Line Failure Risk from Congestion

Incorporating Uncertainty in Renewable Generation

Anderson Optimization

Eric Anderson
Presentation for PIMS at UBC
Wednesday, May 22nd, 2019

My Background

- Ph.D. in Industrial Engineering from UW-Madison
- Focus on optimization models for power systems
  - Cascading power failures
  - Dispatch models incorporating renewable generation
  - Themes
    - Large scale computation
    - Uncertainty
- This talk is based on my thesis research with
  - Jeff Linderoth, Jim Luedtke, and Bernard Lesieutre

Anderson Optimization

- Software for energy analysis workflows
- Primary clients are renewable developers

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- Web platform for energy analysis
  - Prospecting for new development
  - Early stage economic and feasibility analysis
  - Production cost modeling

Why I'm Here

- Interested in both clean energy and math!

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- Potential colloboration in the future
- Potential clients

Why I'm Here

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- Great location!

Context

- Climate change is ongoing, want to reduce emissions
- Reduce through increasing renewables

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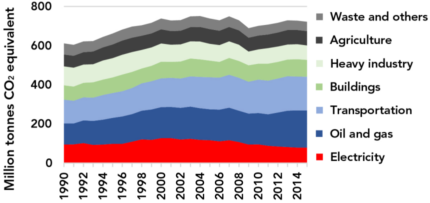
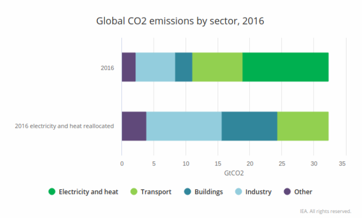
Emmissions of Electricity Generation

Canada



Worldwide



Challenges

Bulk Power Systems (BPS)

- Composed of generation and high voltage transmission equipement.
- Goal to serve load with least cost electricity while maintaining reliability.

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Challenges

- Renewables [often] connect with bulk power system (BPS)
- BPS must maintain system reliability
- Renewables intermittent and uncertain

Bulk Power Systems

US split into 3 interconnected grids

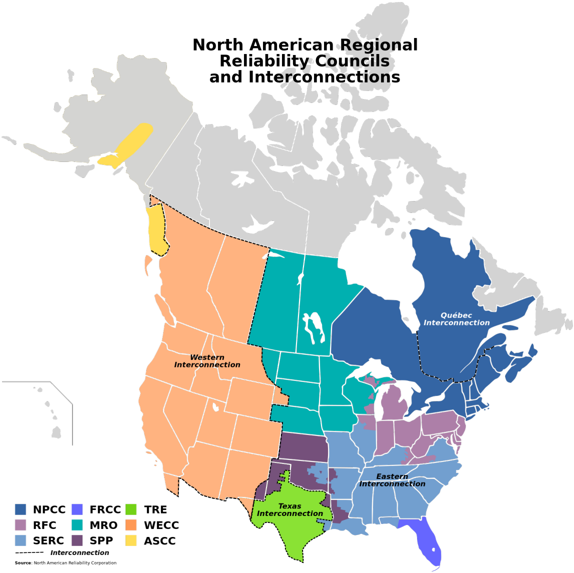
- Generators rotating synchronously with grid
- Connection to every load

Bulk Power Systems

~~US split into 3 interconnected grids~~
North America split into 4 interconnected grids

- Generators rotating synchronously with grid
- Connection to every load

North America Interconnections



Bulk Power Systems

Complex system requiring continuous supply demand balance

- Transient stability, automatic generator control
- Ancillary services market
- 5 minute real time market
- 1-6 hour inter region market
- 24 hour day ahead market
- Long term capacity markets

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Optimization in Power System

- Operational/Markets
  - Real time market / economic dispatch
  - Day ahead market / unit commitment
- Planning
  - Production cost model
  - Capacity expansion
- Reliability
  - Power flow / optimal power flow
  - Dynamics / transient stability

Optimization in Power System

- Operational/Markets
  - Real time market / economic dispatch - LP
  - Day ahead market / unit commitment - MIP
- Planning
  - Production cost model simulation - MIP
  - Capacity expansion MIP / DFO
- Reliability
  - Power flow / optimal power flow - NLP
  - Dynamics / transient stability simulation - NLP

- LP = Linear Program
- MIP = Mixed Integer Program
- NLP = Nonlinear Program
- DFO = Derivative Free Optimization

Power Flow

Laws of physics, can't control branch flow

Control net injects

- Generators
  - Ramping characterstics, limits
- Demand Response
- Storage (hydro, battery)

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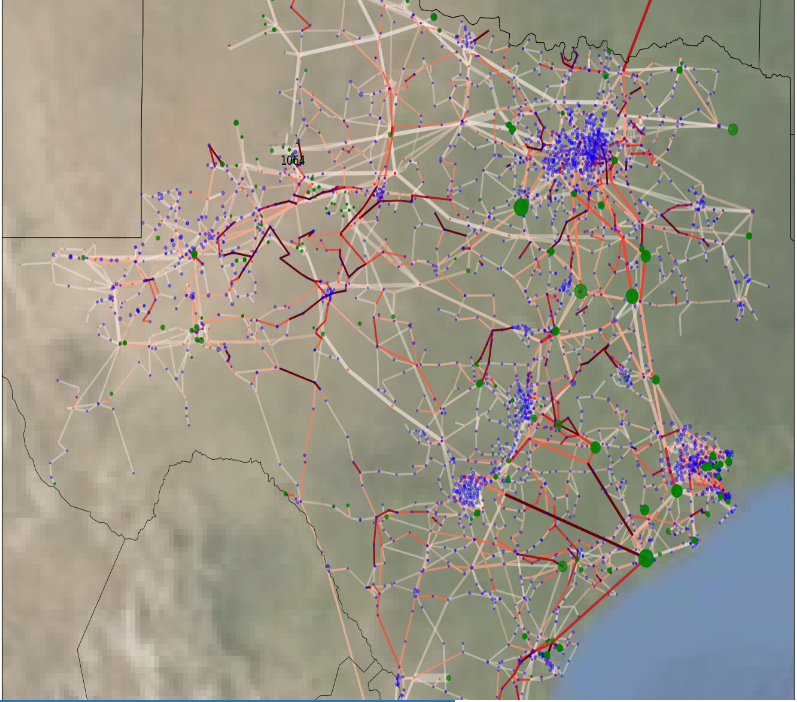
AC power flow - balanced 3 phase power system model

- Nonlinear, nonconvex equations
- Difficult to solve
- We use DC approximation (linear)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Modern Complexity for Power Systems

Uncertainty

Asking more of our transmission grid, robust to uncertainty

- Wind
- Solar
- Demand Response
- Energy Storage
- Electric Vehicles

Reliability Problems

Power Interruptions

- \$79 billion economic loss (2001)
  - \$247 billion electricity sales
- Hidden from system, distributed throughout economy
- New technologies: renewables, EVs, etc. stressful on system

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Cascading power failures

- Rare, but costly
- Equillibrium balancing economics and reliability
- Northeast blackout 2003
  - $6 billion economic loss
  - Loss of life

Uncertain Injects

Uncertainty in Injects to Power System

- Subset of nodes have uncertain injections
  - Solar, wind
  - Demand (relatively certain, however EVs could represent change)

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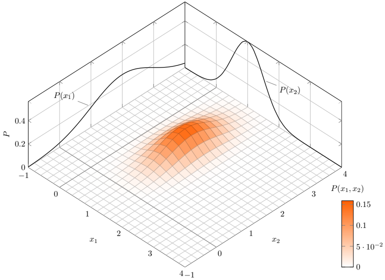
- Subset of nodes have uncertain injections
  - Solar, wind
  - Demand (relatively certain, however EVs could represent change)
- Subset of assets respond to uncertainty (slack distribution)
  - Rotational inertia, peaker plants and regulation
  - Energy storage, enhanced power controls

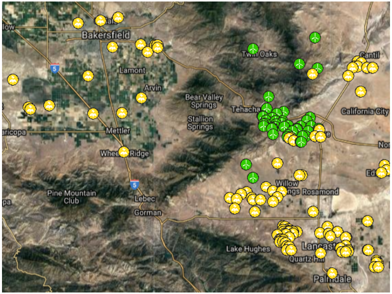
Uncertainty is Multivariate Normal

Assumption

Uncertainty in net injections are Multivariate Normal

- *Uncertainty in errors from forecast*
- Known or can be empirically estimated
- Potentially correlated





Gaussian Injects

Net Injection Uncertainties

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$$\boldsymbol{x} = C_g\left(x_g + \boldsymbol{\Delta}\beta\right) - \left(d + C_M\boldsymbol{\delta^m}\right)$$

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$$\boldsymbol{x} = C_g \left(x_g + \boldsymbol{\Delta} \beta \right) - \left(d + C_M \boldsymbol{\delta^m} \right)$$

$\boldsymbol{x}$	Net injects
x_g	Generator dispatch
β	Slack distribution
d	Expected demand
$\boldsymbol{\delta^m}$	Nodal demand variation ($\mathbb{E}\left[\boldsymbol{\delta^m}\right] = 0$, Σ known)
$\boldsymbol{\Delta}$	Aggregate demand variation ($\boldsymbol{\Delta} = 1^T \boldsymbol{\delta^m}$)

DC Power Flow

Decoupled (DC) Power Flow equations

- Linearization of nonlinear AC Power Flow

DC Power Flow

Decoupled (DC) Power Flow equations

- Linearization of nonlinear AC Power Flow

$$
\begin{aligned}
y &= DC\theta \\
x &= C^T y \\
x &= B\theta
\end{aligned}
$$

DC Power Flow

Decoupled (DC) Power Flow equations

- Linearization of nonlinear AC Power Flow

$$y = DC\theta$$
$$x = C^T y$$
$$x = B\theta$$

x	Net injections, $x < 0 \equiv$demand (N)
y	Branch flows (E)
θ	Phase angle (N)
D	Diagonal branch susceptance matrix (E x E)
B	System matrix, $B = C^T DC$ (N x N)
C	Node-arc incidence matrix (E x N)

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N-Number of nodes, E-Number of edges

Linear Shift Factors

DC Power Flow $->$ Linear Shift Factors

Linear Shift Factors

$$y = Ax$$

where $A = B'CB^{-1}$

Gaussian Branch Flows

Assuming Gaussian injects and linear shift factors

- Branch flows are Gaussian as well

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$$\boldsymbol{y} = y_0 + AC_G\beta\boldsymbol{\Delta} - AC_M\boldsymbol{\delta^m}$$

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$$\boldsymbol{y} = y_0 + AC_G\beta\boldsymbol{\Delta} - AC_M\boldsymbol{\delta^m}$$

$\boldsymbol{y}$	Branch flows
y_0	Branch flows for forecasted system
$AC_g\beta\boldsymbol{\Delta}$	Flow variation due to slack generation movement
$AC_m\boldsymbol{\delta^m}$	Flow variation due to nodal inject changes

Issues with Deterministic Analysis

Normal distributed injects

[1] In a stable system

Issues with Deterministic Analysis

Normal distributed injects → **Normal branch flows**[1]

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Issues with Deterministic Analysis

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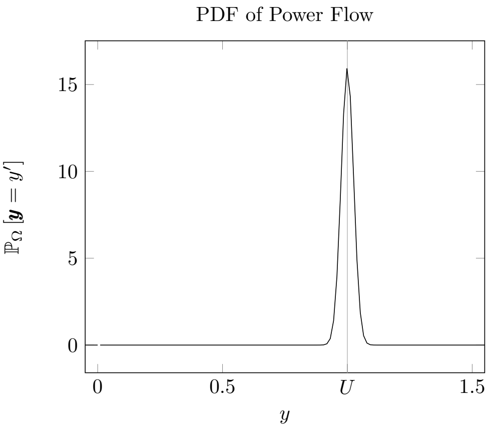
Problem!

- Branch constraints violated half the time when at its limit

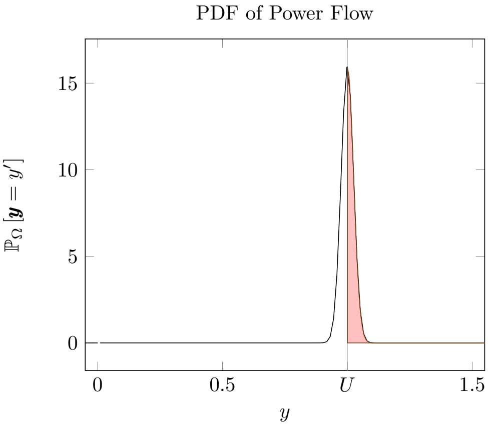
[1] In a stable system

Normal Branch Flow



PDF for Branch flow with mean (forecast) at nominal capacity

Normal Branch Flow



Need to probabilistically enforce constraints

Chance Constraint Model

Replace the standard constraints with probalistic ones [2][3]

$$P\left[-U_e \leq \boldsymbol{y}_e \leq U_e\right] \geq 1 - \epsilon_l \qquad \forall e$$

[1] Bienstock, D. and Chertkov, M. and Harnett, S.

[2] Vrakopoulou, M. and Chatzivasileiadis, S. and Andersson, G.

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Deterministic equivalent

Branch flows

$$y_e + s_e \eta_l \leq U_e \qquad \forall e$$

with

$$\eta_l = \Phi^{-1}(1 - \epsilon_l)$$

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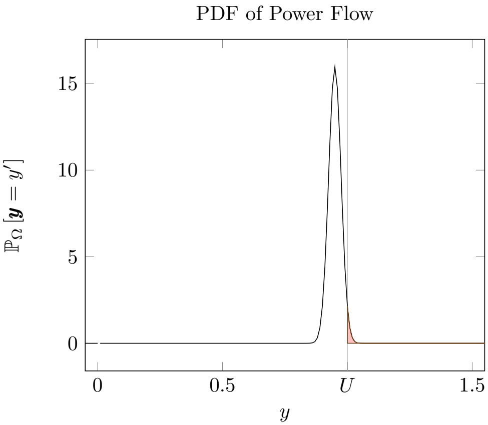
Chance Constraints



Current Models

Determinsitic has fixed line thresholds

- Line is completely okay
- or system is infeasible

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Line thresholds are soft constraints in real life

Current Models

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Line thresholds are soft constraints in real life

- Multiple line ratings (i.e. short term emergency rating)
- Hard limit typically relay tripping

Line Limits

Limited by

- Sagging due to current flow and line heating
- Worst case environmental conditions (seasonally)
- An acceptable probability of line failure
- Enforce N-1 Reliability Constraint

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Dynamic line limits

- Real time limits based on current environmental conditions

System Risk

System risk related to line loadings (severity measure) [4]

[2] Qin Wang and McCalley, J.D. and Tongxin Zheng and Litvinov, E.

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System Risk Probability of line failure

$$h(y) = P_{\Xi}\left[\text{at least one line fails} | y\right]$$

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System Risk

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Intuition

- Grid relatively stressed when more lines are near their limit

[2] Qin Wang and McCalley, J.D. and Tongxin Zheng and Litvinov, E.

Line Risk Function

Risk function takes the normalized flow returns line risk

$$g(y_e) = \mathbb{P}_{\Xi}\left[\text{Line } e \text{ fails} | y_e\right]$$

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Piece-wise linear function chosen

- Below L, there is no risk associated with loading
- After L, the risk increases linearly with loading
- At critical capacity U^c, line fails with certainty

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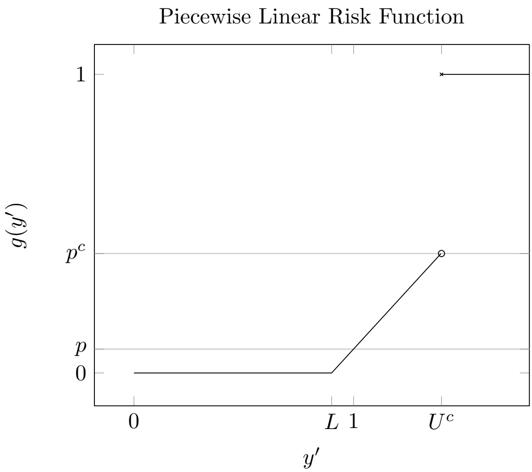
$$g(y_e) = \begin{cases} 0 & y_e \leq L \\ a + by_e & L \leq y_e < U^c \\ 1 & U^c \leq y_e \end{cases}$$

Line Risk Function



System Risk, Fixed Injects

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With fixed line flows, independent failures

$$h(y) = 1 - \prod_{e \in \mathcal{E}} (1 - g(y_e))$$

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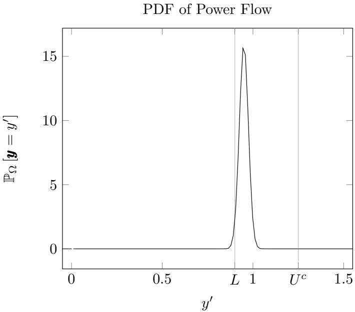
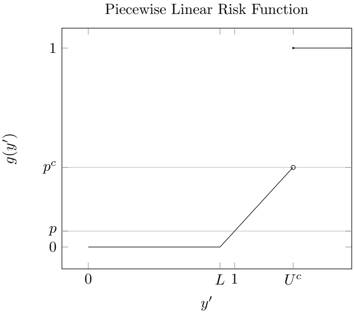
- Implies hard line constraint, line risk=system risk
- $h(y) \leq \epsilon$ not convex
  - But it is log convex, log transform and solve

Gaussian Flow and Risk Function



Gaussian branch flow



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Assume Conditioned on line flow

- Failure probabilities independent
- Bold letters w.r.t. Ω, orthogonal to Ξ
  - Ω: represents demand uncertainty, wind, etc.
  - Ξ: likelihood of failure given flow

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Line flows are not independent!

- But we calculate and account for branch covariance Σ

System Risk Under Uncertainty

Line Risk Function

$$\rho(\mu_e^y, \sigma_e^y) \equiv \mathbb{E}_\Omega \left[g(\boldsymbol{y}_e) \right]$$

Function representation

$$\rho(\mu_e^y, \sigma_e^y) = (a + b\mu_e^y) \left[1 - \Phi(\alpha_L)\right] + b\sigma_e^y \phi(\alpha_L)$$

Function is

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Function is

- Convex with respect to μ_e^y, σ_e^y of branch flow $\boldsymbol{y}_e$
  - σ second order cone representable
- Not expressable due to CDF of standard normal evaluation
  - Derivatives expressable

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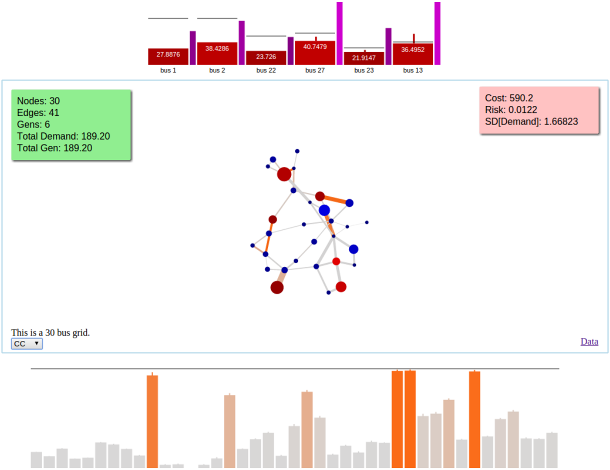
Solve with Cutting Planes!

Solution Exploration Demo

http://eja4.info/pow-explore.html

- Toggle in bottom left to change dispatch model



Conclusion

Review

- Need improved analysis for uncertainty in renewable generation
- Correlation in renewable generation is important
- Line failure risk vs system risk

Next Steps

- Incorporate in analysis such as Capacity Expansion

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Thanks!

Hope you enjoyed!
Questions?

DC Optimal Power Flow

Economic dispatch with quadratic cost function

$$\min_{(x;\theta,y)} \quad \sum_j \left[c_2 x_j^2 + c_1 x_j \ + c_0\right]$$

$$\sum_j C_{ij}^g x_j - \sum_e C_{ie}^b y_e = d_i \qquad \forall i$$

$$y_e - b_e \sum_i C_{ie}^b \theta_i = 0 \qquad \forall e$$

$$y_e \in [-U_e, U_e] \qquad \forall e$$

$$x_j \in \left[G_j^{min}, G_j^{max}\right] \forall j$$

Full JCC Model

$$\min_{(x,\beta;\theta,y,\pi,s,z)} \sum_j \left[c_2\left(x_j^2 + \beta_j^2\sigma_\Delta^2\right) + c_1 x_j + c_0\right]$$

$$\sum_j c_{ij}^g x_j - \sum_j c_{ie}^b y_e = d_i \qquad \forall i$$

$$y_e - b_e \sum_i c_{ie}^b \theta_i = 0 \qquad \forall e$$

$$y_e \in [-U_e^\epsilon, U_e^\epsilon] \qquad \forall e$$

$$x_j + \beta_j \sigma_\Delta^2 \eta_g \in \left[G_j^{min}, G_j^{max}\right] \forall j$$

$$\sum_j \beta_j = 1$$

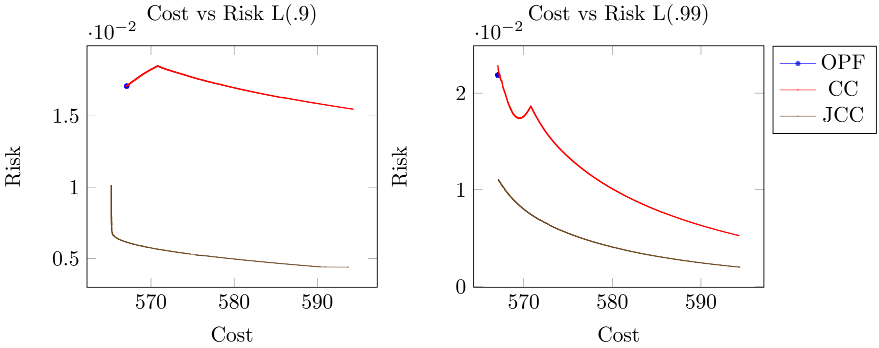
$$\pi_e - \sum_j A_{ej}\beta_j = 0 \qquad \forall e$$

$$s_e^2 - \pi_e^2\sigma_\Delta^2 + 2\pi_e\sigma_{e_1}^2 \geq \sigma_{e_1 e_1}^2 \qquad \forall e$$

$$z_e - \rho(|y_e|, s_e) \geq 0 \qquad \forall e$$

$$\sum_e z_e \leq \epsilon$$

Cost Risk Frontier



- OPF - single point
- CC - tighten probabalistic branch constraint from .5 → infeasible
- JCC - tighten system risk from lowest cost → infeasible