Robust Optimal Power Flow with Uncertain Renewables

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THE ENERGY CHALLENGE

Wind Energy Bumps Into Power Grid's Limits

Mike Groll/Associated Press

The Maple Ridge Wind farm near Lowville, N.Y. It has been forced to shut down when regional electric lines become congested.

By MATTHEW L. WALD
Published: August 26, 2008

When the builders of the Maple Ridge Wind farm spent $320 million to put nearly 200 wind turbines in upstate New York, the idea was to get paid for producing electricity. But at times, regional electric lines have been so congested that Maple Ridge has been forced to shut down even with a brisk wind blowing.

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CIGRE -International Conference on Large High Voltage Electric Systems ’09

- Large unexpected fluctuations in wind power can cause additional flows through the transmission system (grid)
- Large power deviations in renewables must be balanced by other sources, which may be far away
- Flow reversals may be observed – control difficult
- A solution – expand transmission capacity! Difficult (expensive), takes a long time
- Problems **already observed** when renewable penetration high

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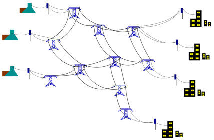
- "Fluctuations" – 15-minute timespan
- Due to turbulence ("storm cut-off")
- Variation of the same order of magnitude as mean
- Most problematic when renewable penetration starts to exceed $20 - 30\%$
- Many countries are getting into this regime

Optimal power flow (economic dispatch, tertiary control)



- Used periodically to handle the next time window (e.g. 15 minutes, one hour)
- Choose generator outputs
- Minimize cost (quadratic)
- Satisfy demands, meet generator and network constraints
- **Constant load (demand) estimates for the time window**

OPF:

$$\min \ c(p) \quad \text{(a quadratic)}$$

s.t.

$$B\theta = p - d \tag{1}$$

$$|y_{ij}(\theta_i - \theta_j)| \ \leq \ u_{ij} \quad \text{for each line } ij \tag{2}$$

$$P_g^{min} \ \leq \ p_g \ \leq \ P_g^{max} \quad \text{for each bus } g \tag{3}$$

Notation:

$p \ = \ $ vector of generations $\in \mathcal{R}^n$, $\quad d \ = \ $ vector of loads $\in \mathcal{R}^n$

$B \ \in \mathcal{R}^{n \times n}$, $\quad$ (bus susceptance matrix)

$$\forall i,j: \quad B_{ij} = \begin{cases} -y_{ij}, & ij \ \in \ \mathcal{E} \text{ (set of lines)} \\ \sum_{k;\{k,j\} \in \mathcal{E}} y_{kj}, & i = j \\ 0, & \text{otherwise} \end{cases}$$

$$\min \; c(p) \quad \text{(a quadratic)}$$

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How does OPF handle short-term fluctuations in **demand** (d)?
Frequency control:

- Automatic control: primary, secondary
- Generator output varies up or down **proportionally** to **aggregate** change

How does OPF handle short-term fluctuations in renewable output?

Answer: Same mechanism, now used to handle aggregate wind power change

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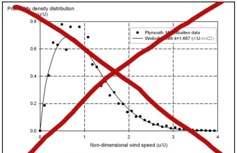
Wind model?

Need to model variation in wind power between dispatches

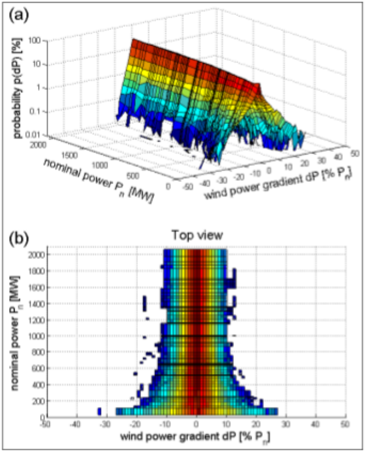
Wind at farm attached to bus *i* of the form $\mu_i + \mathbf{w_i}$ – Weibull distribution?



Weibull fit to Plymouth weather station data.

Wind model

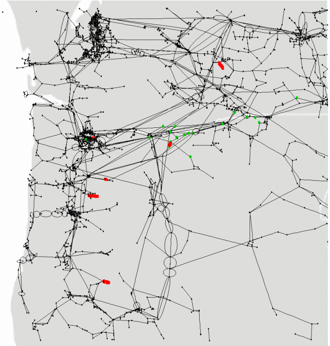
From CIGRE report, aggregated over Germany:



Experiment

Bonneville Power Administration data, Northwest US

- data on wind fluctuations at planned farms
- with standard OPF, 7 lines exceed limit $\geq 8\%$ of the time



Line limits and line tripping

If power flow in a line exceeds its limit, the line becomes compromised and may 'trip'. But process is complex and time-averaged:

- Thermal limit is most common
- Thermal limit may be in terms of terminal equipment, not line itself
- Wind strength and wind direction contributes to line temperature
- In medium-length lines ($\sim$ 100 miles) the line limit is due to voltage drop, not thermal reasons
- In long lines, it is due to phase angle change (stability), not thermal reasons
- In 2003 U.S. blackout event, many critical lines tripped due to thermal reasons, but well short of their line limit

Line trip model

summary: exceeding limit for too long is bad, but complicated

want: "fraction time a line exceeds its limit is small"

proxy: prob(violation on line i) $< \epsilon$ for each line i

Goals

- simple control
- aware of limits
- not too conservative
- computationally practicable

Control

For each generator i, two parameters:

- $\overline{p_i}$ = mean output
- α_i = response parameter

Real-time output of generator i:

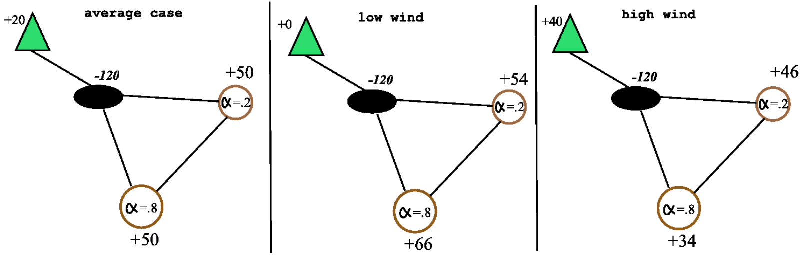
$$p_i = \overline{p}_i - \alpha_i \sum_j \Delta\omega_j$$

where $\Delta\omega_j$ = change in output of renewable j (from mean).

$$\sum_i \alpha_i = 1$$

$\sim$ primary + secondary control

Set up
control



Computing line flows

wind power at bus i: $\mu_i + \mathbf{w}_i$

DC approximation

- $B\boldsymbol{\theta} = \overline{p} - d$
  $+(\mu + \mathbf{w} - \alpha \sum_{i \in G} \mathbf{w}_i)$
- $\boldsymbol{\theta} = B^{+}(\bar{p} - d + \mu) + B^{+}(I - \alpha e^{T})\mathbf{w}$
- flow is a linear combination of bus power injections:

$$\mathbf{f_{ij}} = y_{ij}(\boldsymbol{\theta}_i - \boldsymbol{\theta}_j)$$

Computing line flows

$$\mathbf{f_{ij}} = y_{ij}\left((B_i^+ - B_j^+)^T(\bar{p} - d + \mu) + (A_i - A_j)^T\mathbf{w}\right),$$

$$A = B^+(I - \alpha e^T)$$

Given distribution of wind can calculate moments of line flows:

- $\bar{f}_{ij} = y_{ij}(B_i^+ - B_j^+)^T(\bar{p} - d + \mu)$
- $var(\mathbf{f_{ij}}) := s_{ij}^2 \geq y_{ij}^2 \sum_k (A_{ik} - A_{jk})^2 \sigma_k^2$
  (assuming independence)
- and higher moments if necessary

Chance constraints to deterministic constraints

- recall chance constraints: $P(|\mathbf{f_{ij}}| > f_{ij}^{max}) < \epsilon_{ij}$
- from moments of $\mathbf{f_{ij}}$, can get conservative approximations using e.g. Chebyshev's inequality
- for Gaussian wind, can do better, since $\mathbf{f_{ij}}$ is Gaussian :

$$f_{ij}^{max} \pm \bar{f}_{ij} \geq s_{ij}\phi^{-1}\left(1 - \frac{\epsilon_{ij}}{2}\right)$$

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Formulation:

Choose mean generator outputs and response parameters to minimize expected cost, so that the probability that any given line overloads is small.

$$\min_{\overline{p},\alpha} \mathbb{E}[c(\overline{p})] :$$

$$\text{s.t.} \quad B\delta = \alpha, \delta_n = 0$$

$$s_{ij}^2 \geq y_{ij}^2 \sum_{k \in W} \sigma_k^2 (B_{ik}^+ - B_{jk}^+ - \delta_i + \delta_j)^2$$

$$B\overline{\theta} = \overline{p} + \mu - d, \ \overline{\theta}_n = 0$$

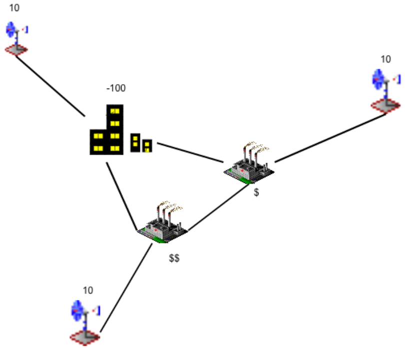
$$\overline{f}_{ij} = y_{ij}(\overline{\theta}_i - \overline{\theta}_j), \ f_{ij}^{max} \pm \overline{f}_{ij} \geq s_{ij}\phi^{-1}(1 - \frac{\epsilon_{ij}}{2})$$

$$\sum_{i \in G} \overline{p}_i + \sum_{i \in W} \mu_i = \sum_{i \in D} d_i$$

$$\sum_{i \in G} \alpha_i = 1, \ \alpha \geq 0$$

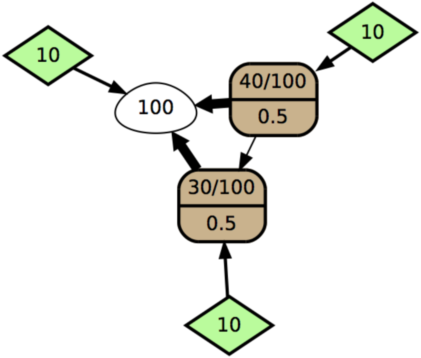
Toy example

1. What if no line limits?
2. What if tight limit on line connecting generators?



Answer 1

What if no line limits?

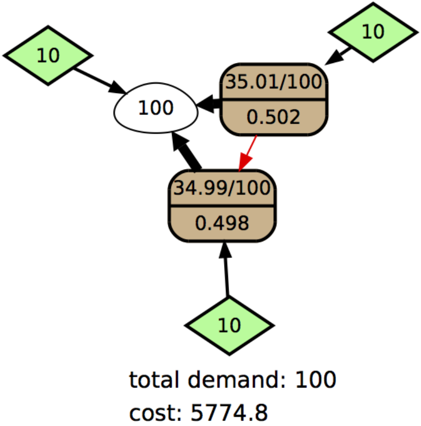


total demand: 100

cost: 5720

Answer 2

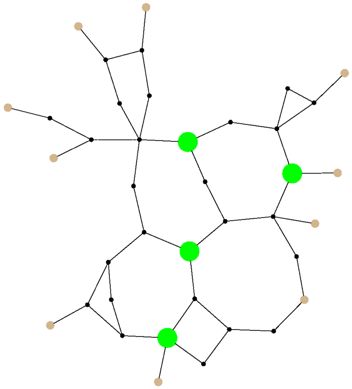
What if small limit on line connecting generators?



Experiment

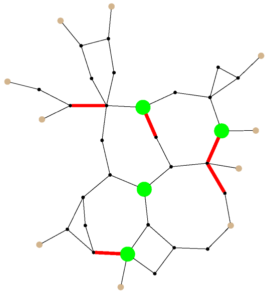
How much wind penetration can we handle?
And how much money does this save?

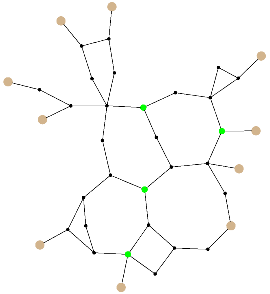
39-bus New England system from MATPOWER



Experiment

'standard' OPF solution with 10% buffer on line limits
feasible only up to 5% penetration (right)

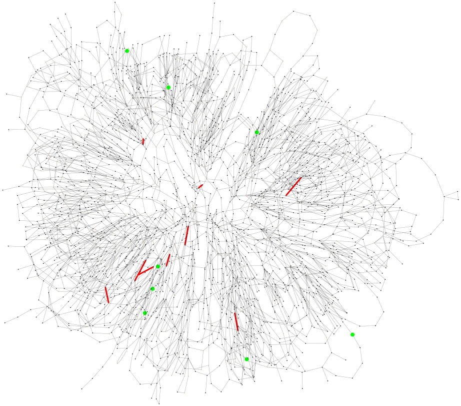




Cost 1,275,000 – almost 5 times greater than chance-constrained

Big cases

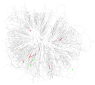
Polish system - winter 2003-04 evening peak



Big cases

Polish 2003-2004 winter peak case

- 2746 buses, 3514 branches, 8 wind sources
- 5% penetration and $\sigma = .3\mu$ each source



CPLEX: the optimization problem has

- 36625 variables
- 38507 constraints, 6242 conic constraints
- 128538 nonzeros, 87 dense columns

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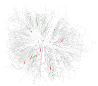

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Big cases

CPLEX:

- total time on 16 threads = 3393 seconds
- "optimization status 6"
- solution is wildly infeasible

Gurobi:

- time: 31.1 seconds
- "Numerical trouble encountered"

Cutting-plane method

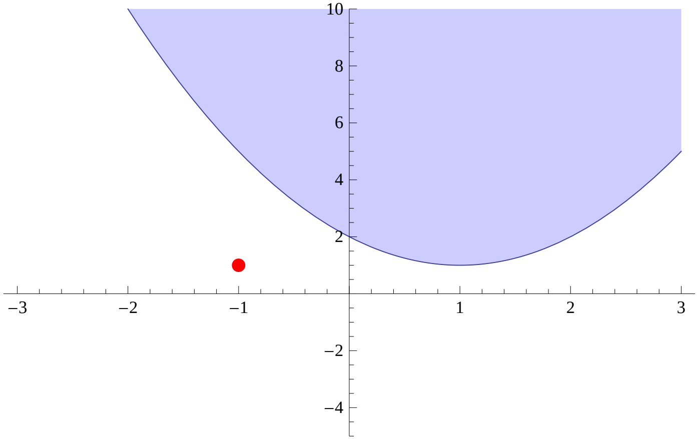
overview

Cutting-plane algorithm:

```
remove all conic constraints
repeat until convergence:
    solve linearly constrained problem
    if no conic constraints violated: return
    find separating hyperplane for maximum violation
    add linear constraint to problem
```

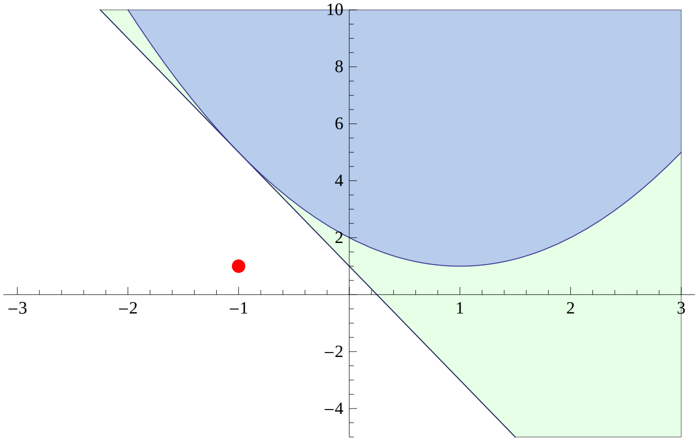
Cutting-plane method

Candidate solution violates conic constraint



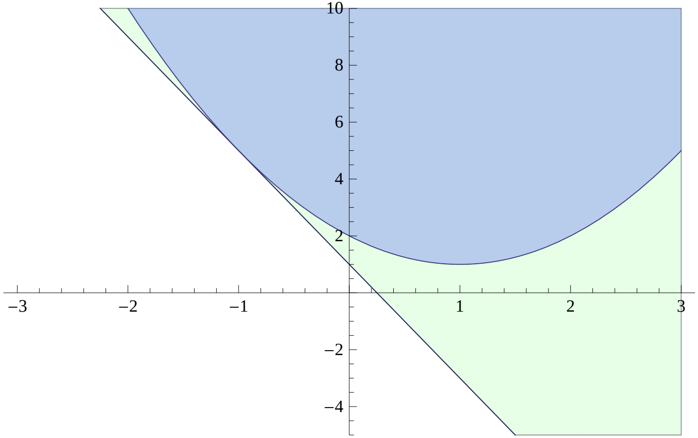
Cutting-plane method

Separate: find a linear constraint also violated



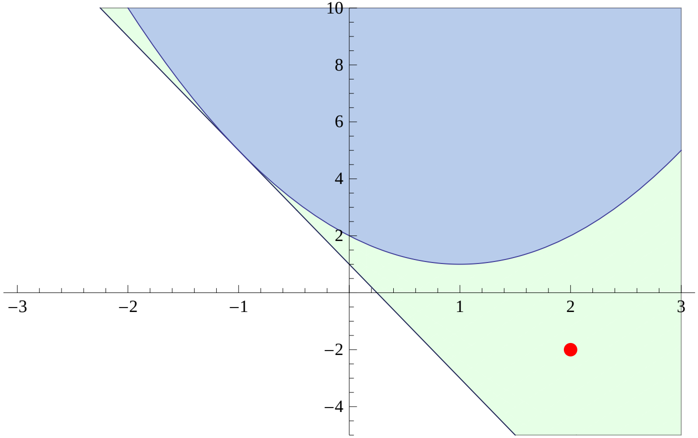
Cutting-plane method

Solve again with linear constraint



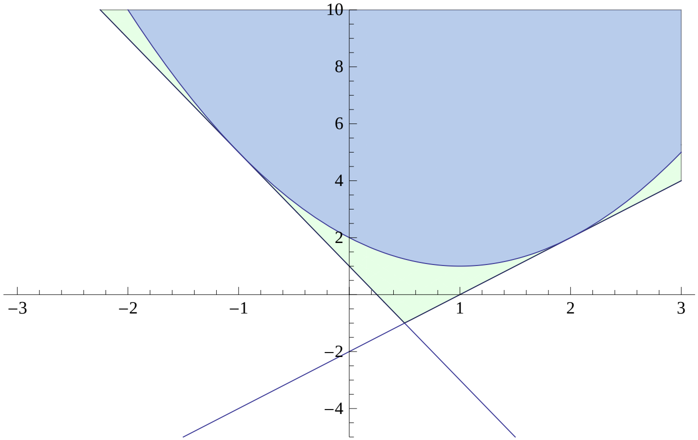
Cutting-plane method

New solution still violates conic constraint



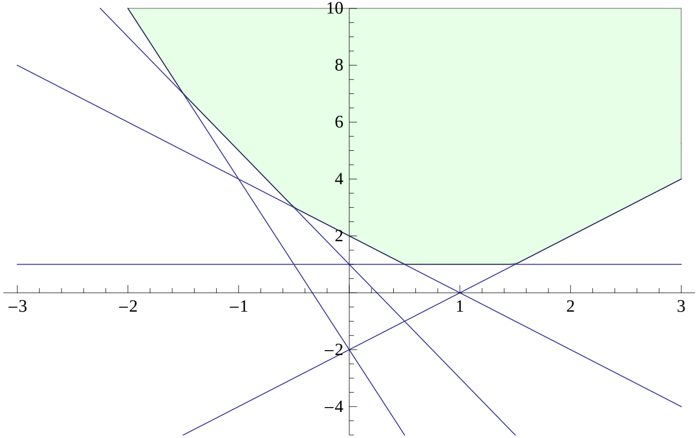
Cutting-plane method

Separate again



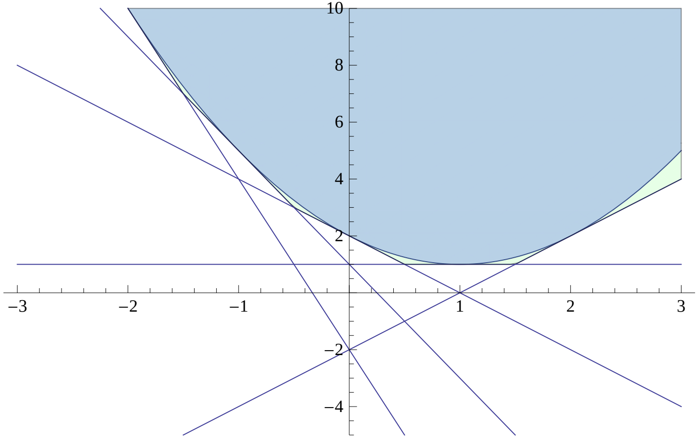
Cutting-plane method

We might end up with many linear constraints



Cutting-plane method

... which approximate the conic constraint



conic constraint:

$$\sqrt{x_1^2 + x_2^2 + ... + x_k^2} = \|x\|_2 \leq y$$

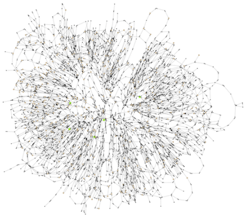
candidate solution:

$$(x^*, y^*)$$

cutting-plane (linear constraint):

$$\|x^*\|_2 + \frac{x^{*T}}{\|x^*\|_2}(x - x^*) = \frac{x^{*T} x}{\|x^*\|_2} \leq y$$

Polish 2003-2004 case
CPLEX: "opt status 6"
Gurobi: "numerical trouble"



Example run of cutting-plane algorithm:

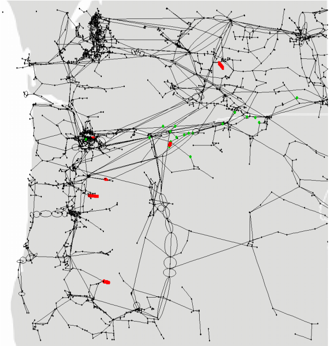
Iteration	Max rel. error	Objective
1	1.2e-1	7.0933e6
4	1.3e-3	7.0934e6
7	1.9e-3	7.0934e6
10	1.0e-4	7.0964e6
12	8.9e-7	7.0965e6

Total running time: 32.9 seconds

Back to motivating example

BPA case

- standard OPF: cost 235603, 7 lines unsafe $\geq$ 8% of the time
- CC-OPF: cost 237297, every line safe $\geq$ 98% of the time
- run time $=$ 9.5 seconds (one cutting plane!)



Back to motivating example

BPA case

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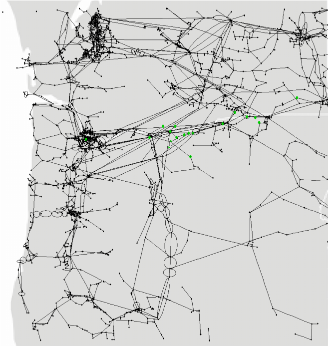

Conclusion

Our chance-constrained optimal power flow:

- safely accounts for variability in wind power between dispatches
- uses a simple control which is easily integrable into existing system
- is fast enough to be useful at the appropriate time scale