

# Inferring Structure from Optimization Model Solutions

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# Themes

- ▶ Solutions of optimization models are often observed while the relevant parameters are not.
- ▶ Common examples include problems from network industries such as electricity.
- ▶ When the data include constraint coefficients, the inverse optimization to discover the parameters is only partially identified.
- ▶ Identification can be possible through norm minimization.

# A Motivating Problem

## Economics of Two-Stage Electricity Markets?

(Veit et al 2006; Sioshansi, Oren, O'Neill 2010; Botterud et al 2011)

## Market Power In Electricity Markets?

(Cardell, Hitt, Hogan 1996; Jiang, Baldick 2005; Hogan 2012)

### **Results rely assumptions r.e. participant objectives:**

⇒ Case Study on Wind Producer Objectives in Midwest ISO

- ▶ Two-stages: Day Ahead (DA), Real Time (RT) markets
- ▶ Forecast: Wind producers submit a DA production commitment
- ▶ Stochastic production: shortfall or surplus made up via RT prices

*Wind DA Revenues:*

$$Rev(Q_{DA}) = Q_{DA} \times P_{DA} + (Q_{RT} - Q_{DA}) \times P_{RT}$$

*Economic value of intermittent generation depends on forecast quality*

(Gowrisankaran, Reynolds, Samano 2011; Skea, Anderson 2008 ...)

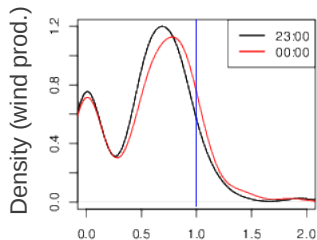
# Quick Look at the Data

Midwest ISO 2010 Data:

Forward Premium

$E(P_{DA} - P_{RT}) > \$2.00$

*But Under-commitment!*



Avg. Day Ahead  
Commitment

Why?

- ▶ Bad forecasting?
- ▶ Risk aversion?
- ▶ **Exercise of Market Power?**

Prerequisite for answer:

estimate  $E(\partial P_{DA}/\partial Q_{DA})$  and

$E(\partial P_{RT}/\partial Q_{DA})$

Hard with standard econometrics due  
to endogeneity

## Research Problem:

- ▶ Ideal solution to endogeneity question:  
**An accurate model of price determination process**
  - ▶ Zonal prices  
uniform price multi-unit auction  
(c.f. Reguant 2012; Hortaçsu, Puller 2008; Wolak 2004)
- ▶ However, Locational Marginal Pricing dominate North American Markets  
(e.g. PJM, Midwest ISO, CAISO, ERCOT)
  - ▶ Prices depend on entire network structure
  - ▶ Network structure not directly observable  
*Critical Infrastructure Information Act (2002)*
- ▶ However, Available information:
  - ▶ Midwest ISO: prices, quantities, bids, active transmission constraints

**Can a useful model of the network be inferred from this information?**

(Useful for market researchers, participants, *designers of CIIA*)

# Roadmap

- ▶ Locational Marginal Price (LMP) Market: *Linear model*
- ▶ The Estimation Problem... *via Inverse Optimization*
- ▶ An Algorithm: *A sufficient explanation*
- ▶ Application to Data: *Midwest ISO*

# Electricity Dispatch Model

Relaxation of the unit commitment problem:

Market Participant  $i \in \{1..N\}$

- ▶ Produces  $x_i$  MWh at an announced cost of  $c_i$ /MWh

**Lossless** network with links  $(i,j)$

- ▶ Transmission between  $i$  and  $j$  of  $y_{(i,j)}$  MWh
- ▶ Topology defined by matrices  $E$ ,  $A$ , and  $D$ 
  - ▶ Network Flow Constraints  $Ey = x$
  - ▶  $R$  Physical Constraints  $Ay = 0$
  - ▶  $L$  Transmission Constraints  $Dy \leq d$

$$\begin{aligned} \min c^T x \\ \text{s.t. } Ey &= x \\ Ay &= 0 \\ Dy &\leq d \\ u \geq x &\geq l \\ y &\geq 0 \end{aligned}$$

# Locational Marginal Prices

► Definition:

1. The Locational Marginal Price (LMP) is the immediate cost of supplying one additional MW of power at a particular node.
2. The LMP is the shadow price of the flow constraint

$\min c^T x$	dual variables
s.t. $Ey = x$	$\pi$
$Ay = 0$	$\sigma$
$Dy \leq d$	$\rho$
$u \geq x \geq l$	$\alpha, \gamma$
$y \geq 0$	

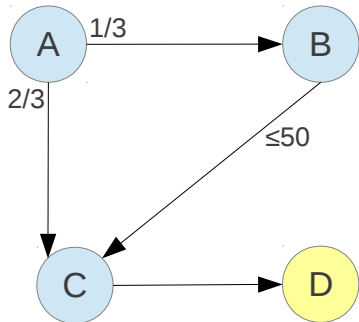


# LMP Example

(Louie, Strunz 2008)

$C_A$ : \$20/MWh

$C_B$ : \$30/MWh



$C_C$ : \$25/MWh

Corresponding LP:

$$\min 20x_A + 20x_B + 20x_C$$

$$\text{s.t. } Ey = x$$

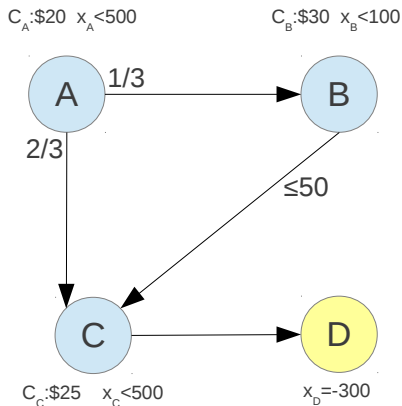
$$2y_{AB} - y_{AC} = 0$$

$$y_{BC} \leq 50$$

A constraints

D constraints

# LMP Example



Corresponding LP:

$$\min 20x_A + 20x_B + 20x_C$$

$$\text{s.t. } Ey = x$$

$$2y_{AB} - y_{AC} = 0$$

$$y_{BC} \leq 50$$

$$0 \leq x_A \leq 500$$

$$0 \leq x_B \leq 100$$

$$0 \leq x_C \leq 500$$

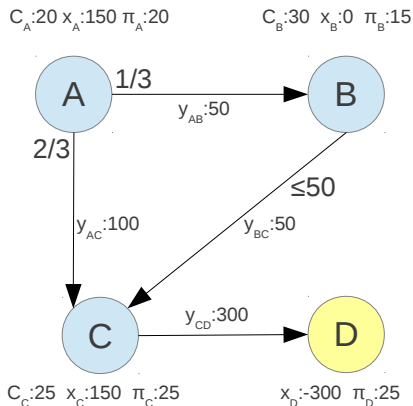
$$-300 \leq x_D \leq -300$$

$$y \geq 0$$

A constraints

D constraints

# LMP Example



Solution:

$x_A = 150$	$\pi_A = 20$
$x_B = 0$	$\pi_B = 15$
$x_C = 150$	$\pi_C = 25$
$x_D = -300$	$\pi_D = 25$
$y_{AB} = 50$	
$y_{AC} = 100$	
$y_{BC} = 50$	$\rho_{BC} = -15$
$y_{CD} = 300$	

# Estimation Problem (Single Sample)

$$\begin{array}{ll} \min c^T x & \text{dual variables} \\ \text{s.t. } Ey = x & \pi \\ Ay = 0 & \sigma \\ Dy \leq d & \rho \\ u \geq x \geq l & \alpha, \gamma \\ y \geq 0 & \end{array}$$

► Given data:

►  $c, x, u, l, \pi, \rho$

► Generate a network model:  $\bar{E}, \bar{A}, \bar{D}, \bar{d}$

► Explaining shadow prices  $\pi$  and  $\rho$

# General Inverse Optimization

Given:

- ▶ a partial specification of an optimization model
- ▶ a (partial) specification of an optimal solution

Infer missing model parameters such that:

- ▶ Consistency:  
*Known Parameters consistent with optimality*
- ▶ Simplicity:  
*Missing parameters minimize a norm*

Standard form Zhang, Liu 1996,1999 (linear); Ahuja, Orlin 2001 (general):

- ▶ Feasible set known
- ▶ Opt. solution known
- ▶ Cost parameters unknown
- ▶ Minimize L1 or L $\infty$  norm

Extensions: Yang, Zhang 2007; Ahmed, Guan 2005; Iyengar, Kang 2005; Wang 2009; Ahuja, Orlin 1998,2002; Cui, Hochbaum 2010

$\min c^T x$       dual variables

s.t.  $Ey = x$        $\pi$

$Ay = 0$        $\sigma$

$Dy \leq d$        $\rho$

# Our Inverse Optimization Problem

## Standard form:

- ▶ Feasible set known
- ▶ Opt. solution known
- ▶ Cost parameters unknown
- ▶ Minimize L1 norm

$$\begin{array}{ll} \min c^T x & \text{dual variables} \\ \text{s.t. } Ey = x & \pi \\ Ay = 0 & \sigma \\ Dy \leq d & \rho \\ u \geq x \geq l & \alpha, \gamma \\ y \geq 0 & \end{array}$$

## Electricity Market Problem:

- ▶ Feasible set **unknown**
- ▶ Opt. solution **partially known**
- ▶ Cost parameters **known**
- ▶ Minimize **L1 norm**

$$\begin{array}{ll} \min c^T x & \text{dual variables} \\ \text{s.t. } Ey = x & \pi \\ Ay = 0 & \sigma \\ Dy \leq d & \rho \\ u \geq x \geq l & \alpha, \gamma \\ y \geq 0 & \end{array}$$

# Our Inverse Optimization Problem

- ▶ Find a “simplest”  $\bar{A}, \bar{D}, \bar{d}, \bar{E}$  satisfying optimality conditions
- ▶ Minimize 1-Norm
- ▶ Regularize  $\bar{A}$  s.t.  $\sigma_r = 1$

Resulting Optimization Problem:

$$\begin{aligned} \min \quad & \|\bar{A}\|_1 + \|\bar{D}\|_1 + \|\bar{d}\|_1 \\ \sum_{r < R} \bar{A}_{r(i,j)} + \sum_{\ell < L} \bar{D}_{\ell(i,j)} \rho(i,j) = & \pi_j - \pi_i & \forall (i,j) \quad \bar{y}_{ij} > 0 \\ \bar{E}\bar{y} = & x \\ \bar{A}\bar{y} = & 0 \\ \bar{D}\bar{y} \leq & \bar{d} \end{aligned}$$

2-Step Algorithm:

1. Find  $\bar{E}$  and  $\bar{y}$ :
2. Find  $\bar{A}, \bar{D}, \bar{d}$ :

## Step 1: Determine $\bar{E}$ and $\bar{y}$

- Assume no loss

$$\bar{E}_{k(ij)} \in \{-1, 0, 1\}$$

- limit to flows between sources and sinks

$$\bar{E}_{i(ij)} = 1 \text{ only if } x_i > 0,$$

$$\bar{E}_{j(ij)} = -1 \text{ only if } x_j < 0,$$

$$\bar{E}_{k(ij)} = 0 \text{ otherwise}$$

- Minimize requirements on  $\bar{A}$  and  $\bar{D}$  to satisfy

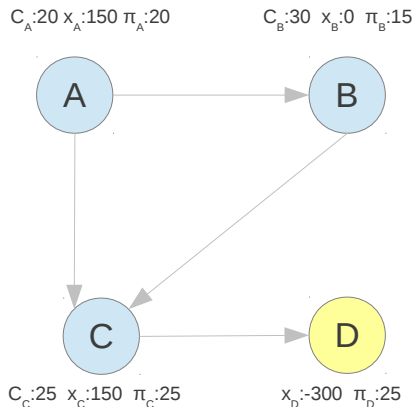
$$\sum_r \bar{A}_{r(i,j)} + \sum_\ell \bar{D}_{\ell(i,j)} \rho_{\ell(i,j)} = \pi_j - \pi_i \quad \forall \bar{y}_{ij} > 0$$

- By solving:

$$\min \sum_{ij} \bar{y}_{ij} \cdot \max\{\pi_i - \pi_j, 0\}$$

$$\text{s.t. } \bar{E}\bar{y} = x$$

$$\bar{y}_{ij} \geq 0$$





# Step 1: Determine $\bar{E}$ and $\bar{y}$

- Assume no loss  
 $\bar{E}_{k(ij)} \in \{-1, 0, 1\}$

- limit to paths between sources and sinks

$$\bar{E}_{i(ij)} = 1 \text{ only if } x_i > 0,$$

$$\bar{E}_{j(ij)} = -1 \text{ only if } x_j < 0,$$

$$\bar{E}_{k(ij)} = 0 \text{ otherwise}$$

- Minimize requirements on  $\bar{A}$  and  $\bar{D}$  to satisfy

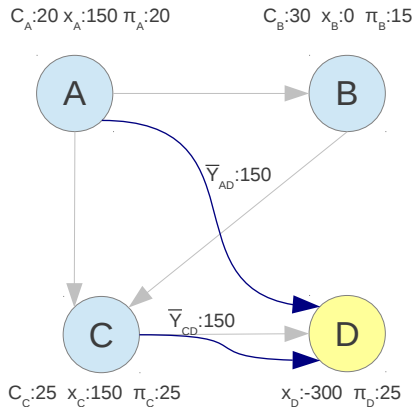
$$\sum_r \bar{A}_{r(i,j)} + \sum_\ell \bar{D}_{\ell(i,j)} \rho_{(i,j)} = \pi_j - \pi_i \quad \forall \bar{y}_{ij} > 0$$

- By solving:

$$\min y_{ij} \cdot \max\{\pi_i - \pi_j, 0\}$$

$$\text{s.t. } \bar{E}\bar{y} = x$$

$$\bar{y}_{ij} \geq 0$$



## Step 2: Determine $\bar{A}$ , $\bar{D}$ , $\bar{d}$

Minimize sum of 1-norms subject to optimality constraints

Solving:

$$\min \sum_{r,(i,j)} |\bar{A}_{r(i,j)}| + \sum_{\ell,(i,j)} |\bar{D}_{\ell(i,j)}| + \sum_{\ell} \bar{d}_{\ell}$$

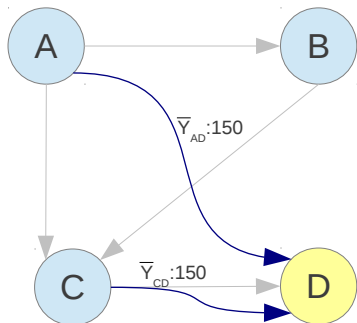
$$\text{s.t. } \bar{A}\bar{y} = 0$$

$$\sum_r \bar{A}_{r(i,j)} + \sum_{\ell} \bar{D}_{\ell(i,j)} \rho_{(i,j)} = \pi_j - \pi_i \quad \forall \bar{y}_{ij} > 0$$

$$d_{\ell} \geq 0$$

$C_A:20 \quad x_A:150 \quad \pi_A:20$

$C_B:30 \quad x_B:0 \quad \pi_B:15$



$C_C:25 \quad x_C:150 \quad \pi_C:25$

$x_D:-300 \quad \pi_D:25$

A and D Constraints:

$$\frac{1}{3}\bar{Y}_{AD} \leq 50$$

# Multiple Samples

For set of samples 1..S

1. Calculate  $\bar{y}^s$  independently
2. Add constraints for each sample

$$\min \sum_{r,(i,j)} |\bar{A}_{r(i,j)}| + \sum_{r,(i,j)} |\bar{D}_{\ell(i,j)}| + \sum_{\ell} \bar{d}_{\ell}$$

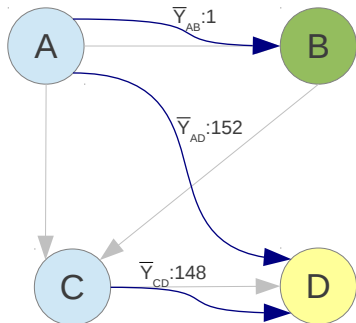
$$\text{s.t. } \bar{A}\bar{y}^s = 0$$

$$\sum_r \bar{A}_{r(i,j)} + \sum_{\ell} \bar{D}_{\ell(i,j)} \rho_{(i,j)}^s = \pi_j^s - \pi_i^s \quad \forall \bar{y}_{ij}^s > 0$$

$$\bar{d}_{\ell} \geq 0$$

$C_A:20 \quad x_A:153 \quad \pi_A:20$

$C_B:30 \quad x_B:1 \quad \pi_B:15$



$C_C:25 \quad x_C:150 \quad \pi_C:25$

$x_D:-300 \quad \pi_D:25$

A and D Constraints:

$$\frac{1}{3}(\bar{y}_{AD} - 2\bar{y}_{AB}) \leq 50$$

# General Implementation

- ▶ Observations for each day and hour
  - ▶  $x, \pi, \rho, c$  vary
  - ▶  $E, D, A, d$  constant (approximately)
- ▶ Transmission and generation outages may change  $d$
- ▶ Transmission losses not included
- ▶ Original "optimization" may be adjusted for other reasons (e.g., frequency, reliability)

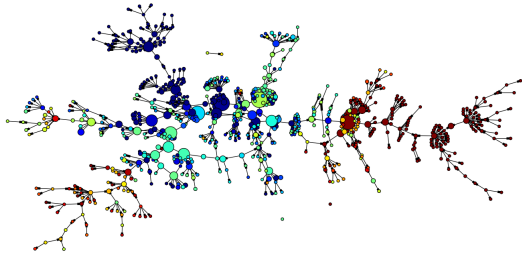
# Algorithm Observations

- ▶ Extension with multiple observations
  - ▶ Step 1 performed independently
  - ▶ Step 2 single optimization adding all constraints
- ▶ Algorithm feasible if rows in  $A$  greater number of samples
- ▶ Polynomial approximation
  - ▶ Step 2: LP standard transformation
  - ▶ Each step presents  $O(n^2)$  variables

# Results: Application to Midwest ISO

2010/01/01 00:00:00

- ▶ 1403 Nodes
- ▶ 768 Aggregated Nodes
- ▶ 772 Active Links
- ▶ Transmission bounds per hour
- ▶ Imperfect data
- ▶ Naive implementation  
20 ARows →  
40min



Power Flow in Midwest ISO Network

# Additional Examples

- ▶ Macro-economic models
  - ▶ Prices observed in different regions
  - ▶ Purchase quantities observed
  - ▶ Equilibrium model set up as potential optimization
  - ▶ Unknown transportation routes and costs to discover
- ▶ Supply chain interactions
  - ▶ Prices and quantities observed
  - ▶ Unobserved relationships between suppliers and customers
  - ▶ Discover relationships and transactions

# Future Directions

- ▶ Discussed modelling price determination process in LMP based Electricity Markets
  - ▶ Inverse optimization based formulation/algorithm consistent with dual interpretation of LMPs

## Next Steps

- ▶ Predicting market characteristics: *price response, congestion costs...*
- ▶ Structural estimation: *model participant decision making*
- ▶ Solution quality: *solution robustness to data imperfections*
- ▶ Econometrics of general competitive markets: *extend to linear market models*



# Conclusions

- ▶ Inverse optimization to discover constraints
  - ▶ Needed to determine objective of market participants
  - ▶ Many markets include price and quantity observations but not constraints
  - ▶ Difficulty from bilinear form with constraint and unknown variable values
- ▶ Solution method
  - ▶ Two-step process
  - ▶ Determine consistent primal variables first
  - ▶ Choose constraint coefficients with minimum 1-norm
- ▶ Results
  - ▶ Possible to discover simple network configurations
  - ▶ Reasonable results with multiple data observations
  - ▶ Possible inconsistencies from unknown parameter changes