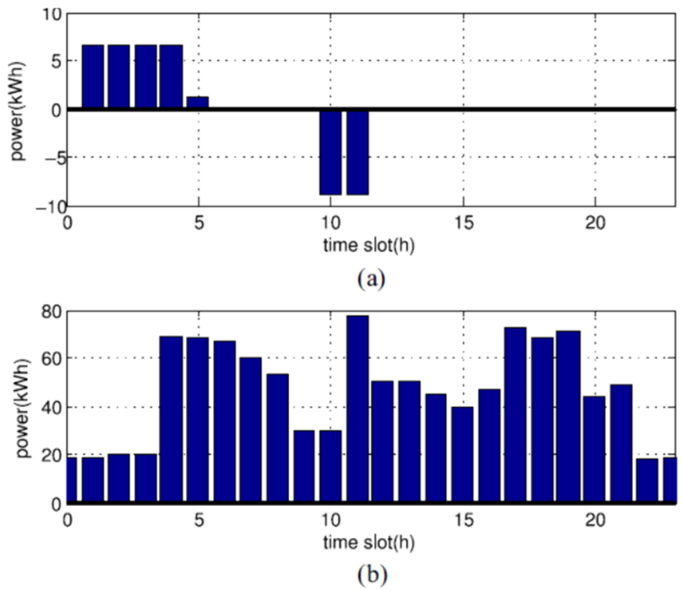


Fig. 6. Load of demand side. (a) Battery. (b) Smart appliance.

Extensions: green commercial building[8]

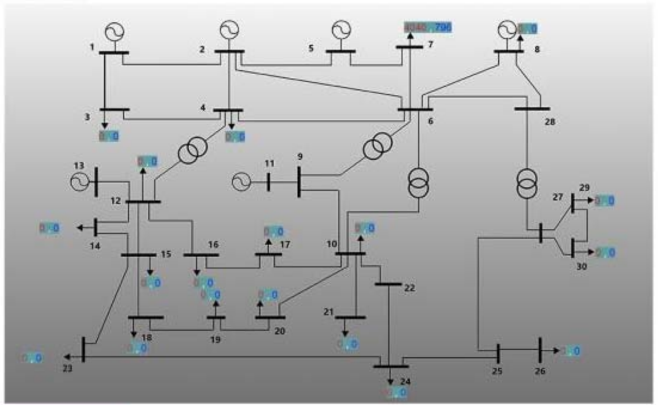
- 42% energy consumption in big cities
- Meeting scheduling for cost saving of HVAC
- Consider: thermodynamics, time, venue, attendees and dynamic price
- 28.48% cost saving

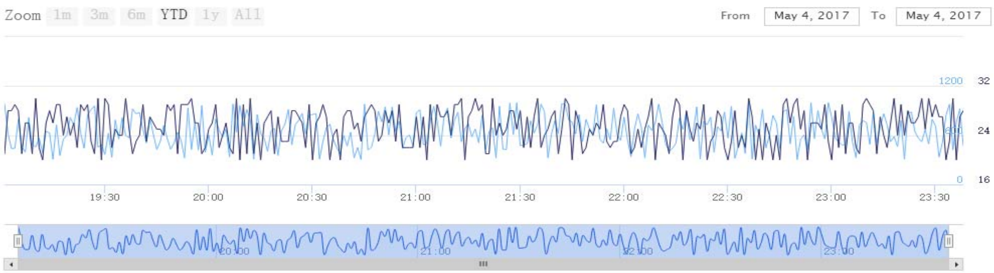
Rooms	Meetings	Cost savings	Optimal gap
5	5	33.52%	4.02%
5	10	32.28%	6.76%
5	15	24.27%	5.28%
5	20	12.47%	3.25%
7	10	35.08%	5.08%
7	15	32.48%	3.64%
7	20	28.62%	5.04%
7	25	18.86%	1.41%
9	15	35.80%	5.65%
9	20	37.12%	3.31%
9	25	30.05%	7.38%
9	30	21.17%	4.35%
average		28.48%	4.60%

[8] Chai, B. Yang, ZY, et al., Optimal Meeting Scheduling in Smart Commercial Building for Energy Cost Reduction, IEEE TSG, to appear, 2017;

Extensions: smart plug

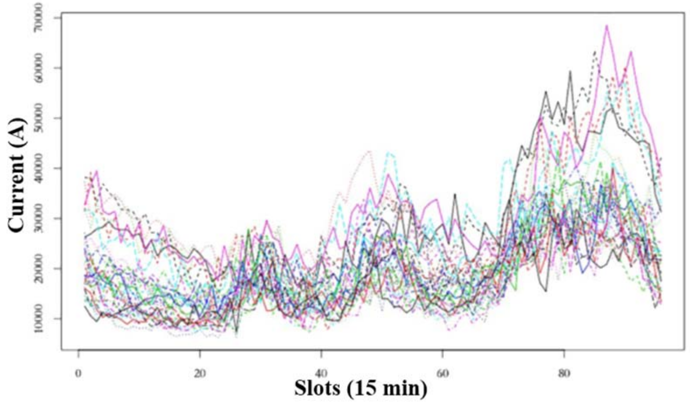
- Make common appliance smart
- Hardware and database
- Automated measure and control
- Monitoring platform and data analytics

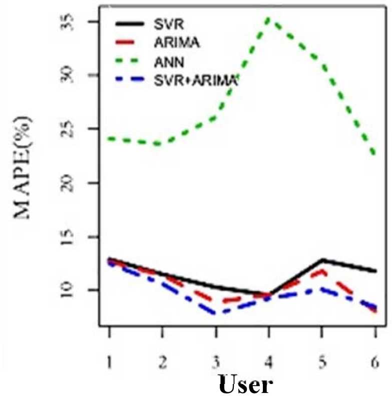




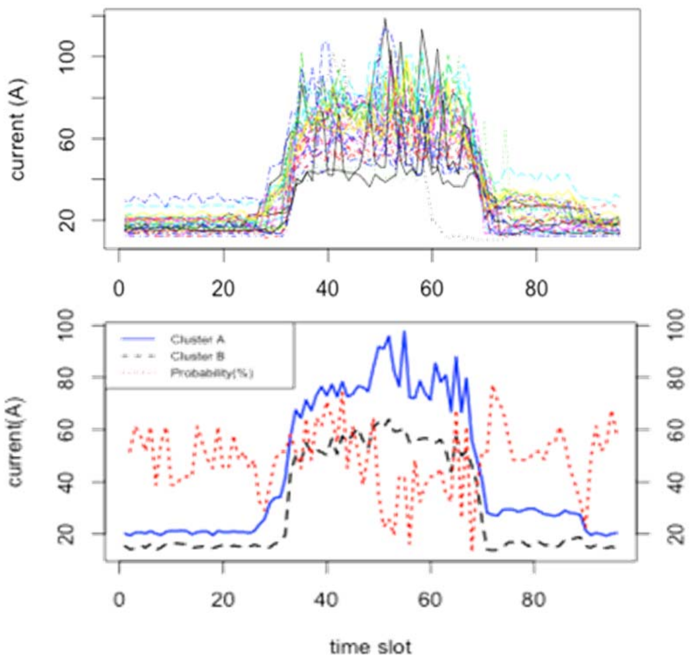
Extensions: real load data analytics for grid operation*

- Hybrid load forecast
  - Geo-neighbor, weather, date
- Estimate DSR capability

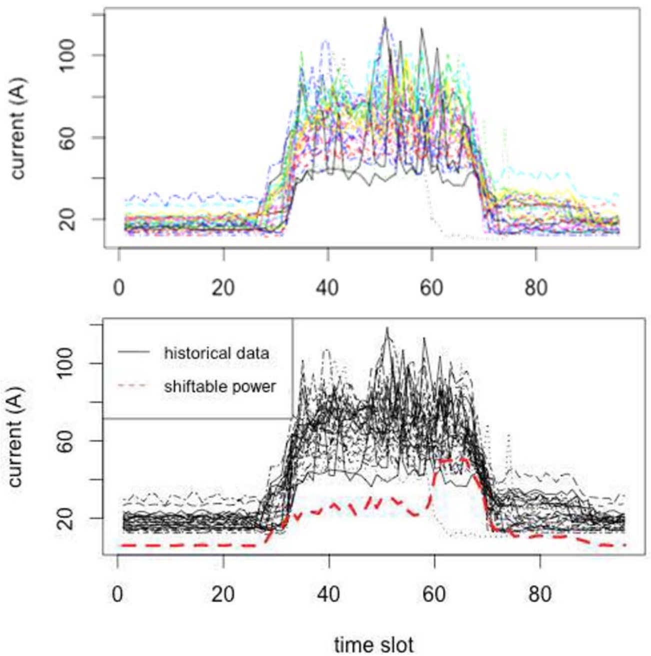




reducible load



shiftable load



*Data sets: Xuzhou city, per 15 min in 1 year, 153 public transformers; Fushun city, per 15 mins in 1 month, 84229 households

Electric Transportation

E-transportation

1/3 energy consumption and 1/4 emission

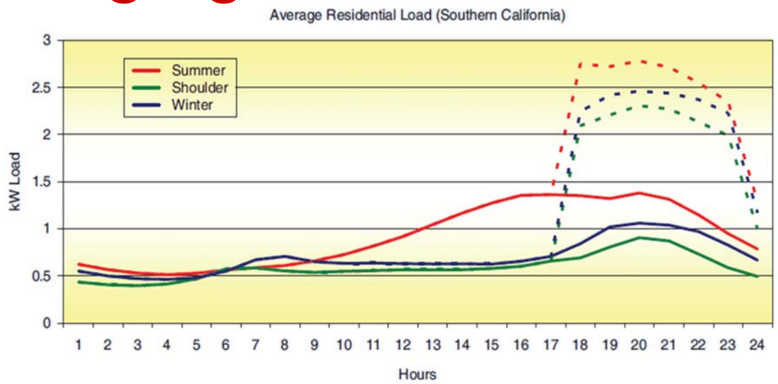
- EV is twice energy efficient than petrol vehicle
- Is EV financially beneficial?
  - ✗ Private: > 200k KM (15yrs)
  - ✓ Taxi: > 200k KM (1.5yrs)
  - ✓ Bus: > 150k KM (2.5yrs)
  - ✓ Van: > 130k KM (2yrs)

Non-private EV is more important, but less noticed!!

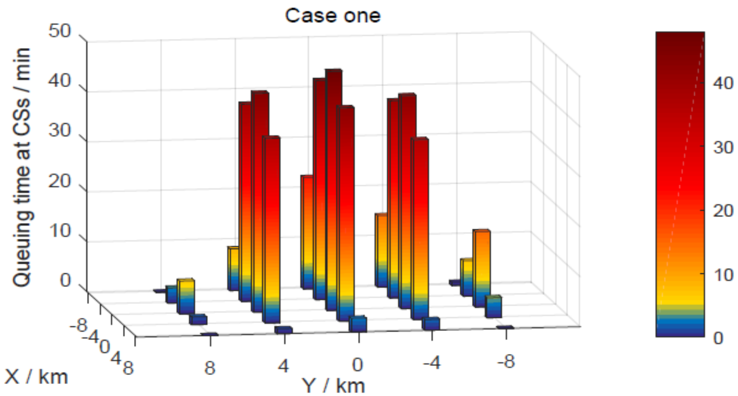
Shenzhen, 100% by 2017 (e-bus) and 2018 (e-taxi); Taiyuan,100% e-taxi since 2017

System level challenge: fleet charging

- **Must coordinate**
  - Large power: 30~120kW
  - Temporal/spatial load unevenness
  - Affect grid stability/efficiency
  - Decide **when and where** to charge



Charging load [Albuyeh'09]



- How to coordinate **E-taxi fleet** in a **distributed** way?
  - Central coordination is impractical
    - Selfish driver, random status and position
  - 2-stage distributed method **for drivers**: **temporal scheduling** + **spatial selection**[8]
    - Benefits: increase driver **revenue**; increase **utilization** of charging facilities; reduce grid load **unevenness**

[8] Guo, TC, and Yang, ZY, Joint Temporal-Spatial Coordination of Charging Decision of Electric Taxi Fleet, IEEE TPWRS, under review, 2017;

Temporal scheduling

- What will a rational taxi driver do?
  - Max revenue ➔ Min charging cost (income loss) by picking a good time slot

$$\min_{x} \; C(x) \equiv \min \sum_{\tau=t}^{t+L(t)-1} x(\tau)c(\tau)$$

binary decision

drive queue charge income loss

cost: $c(\tau) = \sum_{i=\tau}^{\tau+\chi+\lambda(\tau)+\gamma(\tau)-1} g(i)$

- Cost mainly depends on queuing time, not electricity price
- Current cost is known, but future ones are unknown yet

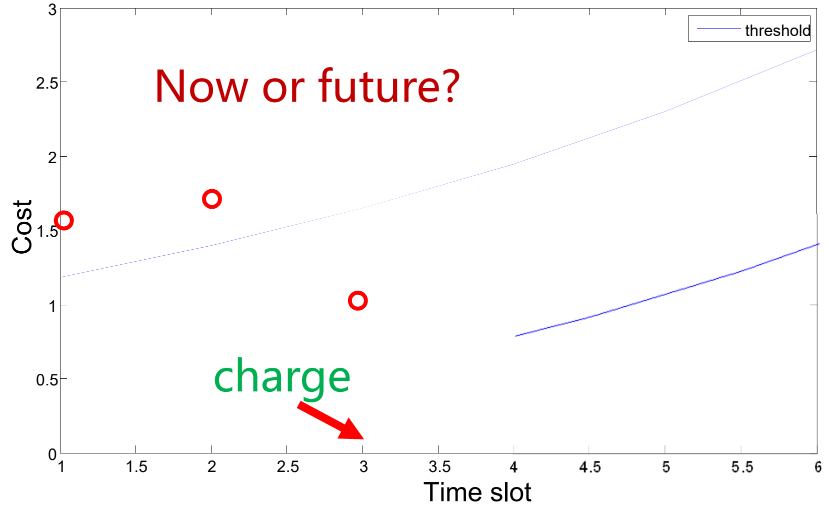
Stochastic decision process

- Thresholding method

$$x(t) = \begin{cases} 1, & c(t) \le \boxed{f(t+1)} \\ 0, & c(t) > f(t+1) \end{cases}$$

exp. future cost

Simple and distributed



- Backward induction of $f(t+1)$
  - Last slot:

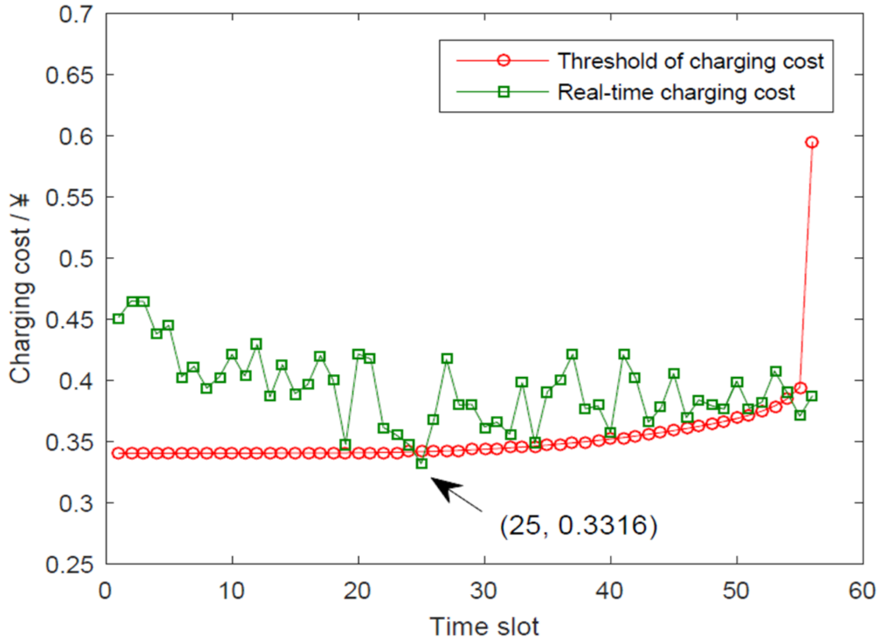
$$f(L) = E\left[\frac{1}{NR_d\theta}\sum_{i=L}^{L+\chi+\lambda(L)+\gamma(L)-1} g(i)\right]$$

  - Recursion:

$$f(\tau) = \alpha(\tau)\tilde{c}(\tau) + (1-\alpha(\tau))f(\tau+1)$$

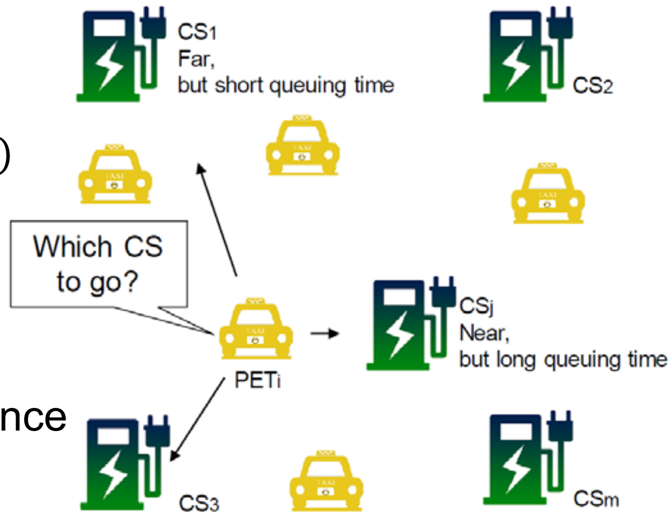
probability of charging at τ

conditional expected cost

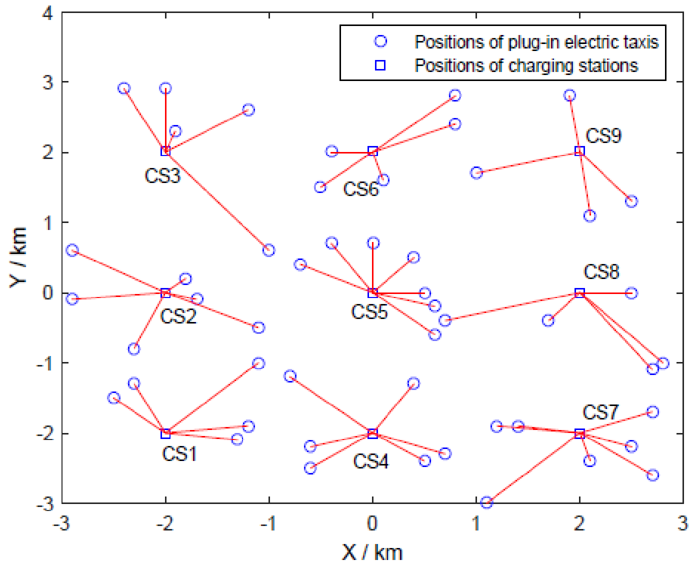


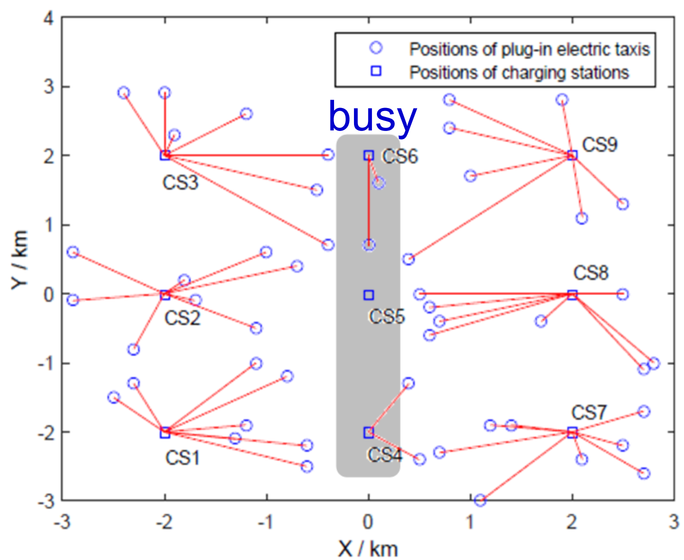
Spatial selection

- After decide charging now, I drivers select M CSs
  - Rational driver: $\min(traveling\ time + queuing\ time)$
  - Early arriving EVs affect queue length



- Game of EVs: distributed decision
  - Theorem: Nash Equilibrium existence and convergence
  - Low cost and fairness at NE





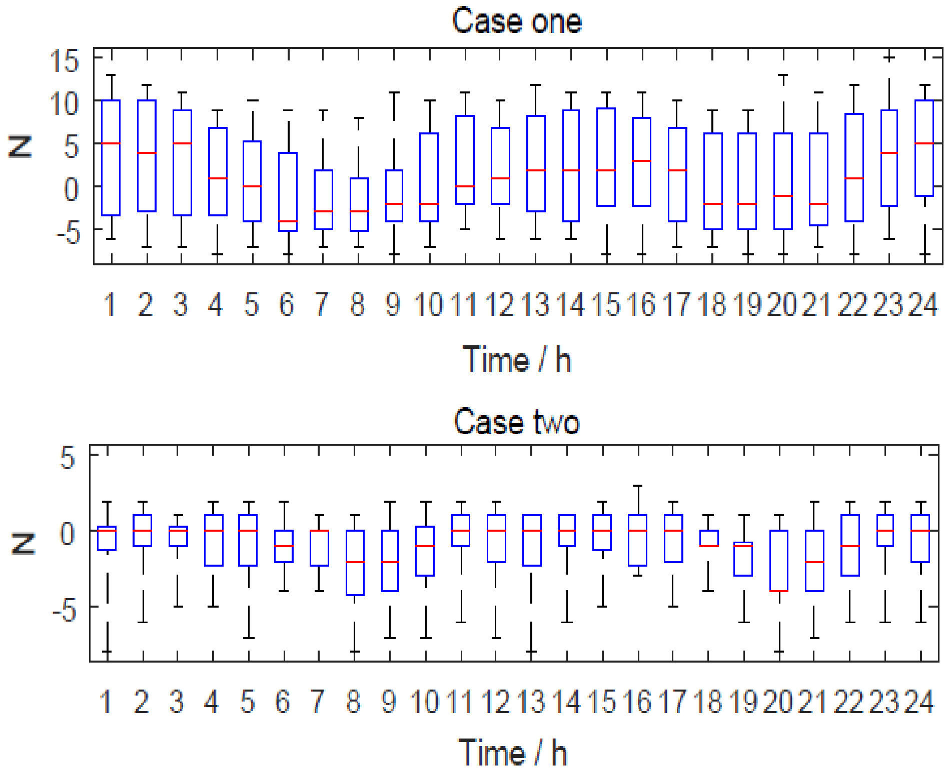
Performance (v.s. no coordination)

- Increase revenue for driver

Item \ Case	One	Two
Average income of PETs (¥/day)	592.41	635.81
Average traveling time of PETs (min)	6.00	7.37
Average queuing time of PETs (min)	60.67	5.27
Average queuing rate of PETs (%)	67.38	35.37
Average idle rate of charging piles (%)	23.52	16.96

Statistics

- Increase utilization ratio for charging facilities

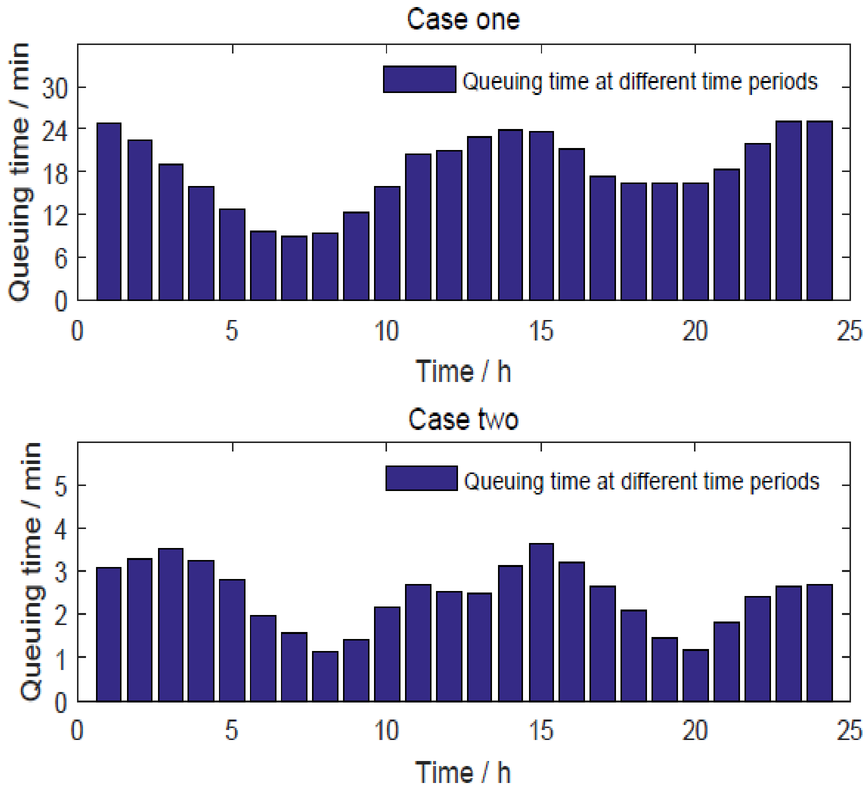


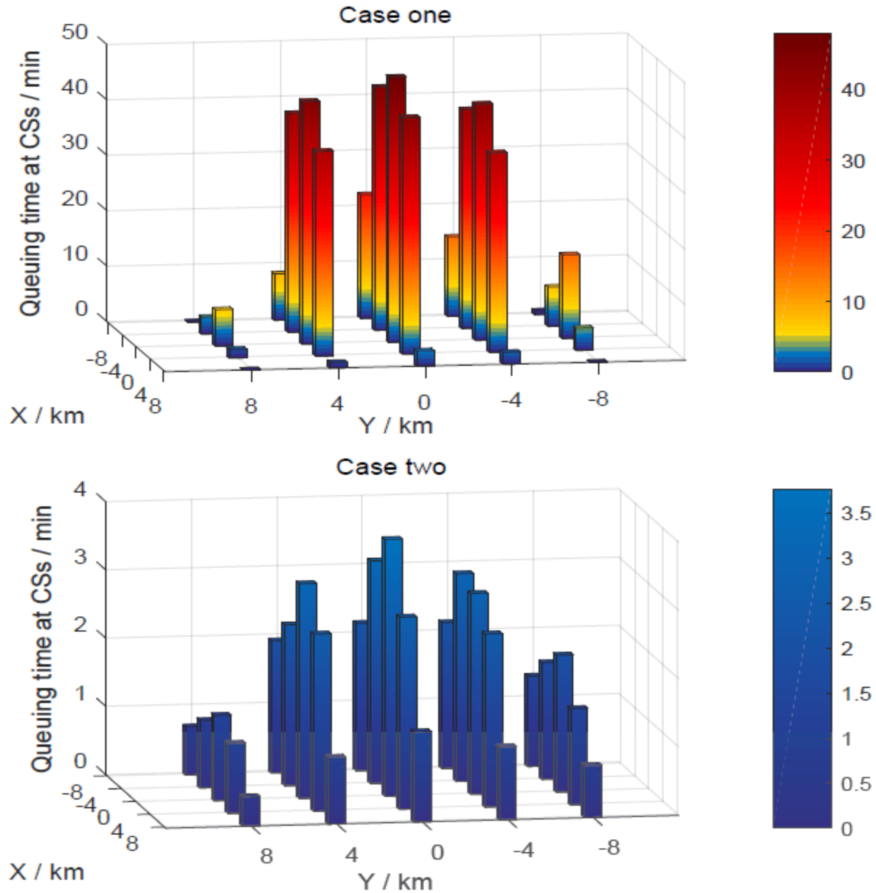
Charging pile utilization

N > 0, queue length; N < 0, vacant charging piles

Performance (v.s. no coordination)

- Reduce charging demand unevenness for grid

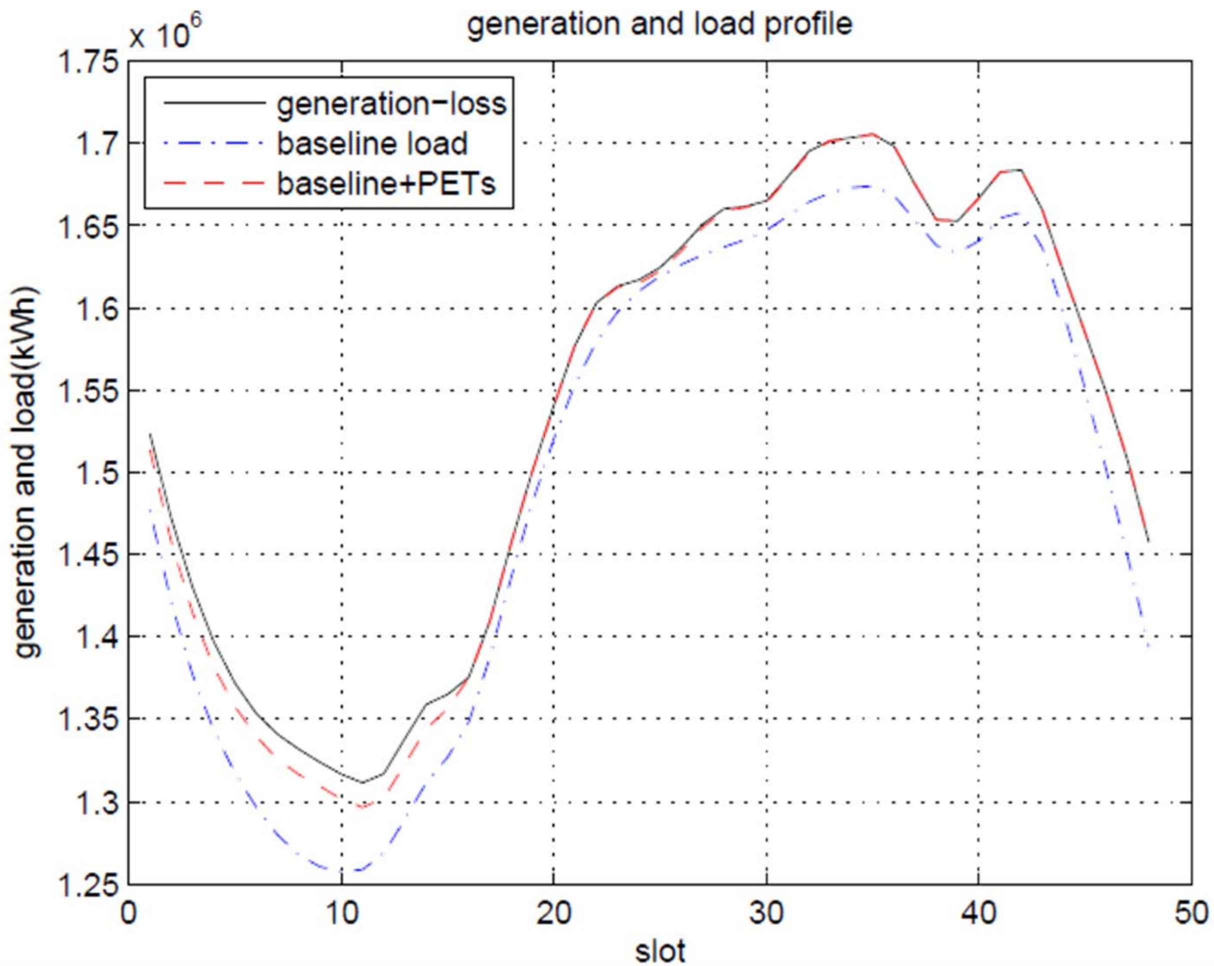




Queue reduction in temporal domain **Queue reduction in spatial domain**

Extensions: track varying generation

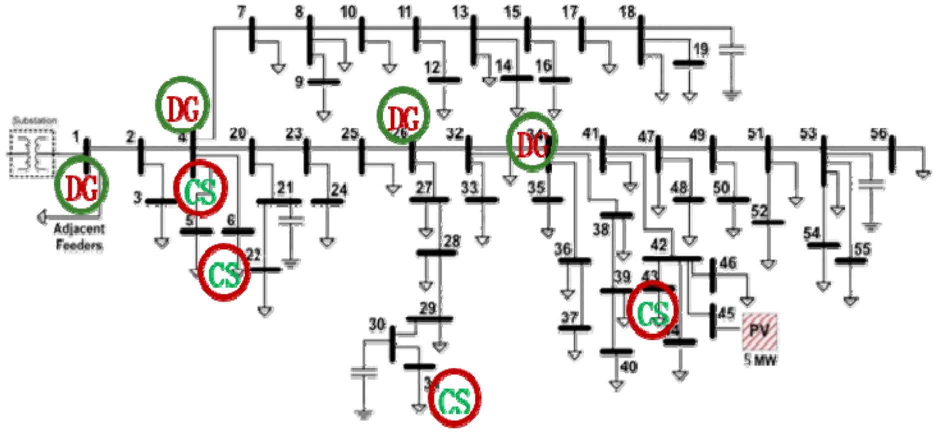
- **Grid operator** adjusts the aggregated charging load of e-taxi fleet, to track the desired profile[9]

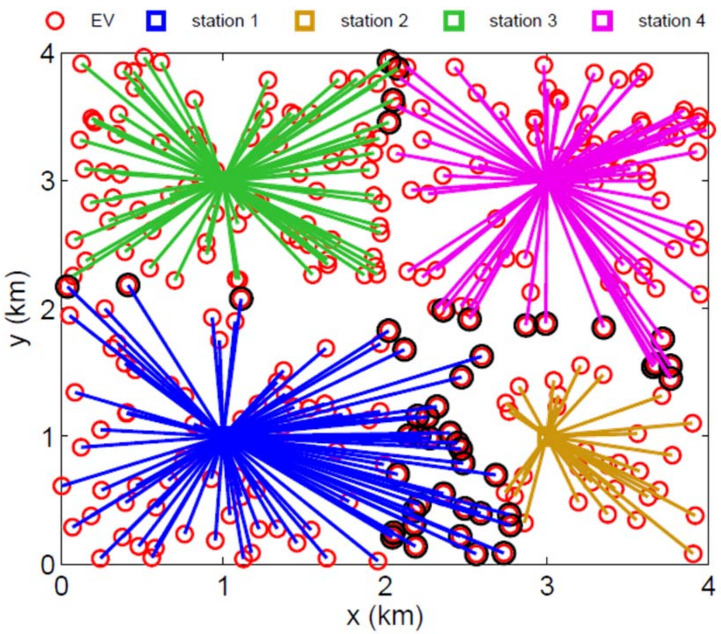


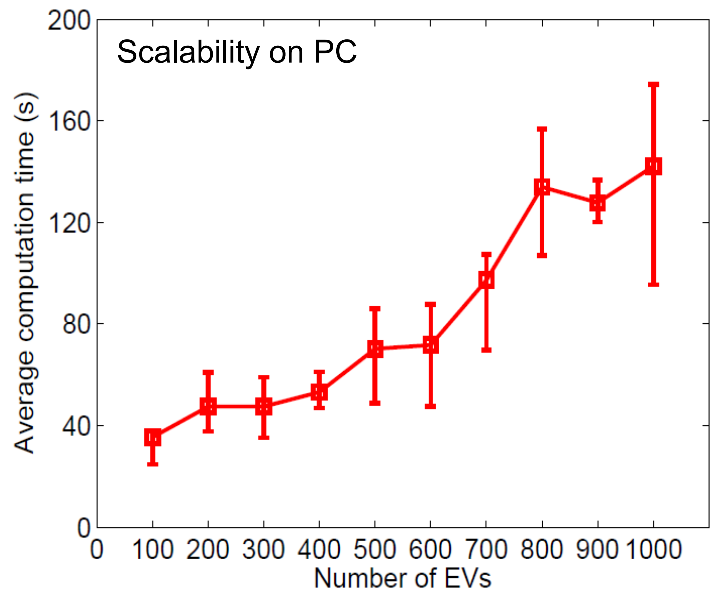
[9] Yang, J., Xu, Y. and Yang, Z., Regulating the Collective Charging Load of Electric Taxi Fleet via Real Time Pricing, IEEE TSG, 2017;

Extensions

- With power network model[10]
  - Kirchhoff's law, optimal power flow
  - Charging cost + dis. gen. cost, line loss, voltage drop
  - Distributed solutions with privacy



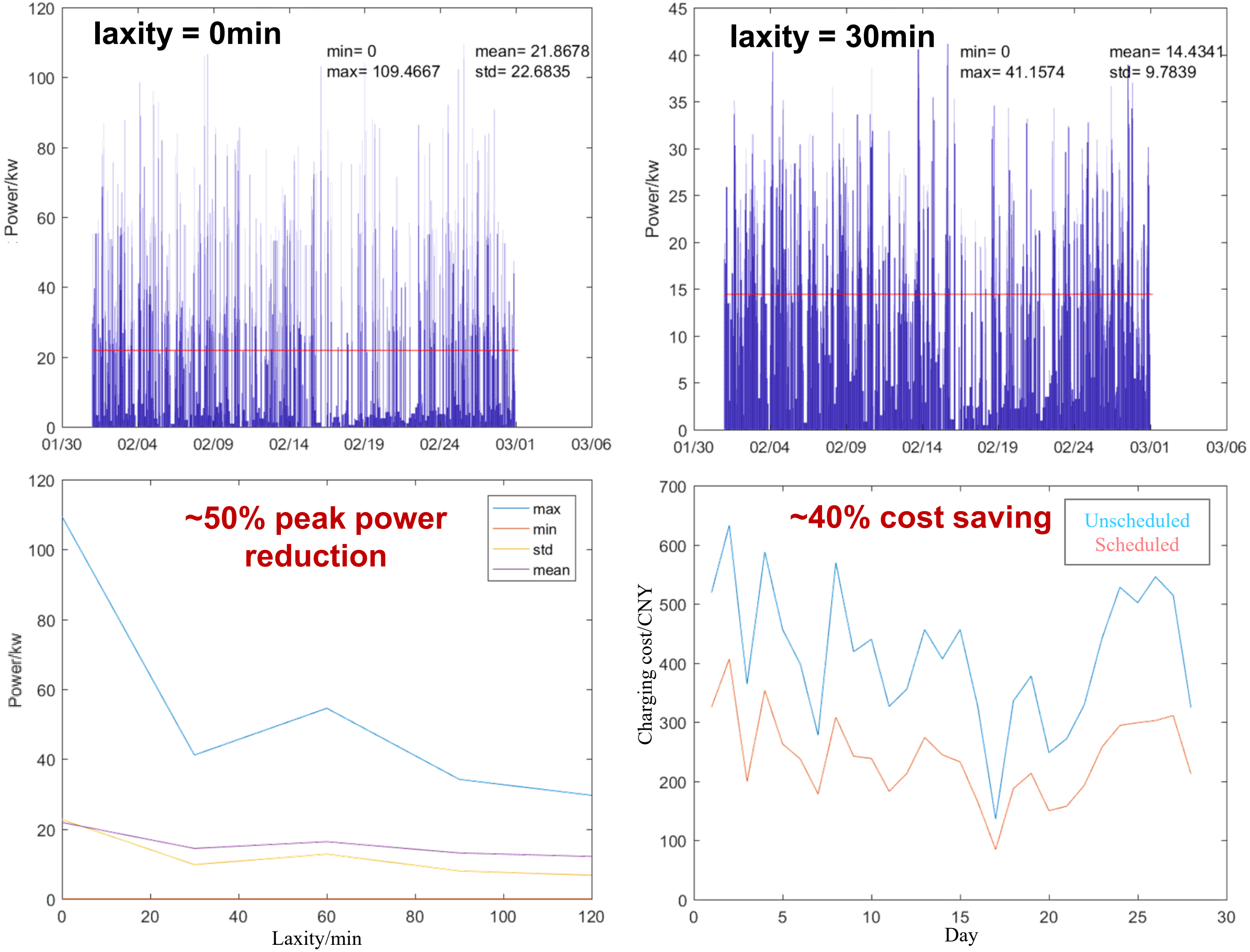




- Bus[11] and private[12]

[10] You, PC, Yang, ZY, et al., Scheduling of EV Battery Swapping, parts I and II, IEEE TCONS, 2018;
[11] You, PC, Low, S. and Yang, ZY, Optimal Charging Schedule for a Battery Switching Station Serving Electric Buses, IEEE TPWRS, 31(5), 2016;
[12] You, PC, Yang, ZY, Chow, et al., Optimal Cooperative Charging Strategy for a Smart Charging Station of Electric Vehicles, IEEE TPWRS, 31(4), 2946-2956, 2016;

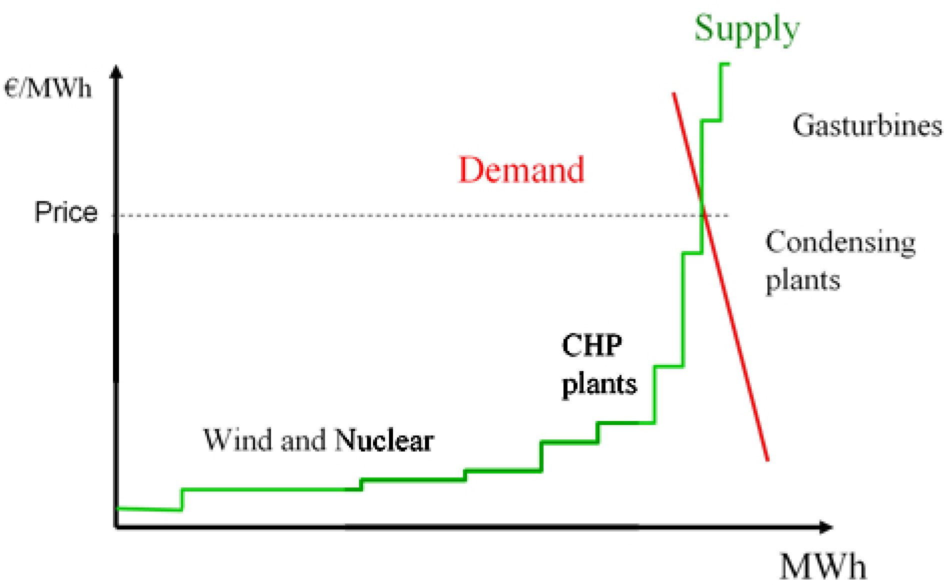
Extensions: in-station charging power scheduling*



Scheduling makes real impact!

*Data set: Huanan Charging Ltd., 811 charging piles in more than 2 years

Deregulated Electricity Market



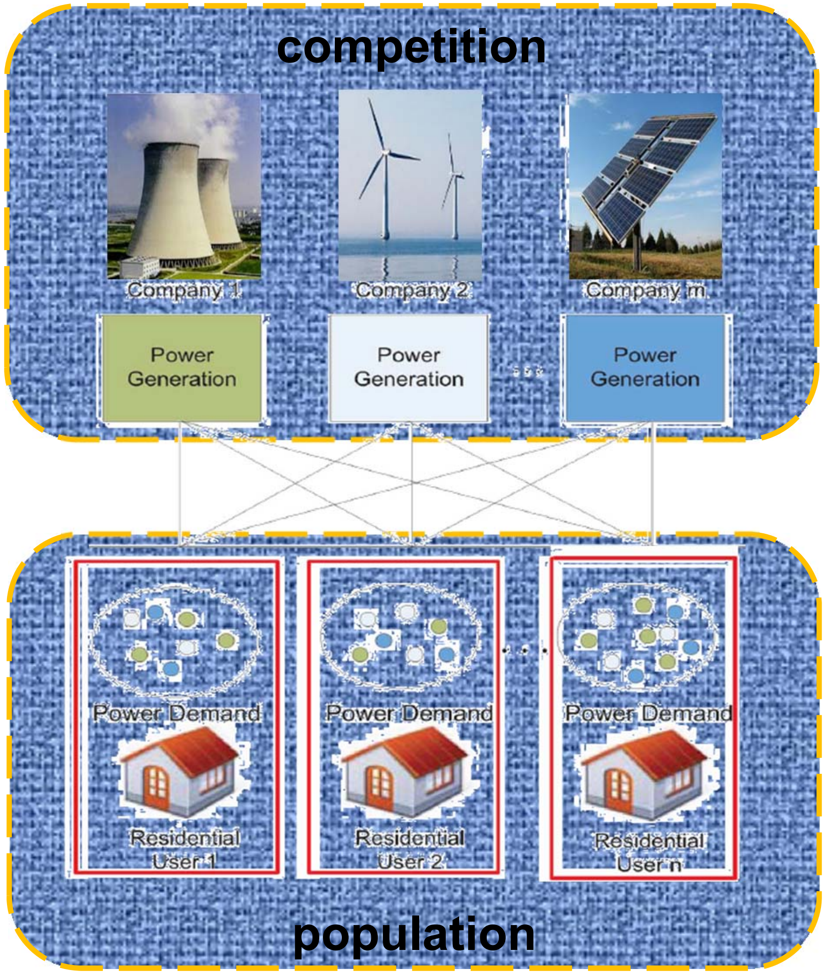
Deregulated v.s. regulated

- Many choices; supplier competition; high efficiency, low price

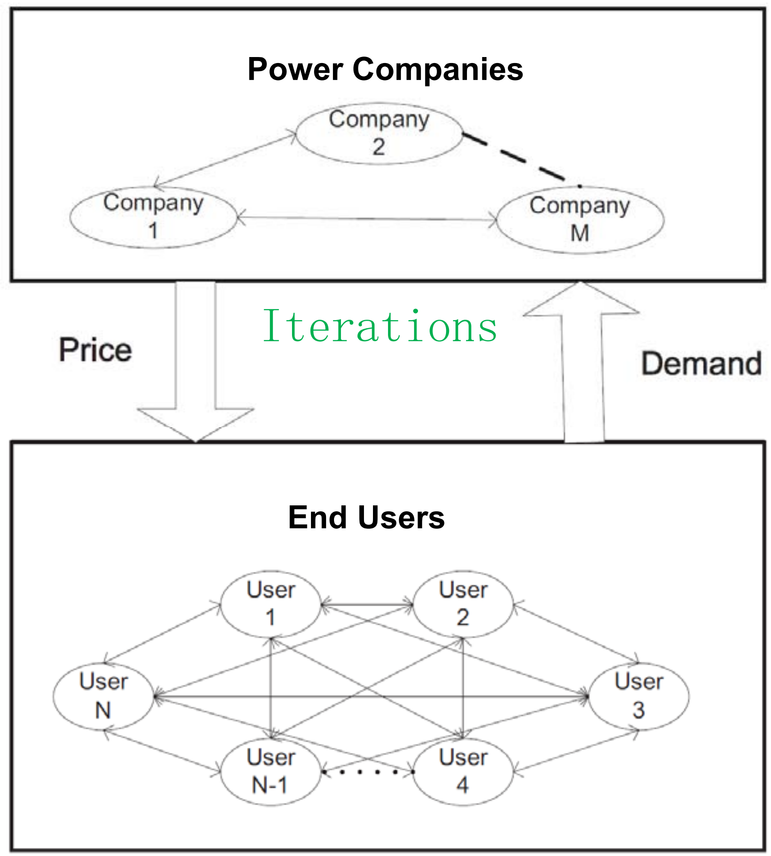
- Example: Japan
  - Price reduction: 16.9% in 10 yrs; 300+ electricity companies
- Challenges
  - Multi-buyer-multi-seller complex market; how do individuals act; how to accommodate uncertain renewable gen. in market

Problem formulation

- Two-level game[13]



Upper: non-cooperative game



Lower: evolutionary game

[13] Chai, B., Yang ZY, et al., Demand Response Management with Multiple Utility Companies: A Two-Level Game Approach, IEEE TSG, 5(2), 722-731, 2014;

User: choose the best company

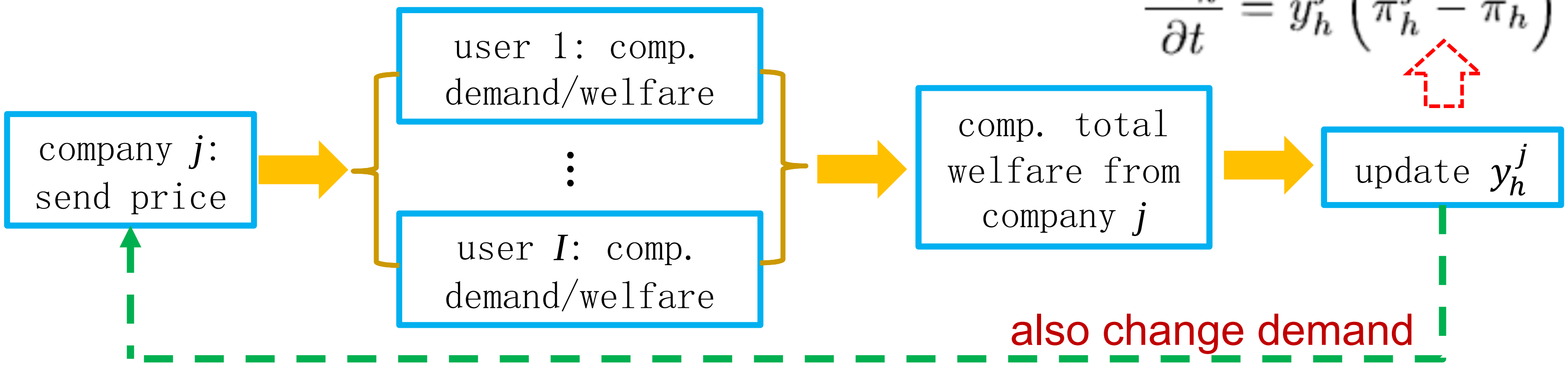
- **Max welfare**: via company selection and DSR
- Strategy of the user population:

$$Y_h = [y_h^1, y_h^2, \ldots, y_h^j, \ldots y_h^J] \qquad y_h^j\text{: prob. of choosing company } j \text{ at time } h$$

- How does it work?

Choose the best company

$$\frac{\partial y_h^j}{\partial t} = y_h^j \left(\pi_h^j - \bar{\pi}_h\right)$$



- Theorem: guaranteed convergence to evolutionary equilibrium.

Equilibrium: $\dot{y}_h^j = 0$, or $\pi_h^1 = \cdots = \pi_h^J = \bar{\pi}_h$

Different companies give same welfare

Company: compete via price adjustment

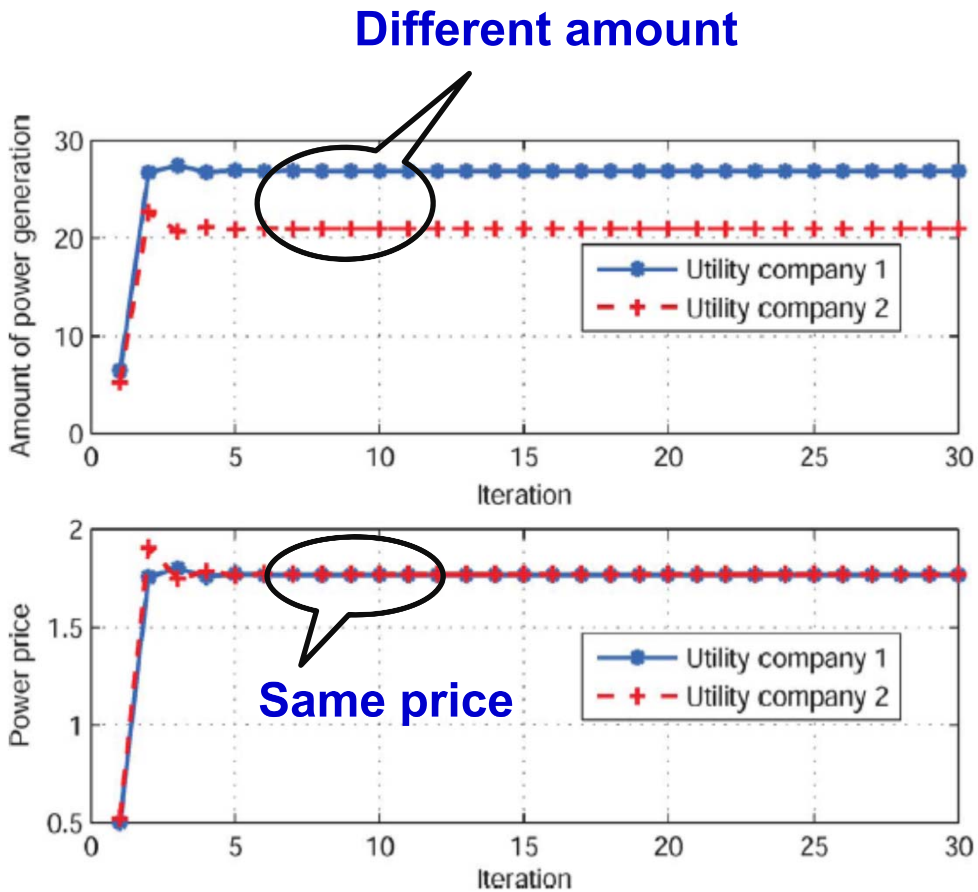
- **Max individual revenue**
  (sold elec. – generation cost)

- Price updating law:

$$p_h^j(m+1) = p_h^j(m) + \sigma_2 \left(1 - r_h^j(m)\right)$$

r_h^j: Gen. to demand ratio

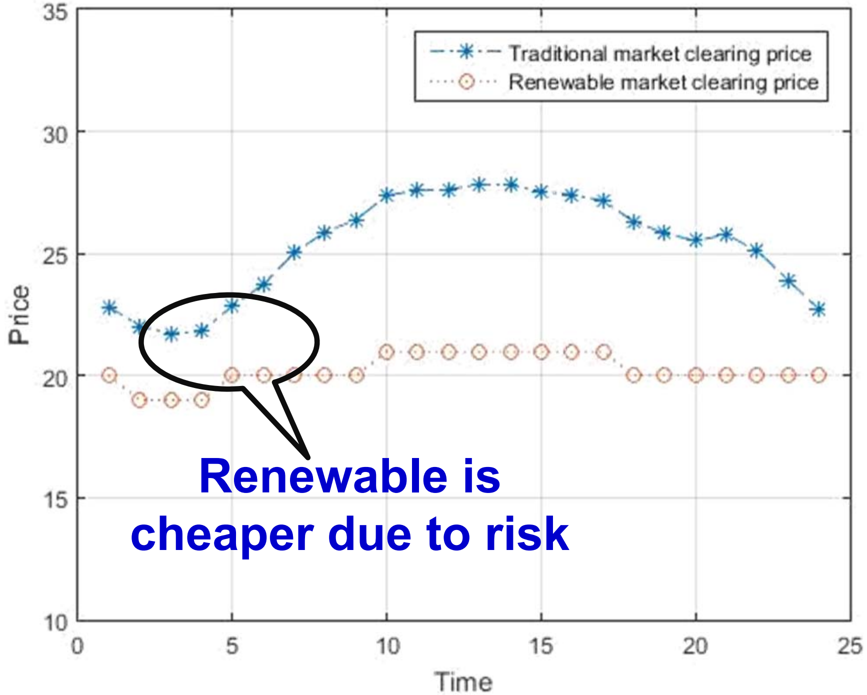
- Theorem: convergence to a unique Nash equilibrium



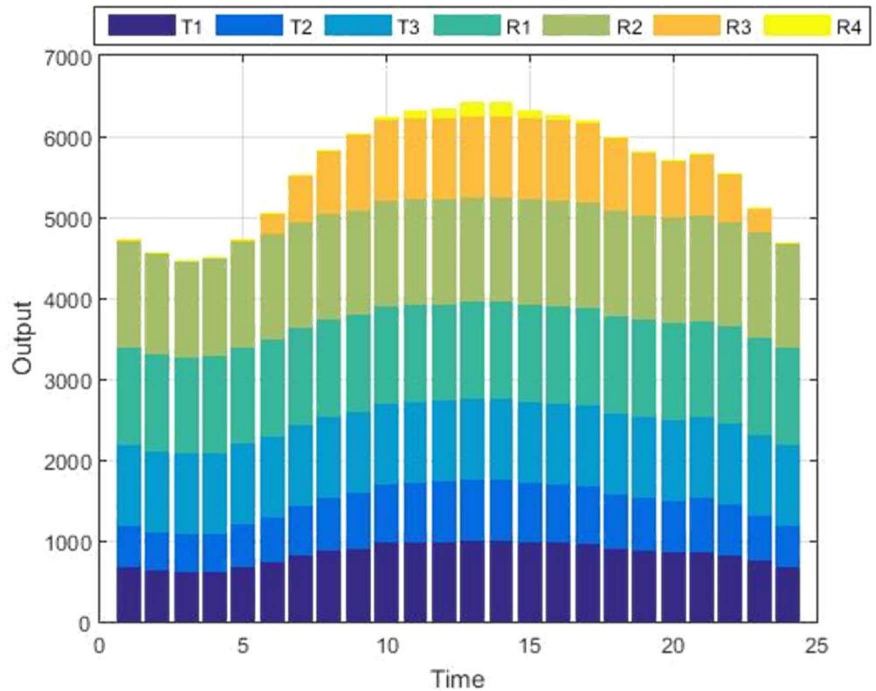
Same product has same price.
How about different products?

With renewables

- Difference: **uncertainty**
  - Risk of using renewables: more renewable demand, higher risk (monotonically increasing)
  - 2 markets and 2 prices



Market prices



Gen. of different plants

Summary

How to achieve energy sustainability?

Use system approaches to exploit interdependency

Enable components working together

Optimization problems
Distributed algorithms

Current work

- Efficient/optimal
  - Fast DSR
  - EV Charging coordination
  - Decision in deregulated electricity market
  - ……

Vulnerability: deviations (error, fault, accident) may quickly propagate from one system to the others

Future work

- Secure/robust
  - Secure power-transportation system
  - Deregulated electricity-flexibility co-market
  - ……

Thank You!
Q & A

Acknowledgement

PhD: R. Deng (Alberta), B. Chai (SGCC), X. Shi(ZJU), P. You, J. Sun, Z. Guo, Z. Wang

Collaborators: Prof. S. Low (Caltech), Prof. M.Y. Chow (NCSU), Prof. G. Giannakis (UMN)