Coalitions in Power Systems

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Changing Energy Sources

- Centralized to **Distributed**
- Deterministic to **Stochastic**
- Tension in these two trends
Centralized vs. Distributed

- Many new resources are uncertain
  - Wind, solar, load, ...
- Aggregation helps

1 Wind Farm

5 Wind Farm

10 Wind Farm

50 Wind Farm
Centralized vs. Distributed

- Many new resources are uncertain
  - Wind, solar, load, ...
- Aggregation helps

- What about market power?

- Or demand side program design?
Coalitions in the System

How do we understand the trade-off between uncertainty and efficiency?

This talk: There is often a “best” coalition structure that optimizes the trade-off
Outline

• Supply side coalitions
  – Grouping of wind farms

• Demand side coalitions
  – Grouping of customers
Electricity markets

- Current Structure: “Deterministic”

- What about wind?
Wind power

- Wind is *uncertain*
- Currently taken as negative load
- 30% renewable by 2030 in CA, 50% by 2050
- Needs to participate in the market...

  ...but uncertainty limits wind participation
Uncertainty vs. Market Power

• Spatial diversity: coalitions reduce uncertainty

• What about market power?
  – Traditional generators are not allowed to form coalitions
  – A major concern in current market

• PJM: 10% of wind could reduce the day-ahead price by half
Uncertainty vs. market power

- Coalitions reduce uncertainty
- What about market power?

Contribution:
- We consider a stylized Cournot game to study the tradeoff between uncertainty and market power

- We characterize the optimal size of coalitions
Model setup

- We focus on the *day-ahead market*

- $N$ wind farms with real-time output $W_1, \ldots, W_N$

- Farm $i$ bids $w_i$, gets profit

$$
\pi_i(w_i, w_{-i}) = p(w_1, \ldots, w_N)w_i - q \mathbb{E}[ (w_i - W_i)^+] 
$$

- Quantity
- Day-ahead Price
- Real-time Shortfall
- Bid
Assumptions I

- Note that we assume a *real-time shortfall penalty* in the form of $q \mathbb{E}[(w_i - W_i)^+]$
  - Generalizes to convex risks

- In practice there is a rebalancing at the real-time market: a second game
Assumptions II

• Day-ahead price is a *linear* function of wind:

\[ p(w) = 1 - \alpha \sum w_i \]

• Generalizes to concave price functions

• Traditional generators do not react to wind farms
Residual supply curve

- Two kinds of generators: Traditional and wind
- Residual supply curve for traditional generators:

![Graph showing residual supply curve with 15% wind penetration.]

PJM 2008 Data
Linear approximation

- Price is a *linear* function of wind:

\[ p(w) = 1 - \alpha \sum w_i \]

\[ \alpha = 3.2 \]
Coalitions and Efficiency

- Payoff for a coalition \( S \subset \{1, \ldots, N\} \)

\[
\pi_S(w_S, w_{-S}) = p(w)(\sum_{i \in S} w_i) - q\mathbb{E}\left[\left(\sum_{i \in S} w_i - \sum_{i \in S} W_i\right)^+\right]
\]

Risk Sharing

- Always beneficial for producers to form groups
- Wind injected under Nash equilibrium: \( w^* = \sum_S w^*_S \)
- Wind injected by the social planner: \( w^{social} \)

- Efficiency ratio:

\[
\mathcal{R} = \frac{w^*}{w^{social}}
\]
Independent Wind Farms

- Suppose $W_i$ are i.i.d.
- Large $N$ regime: Fix $\mathbb{E}[\sum W_i] = \mu$, take $N \to \infty$

Then asymptotically:

- Individual: Groups of size 1

$$r = \frac{w^*}{w_{social}} < 1 - c$$ Due to Uncertainty

- Grand coalition: One group of size N

$$r = \frac{w^*}{w_{social}} \leq \frac{1}{2}$$ Due to Market Power
Optimal Grouping

- There are groups that achieve $r \to 1$ as $N \to \infty$

- Divide $N$ producers into $K$ groups, each of size $N/K$

Then $r$ scales as:

$$r = 1 - O\left(\frac{1}{K}\right) - O\left(\frac{K}{N}\right)$$

- Optimal rate given by balancing the two terms:

$$K = \sqrt{N}$$
Example

- \( W_i \) Gaussian, \( q = 1, \alpha = 3.2 \)
Sketch of Proof

- Given $K$ groups

Nash Equilibrium With Uncertainty $\iff$ Nash Equilibrium Without Uncertainty $\iff$ Social Optimal Allocation

$O\left(\frac{K}{N}\right)$ $\iff$ $O\left(\frac{1}{K}\right)$
Correlated Producers

- Wind farms are correlated
- $W_i$ are the forecast errors: still correlated but less so

We adopt the following model:

$$W_i = \hat{W}_i + Z$$

$Z$: common randomness
$\hat{W}_i$: private randomness

- Same question as before: behavior of $r = \frac{w^*}{w_{social}}$
Scaling Rate

• Same rate as before

\[ r = 1 - O\left(\frac{1}{K}\right) - O\left(\frac{K}{N}\right) \]

  Market Power  Uncertainty

• Rate hold as long as the correlation structure of \( W_1, \ldots, W_N \) is "symmetric"

• Smaller constants: \( r \) goes to 1 “faster” than i.i.d. case
Finite Number of Producers

- Finite producers with given correlation structure
- Optimization problem: \[ \max_{S_1, \ldots, S_K} \sum_{S_k} w^*_k \]
- E.g., NREL dataset (300 wind farms)
Next Steps

Our model takes a first step towards understanding how
• market power; and
• uncertainty
influence coalition formation in power markets.

Lots of work can be done
• What about the real-time market?
• What about traditional generators?
Outline

• Supply side coalitions
  – Grouping of wind farms

• Demand side coalitions
  – Grouping of customers
Current Demand Management

Market

Utility

Customers
Aggregator Size

- Intuitively, monopolistic utilities are inefficient
  ERCOT (Texas System operator) allows retail competition: 200+ plans

How does an aggregator choose customers and design pricing?

How big should a group be?
Uncertainty in Load

- Load, like renewables, are uncertain
- Generators are slow, load need to bid day-ahead
- Forecast error are exposed to real-time price

ISO-NE Data
Load Forecast Error

Hourly forecast, day-ahead
  • Single Household: 100%
  • Substation Level (200,000 households) : 2%
Forecasting

- PG&E dataset, hourly smart meter data, 1 million households
- AR Model based on temperature

![Graph showing the Law of Large Number and a knee point.](Image)
Forecast Examples

200 Households

200,000 Households
Error Floor

- Stochastic Error
- Systematic Error

No Improvement
Loss of Efficiency

% error

log(# households)
Behavior Data

- Aggregate Consumption
  Aligns with the electricity price

- Cost is shared equally among the users
Consumers are different

- Why not group “off-peak” households?
- More efficient to group users of similar profiles
Price of Uncertainty

- Load aggregator solve

\[
day \text{ ahead cost} + E[\text{realtime risk}]\]

- Assumption: Given \(K\) customers, the forecast error depends only on \(K\)
- Measured as \(\sigma_K\)
- For a class of risk functions

\[
E[\text{realtime risk}] = \sigma_K \cdot r
\]

Price of Uncertainty
Read of from forecast error curve

33/38
Day-Ahead Cost

- Given $K$ customers, find the lowest rate

\[ \text{cost} = \text{rate} \cdot K \]

- Price and demand are vectors

- Rate for $K$ customers

\[
\frac{\sum_{i=1}^{K} p^T d}{\sum_{i=1}^{K} 1^T d}
\]

- Optimization Problem

\[
\min \text{rate} \\
\text{s. t. } K \text{ total customers}
\]

- Integer program, but there is an LP relaxation

- Use historical demand data
Uncertainty-Rate Tradeoff

- Rate increases as group size
- Cost of uncertainty decreases
Fairness

- Enables small scale load serving entities
Data and Customers

• Data can tell us a lot more

• Causal inference: why customer behave the way they do

• Real-time operations
  – Topology identification
  – Fault detection
Conclusion

- Centralized vs. distributed architecture of the grid
- Trade-off between uncertainty and efficiency: “optimal” coalitions

- Collaborators

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