Towards energy sustainability: a system point of view

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

- Quick facts
  - Est. 2011, 1.9 km²
  - 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

We are recruiting!
Energy sustainability and smart grid

Greenhouse Gas (GHG) Emissions

40% from gen./transp.

Promising solutions

- Renewable generation
- Energy efficiency
- E-transportation

All related to smart grid technologies

~60% in US
SG technologies: component level

Power system structure

Generation
Fossil + nuclear
Renewables

Power grid
(physical laws)
+E-market
(market rules)

IT infrastructure (Cyber-physical system)

Demand
Resid.
Comme.
Transp.
Indus.

pwr. electronics, UHV

Are they enough?

EV, high speed train, metro, storage, smart appliance
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\(^3\)

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\(^1\) 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
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*

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*Advanced energy economy, 2014*
The building block in DSR

- **Structure**

  - Utility company
  - Price → Demand
  - Competition[5]/Coupling constraints[6]

- **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

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Mathematical formulation

- **Objective**\(^7\) (MILP, mixed integer linear program)

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

Total cost = gen. + purchase + user dissatisfaction + batt. loss

- **Constraints: individual + balance**

\[
\sum_{g \in G} u_g^h p_g^h + s^h + \sum_{b \in B} p_{b,d}^h + \omega^h p_{rate} = \sum_{a \in A} p_a^h + p_0^h + \sum_{b \in B} p_{b,c}^h
\]

Spatially coupled over all components
Distributed algorithm

- Problem transformation

Primal \rightarrow LR decouple \rightarrow Dual problem

Batt. set \rightarrow Sub-gradient
Gen. \rightarrow
App. \rightarrow
Benders decom. \rightarrow Unit commit. \rightarrow Direct projection
Direct projection

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

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

subject to:

$$p_a^{\min} \leq p_a^h \leq p_a^{\max}, \quad \sum_{h \in \mathcal{H}} p_a^h = D_a$$

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

\[
\begin{align*}
2\alpha_a^h p_a^h + \alpha^h - \tau_a + \psi_a^h - \xi_a^h &= 0 \\
\tau_a \left( D_a - \sum_{h \in \mathcal{H}} p_a^h \right) &= 0 \\
\psi_a^h \left( p_a^h - p_a^{\max} \right) &= 0 \\
\xi_a^h \left( p_a^{\min} - p_a^h \right) &= 0
\end{align*}
\]

$p_a^h$ as a func. of $\tau_a$

\[
\begin{align*}
p_a^h(\tau_a) &= \max \left\{ \min \left\{ \frac{\tau_a - \alpha_a}{\alpha_a^h}, p_a^{\max} \right\}, p_a^{\min} \right\} \\
\psi_a^h(\tau_a) &= \max \left\{ \tau_a - \alpha_a - 2\alpha_a^h p_a^{\max}, 0 \right\} \\
\xi_a^h(\tau_a) &= \max \left\{ 2\alpha_a^h p_a^{\min} + \alpha_a - \tau_a, 0 \right\}
\end{align*}
\]

Comp. reduced from H-d to 1-d
Direct projection

- How to find $\tau_a$

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

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

- Bisection and interpolation
Results

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

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.

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

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<th>Meetings</th>
<th>Cost savings</th>
<th>Optimal gap</th>
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<td>5</td>
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<td>33.52%</td>
<td>4.02%</td>
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<td>15</td>
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<td>15</td>
<td>35.80%</td>
<td>5.65%</td>
</tr>
<tr>
<td>9</td>
<td>20</td>
<td>37.12%</td>
<td>3.31%</td>
</tr>
<tr>
<td>9</td>
<td>25</td>
<td>30.05%</td>
<td>7.38%</td>
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<tr>
<td>9</td>
<td>30</td>
<td>21.17%</td>
<td>4.35%</td>
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<tr>
<td>average</td>
<td>28.48%</td>
<td>4.60%</td>
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</table>

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

*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

PROterra® vehicles cost much less to maintain than others:

- **30% fewer parts**
- **75% fewer brake repairs**
- **No expensive exhaust after-treatments**
- **No oil changes**
- **No liquid fuels**

**Save up to $237,000.**

On maintenance costs over the lifetime of the bus

vs. diesel-hybrid

$194K vs CNG  $151K vs Diesel
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

- 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

Temporal scheduling

What will a rational taxi driver do?

- Max revenue ➔ Min charging cost (income loss) by picking a good time slot

\[
\min_x C(x) \equiv \min \sum_{\tau=t}^{t+L(t)-1} x(\tau)c(\tau)
\]

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

drive queue charge income loss

binary decision

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

- Thresholding method
  \[ x(t) = \begin{cases} 
  1, & c(t) \leq f(t + 1) \\
  0, & c(t) > f(t + 1) 
  \end{cases} \]
  \(\text{exp. future cost}\)

- Backward induction of \(f(t + 1)\)
  - Last slot:
    \[ f(L) = E \left[ \frac{1}{N R_d \theta} \sum_{i=L}^{L+\chi+\lambda(L)+\gamma(L)-1} g(i) \right] \]
  - Recursion:
    \[ f(\tau) = \alpha(\tau) \tilde{c}(\tau) + (1 - \alpha(\tau)) f(\tau + 1) \]

\(\text{Simple and distributed}\)

Now or future?

- Probability of charging at \(\tau\)
- Conditional expected cost

![Graph showing thresholding method and backward induction](image-url)
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
- Increase utilization ratio for charging facilities

### Statistics

<table>
<thead>
<tr>
<th>Item</th>
<th>Case One</th>
<th>Case Two</th>
</tr>
</thead>
<tbody>
<tr>
<td>Average income of PETs (¥/day)</td>
<td>592.41</td>
<td>635.81</td>
</tr>
<tr>
<td>Average traveling time of PETs (min)</td>
<td>6.00</td>
<td>7.37</td>
</tr>
<tr>
<td>Average queuing time of PETs (min)</td>
<td>60.67</td>
<td>5.27</td>
</tr>
<tr>
<td>Average queuing rate of PETs (%)</td>
<td>67.38</td>
<td>35.37</td>
</tr>
<tr>
<td>Average idle rate of charging piles (%)</td>
<td>23.52</td>
<td>16.96</td>
</tr>
</tbody>
</table>

### 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\(^9\)

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\[^9\] 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\(^{[12]}\)

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\(^{[10]}\) 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!

~50% peak power reduction

~40% cost saving

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

[Diagram showing supply and demand curves with labels for different plant types: Wind and Nuclear, CHP plants, Condensing plants, and Gasturbines.]
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

User: choose the best company

- **Max welfare**: via company selection and DSR
- Strategy of the user population:
  \[ Y_h = [y_h^1, y_h^2, \ldots, y_h^j, \ldots y_h^J] \]
  \[ y_h^j: \text{prob. of choosing company } j \text{ at time } h \]

- 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.

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

  - Different companies give same welfare
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](image1)

Renewable is cheaper due to risk

![Gen. of different plants](image2)
Summary

How to achieve energy sustainability?

Use system approaches to exploit interdependency

Enable components working together

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

Optimization problems
Distributed algorithms

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

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

Current work

Future work
Thank You!

Q & A

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