Uncertainty Management in Interdependent Gas-Electric Infrastructure: Capturing the Benefits of Gas System Dynamics

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Uncertainty Management in Interdependent Gas-Electric Infrastructure: Capturing the Benefits of Gas System Dynamics

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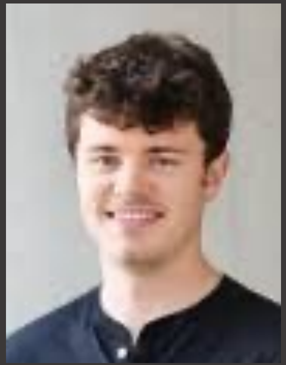


A. Zlotnik, L. Roald, S. Backhaus, M. Chertkov, G. Andersson, "Coordinated Scheduling for Interdependent Electric Power and Natural Gas Infrastructures", IEEE Trans. Power Systems, 2017

C. O'Malley, L. Roald, D. Kourounis, O. Schenk and G. Hug, "Security Assessment in Gas-Electric Networks", Power System Computation Conference, 2018

Conor O'Malley, Stefanos Delikaraoglou, Line Roald, Gabriela Hug, "Natural gas system dispatch accounting for electricity side flexibility", Electric Power Systems Research, Volume 178, 2020

L. Roald, K. Sundar, A. Zlotnik, S. Misra and G. Anderson, "An Uncertainty Management Framework for Integrated Gas-Electric Energy Systems", Proceedings of the IEEE, 2020

C. O'Malley, G. Hug and L. Roald, "Stochastic Hybrid Approximation for Uncertainty Management in Gas-Electric Systems", IEEE Trans. Power Systems, 2021

C. O'Malley, G. Hug and L. Roald, "Impact of Gas System Modelling on Uncertainty Management of Gas-Electric Systems", submitted

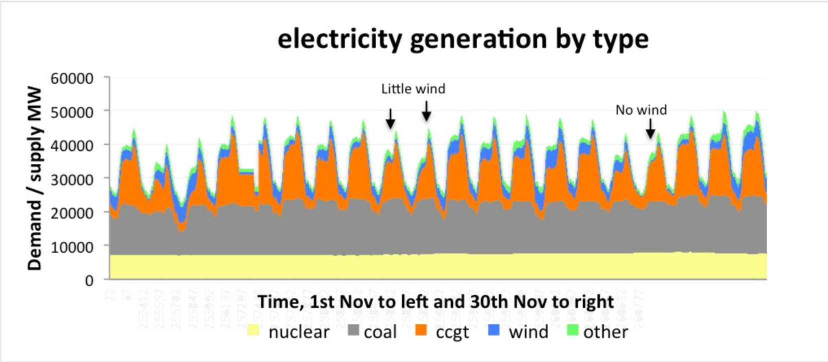
Natural gas – electric system interdependence

Gas-fired power generation is expanding:

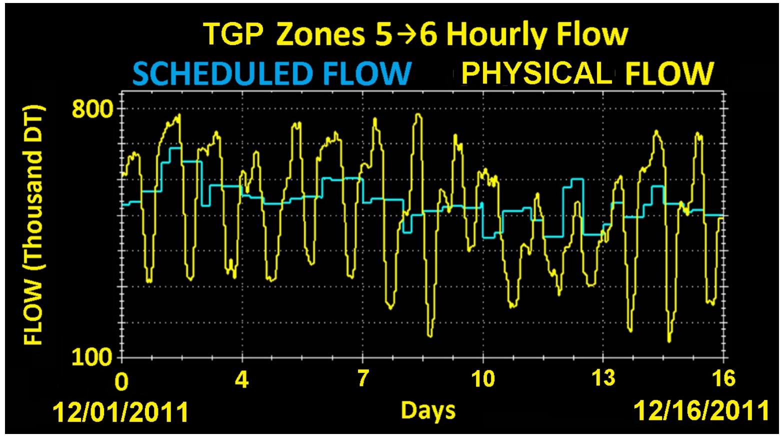
- Economic: Availability of cheap gas
- Environmental: Lower emissions, more flexibility

Gas pipeline loads are changing:

- Increasing in volume & variation
- More intermittent & uncertain



Source: www.nationalgrid.com/uk



Source: El Paso Pipeline

Natural gas – electric system interdependence

Gas-fired power generation is expanding:

- Economic: Availability of cheap gas
- Environmental: Lower emissions, more flexibility

Electric system is vulnerable to disruptions in the natural gas supply chain!

- Residential customers have priority

Winter freeze in Texas (Eli Hartman, AP)

Gas leak in Aliso Canyon (EDF)

Modeling of gas-electric systems

Electric grid market clearing

DC Optimal power flow

$\min \quad \sum c_i p_i$ **Minimize generation cost**

s.t.: **Power balance**

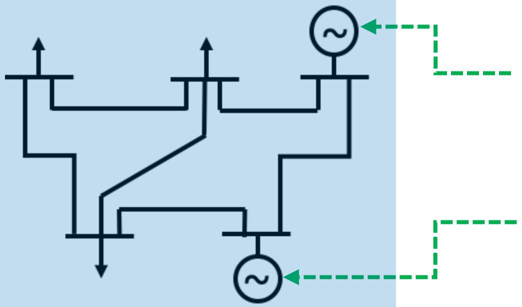
$$\Sigma p_i = \Sigma d_i$$

Transmission line constraints

$$p_{ij} = M_{ij}(p - d) \leq p_{ij}^{max}$$

Generation constraints

$$p_i^{min} \leq \boldsymbol{p_i} \leq p_i^{max}$$



Optimization problem to minimize the cost of electricity generation

Generation dispatch determines demand for natural gas

How much gas is available?

How can electric system operators preemptively address risk?

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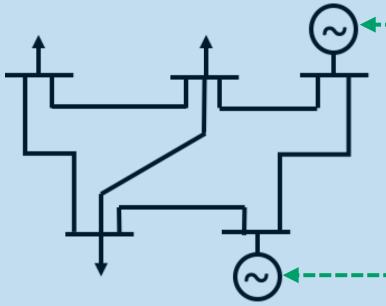
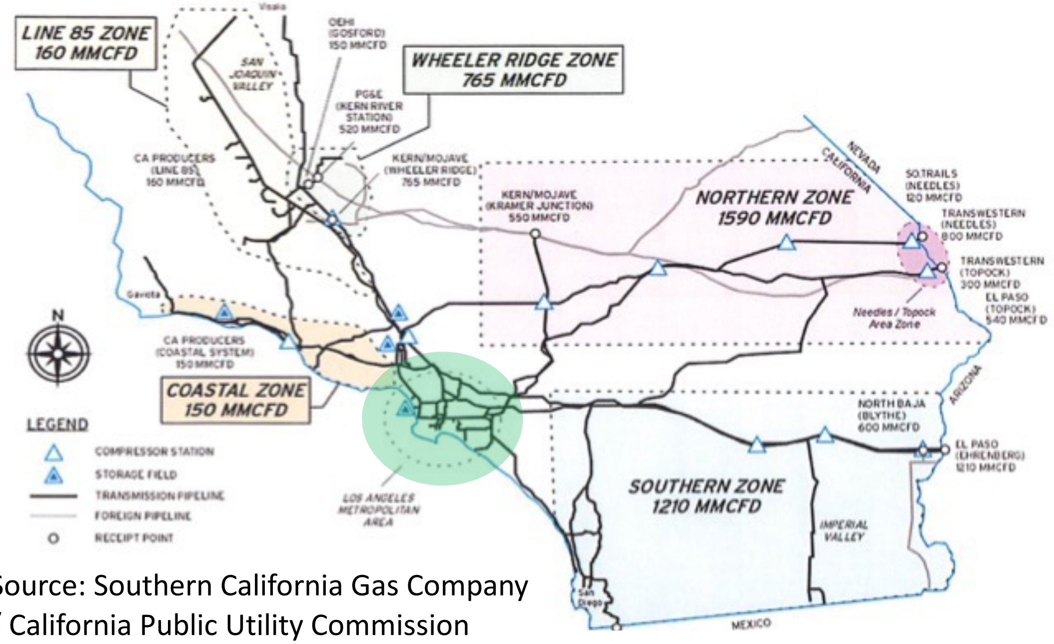


Optimization problem to minimize the cost of electricity generation

CAISO: Impose restrictions on gas generation in Los Angeles area after Aliso Canyon leak



Source: Southern California Gas Company / California Public Utility Commission

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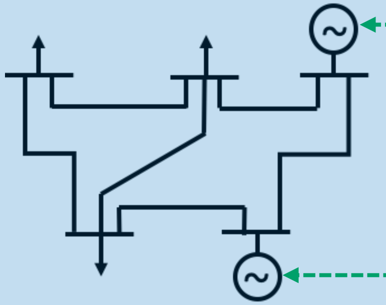
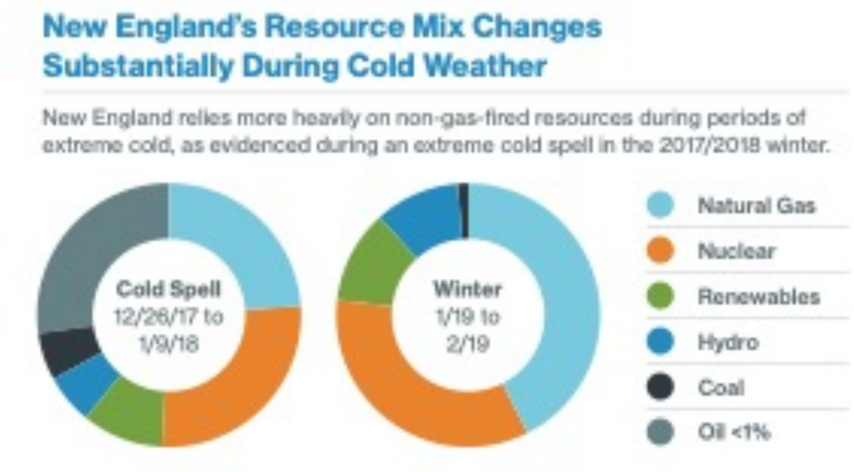


Optimization problem to minimize the cost of electricity generation

ISO New England: Proactively assess fuel availability



Source: ISO New England 2020/2021 Winter Outlook

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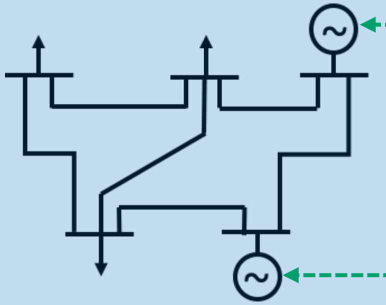

Optimization problem to minimize the cost of electricity generation

Can we do better through improved coordination and control?

Joint optimization

(full exchange of information)

Literature review: LR, K. Sundar, A. Zlotnik, S. Misra and G. Andersson, (2020). An uncertainty management framework for integrated gas-electric energy systems. *Proceedings of the IEEE*, *108*(9), 1518-1540.

Modeling of gas-electric systems

Electric grid market clearing

Gas system operations

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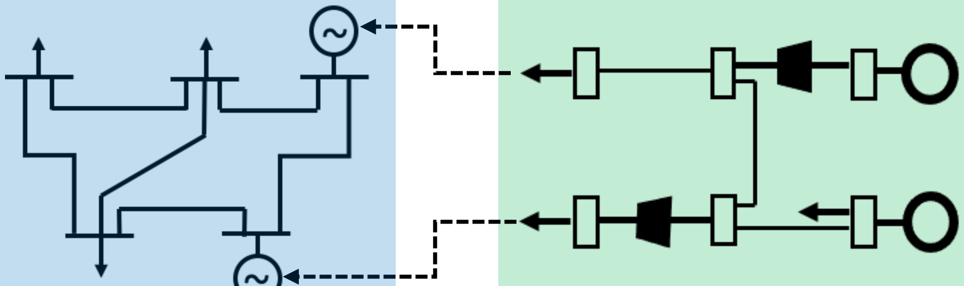

Mass Conservation

$\partial_t \rho(x,t) + \partial_x \phi(x,t) = 0$

Momentum Balance

$\phi(x,t) = F(\rho(x,t), \partial_x \rho(x,t))$

Flow Conservation

$\Sigma \phi_{ij} = \boldsymbol{q_i}(\boldsymbol{p_i})$ **Heat rate curve**

Pressure Constraints

$\underline{\rho_i} \leq \rho_i(t,x) \leq \bar{\rho}_i$

Compressor Constraints

$\underline{\alpha_i} \leq \alpha_i(t,x) \leq \bar{\alpha}_i$

Goal: **Predict** how the system is evolving and **optimize** operation!

Why are gas dynamics so important?

- An important feature of the natural gas system is **slowly evolving dynamics**

$$\frac{\partial \pi}{\partial t} + \frac{c^2}{A}\frac{\partial m}{\partial x} = 0$$

Conservation of mass

$$\frac{\partial m}{\partial t} + A\frac{\partial \pi}{\partial x} = -\frac{f^D c^2 m|m|}{2dA\pi}$$

Conservation of momentum

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$$\frac{\partial m}{\partial t} + A\frac{\partial \pi}{\partial x} = -\frac{f^D c^2 m|m|}{2dA\pi}$$

- It takes time to move gas:
  It is necessary to **plan ahead**!

Source: UK National Grid

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- It takes time to move gas:
  It is necessary to plan ahead!
- Allows unbalanced operation:
  There is **time to react**!

Sources: Southern California Gas Co., Times reporting

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Challenges:

- **Non-convex equations** (no good relaxations)
- **Lots of variables** (time and space discretization)

Discretization

$$\frac{u\left(\pi_{ij,t,\omega} - \pi_{ij,t-1,\omega}\right)}{\Delta t} + V_m \frac{m_{j,t,\omega} - m_{i,t,\omega}}{\Delta x} = 0$$
$$\frac{u\left(m_{ij,t,\omega} - m_{ij,t-1,\omega}\right)}{\Delta t} + V_f \frac{m_{ij,t,\omega}|m_{ij,t,\omega}|}{\pi_{ij,t,\omega}} + V_p \frac{\pi_{j,t,\omega} - \pi_{i,t,\omega}}{\Delta x} = 0$$

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Steady-state gas system model

- What happens if the gas dynamics are ignored?

Problem becomes easier to solve!

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$$\cancel{\frac{\partial \pi}{\partial t}} + \frac{c^2}{A}\frac{\partial m}{\partial x} = 0$$

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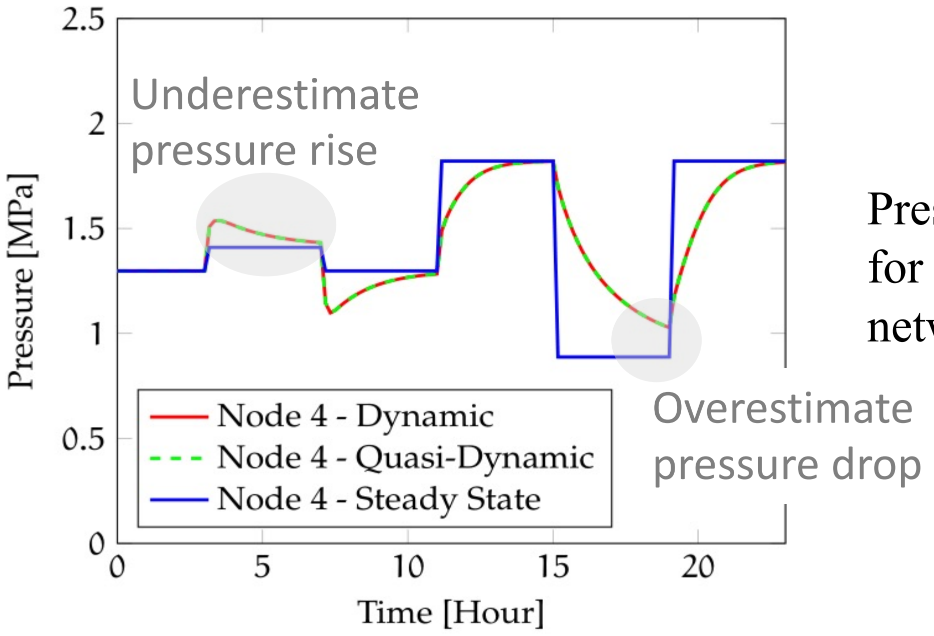
Steady-state gas system model

- What happens if the gas dynamics are ignored?
  Too **conservative**.
  Too **optimistic**.



Pressure Profile for different gas network models

Three key challenges

1. It is important to capture **gas system dynamics**

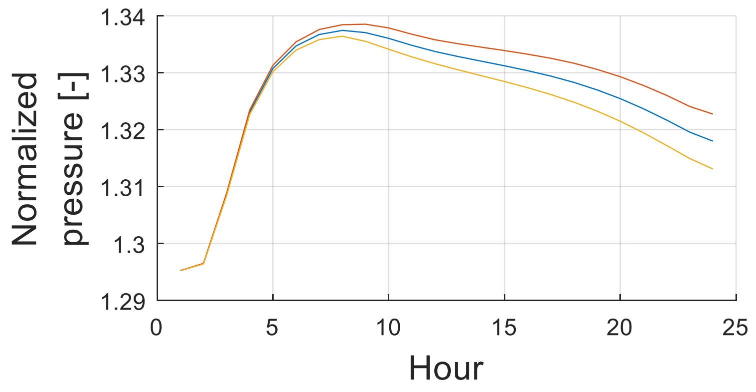
$$\frac{\partial \pi}{\partial t} + \frac{c^2}{A}\frac{\partial m}{\partial x} = 0$$

$$\frac{\partial m}{\partial t} + A\frac{\partial \pi}{\partial x} = -\frac{f^D c^2 m|m|}{2dA\pi}$$

Three key challenges

1. It is important to capture **gas system dynamics**

2. It is important to consider the **impact of uncertainty**



Particularly scenarios in which forecast errors **accumulate over time** (e.g., gas generation is consistently over or under-estimated)

Three key challenges

1. It is important to capture **gas system dynamics**

Non-convex,
large scale

2. It is important to consider the **impact of uncertainty**

Uncertainty
representation

3. How to combine those into one
   tractable optimization problem!?!

Three key challenges

1. It is important to capture **gas system dynamics**

Non-convex, large scale

2. It is important to consider the **impact of uncertainty**

Uncertainty representation

3. How to combine those into one **tractable optimization problem**!?!

Let’s see!

Joint optimization model

$$\underset{x\in\mathcal{X}}{\text{Min.}} \quad f(x) + \underset{\omega\in\Omega}{\mathbb{E}}[Q(x,\omega)]$$

First-stage: Day-ahead

Minimize **cost of day-ahead electricity dispatch** and **expected cost of intra-day operation**

where $Q(x,\omega) = \text{Min.} \;\; g(y,\omega)$

$$\text{s.t.} \quad h(y) = x$$
$$y_\omega^{\text{gas}} \in \mathcal{Y}_\omega^{\text{gas}}(x)$$
$$y_\omega^{\text{elec}} \in \mathcal{Y}_\omega^{\text{elec}}(x)$$

Second-stage: Intra-day

Minimize cost of **intra-day operation for scenario ω**

Matching first stage variables across all scenarios

Electric system constraints (generation dispatch, DC power flow)

Gas system constraints (compressor operation, dynamic gas model)

Joint optimization model

$$\underset{x \in \mathcal{X}}{\text{Min.}} \quad f(x) + \underset{\omega \in \Omega}{\mathbb{E}}[Q(x, \omega)]$$

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Minimize cost of **intra-day operation for scenario ω**

Matching first stage variables across all scenarios

Electric system constraints (generation dispatch, DC power flow)

Gas system constraints (compressor operation, dynamic gas model)

- **Challenging** to solve for one scenario (non-convex, large scale, …)
- **Intractable** for many scenarios at once

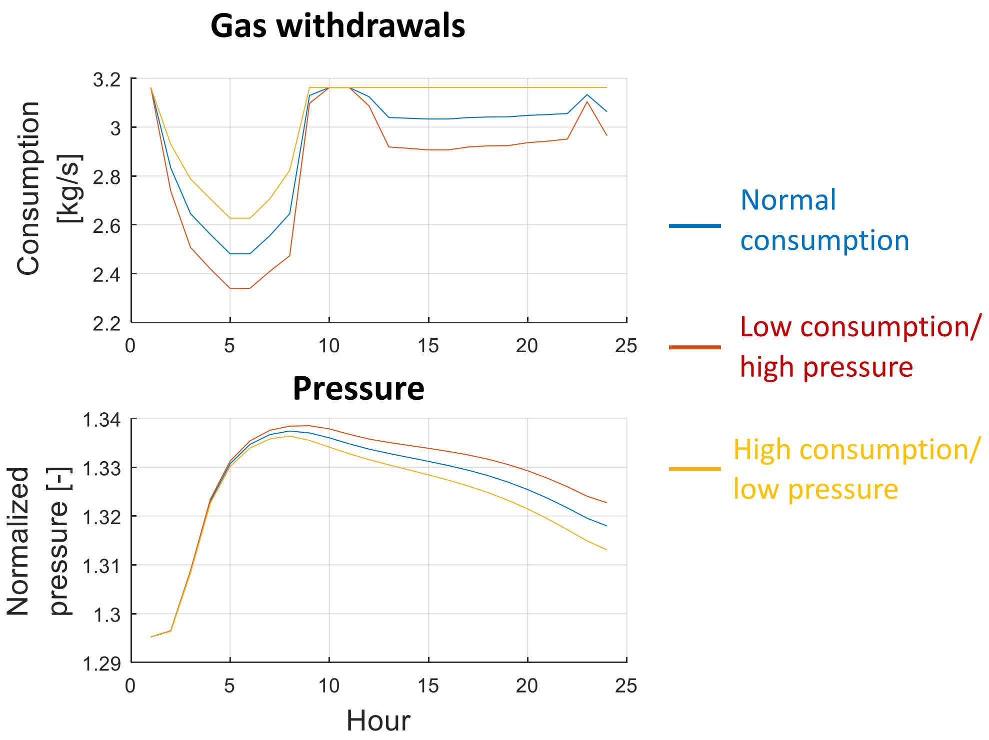
Two methods

1. Robust optimization

Use monotonicity properties to replace the uncertainty scenarios with **two provably worst-case scenarios:**

$$\overline{\omega} = \max_{\omega \in \Omega}(\text{gas consumption}) \quad \forall\, t \in T, n \in N$$

$$\underline{\omega} = \min_{\omega \in \Omega}(\text{gas consumption}) \quad \forall\, t \in T, n \in N$$



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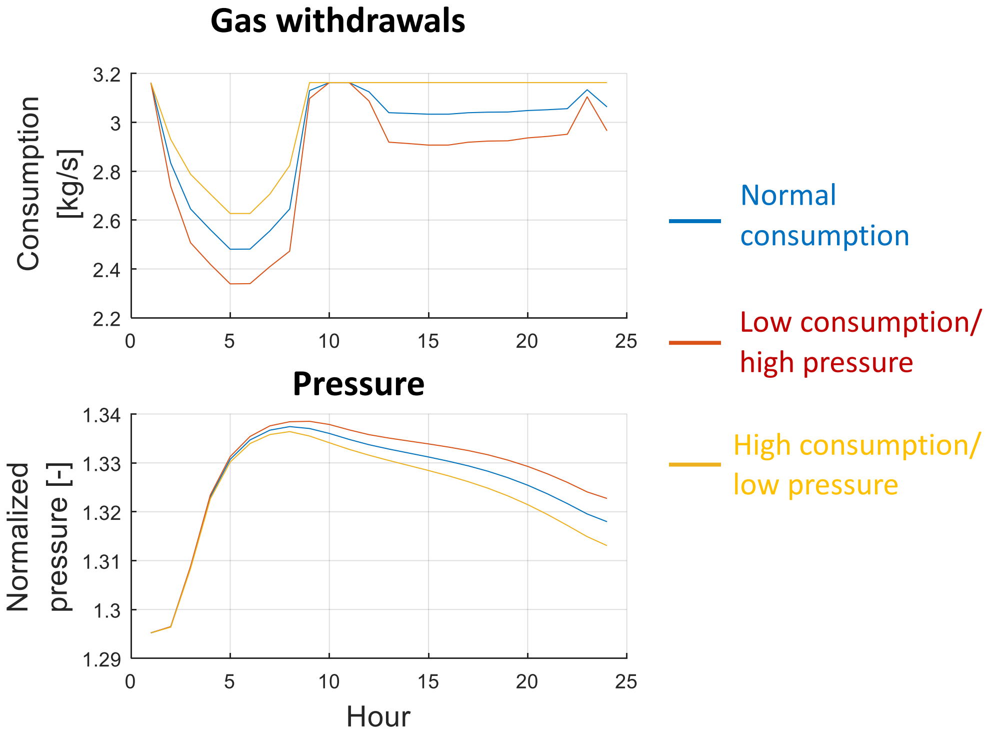
Challenges:

- Modeling limitations on compressor operation
- Conservative (and accumulating over time)



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Two methods

1. Robust optimization

2. Stochastic hybrid approximation

+ Solve for one scenario at a time (or multiple in parallel)!
+ More modeling flexibility!

C. O'Malley, G. Hug and L. Roald, "Stochastic Hybrid Approximation for Uncertainty Management in Gas-Electric Systems," accepted to *IEEE Transactions on Power Systems*, in press

Stochastic Hybrid Approximation

A well-established approach, first application to gas-electric optimization.

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Stochastic Hybrid Approximation

A well-established approach, first application to gas-electric optimization.

1. Solve the **first stage problem** while using a **simple approximation** of the second stage

$$\underset{x \in \mathcal{X}}{\text{Min.}} \quad f(x) + \underset{\omega \in \Omega}{\mathbb{E}}\Big[g(x,\omega)\Big] \xrightarrow{\text{Approximation}} \underset{x \in \mathcal{X}}{\text{Min.}} \quad f(x) + \hat{Q}_0(x) + \sum_i \overline{\lambda}_i^{(\nu)} x_i$$

Initial approximation + Iterative update based on stochastic subgradient λ_i

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Initial approximation + Iterative update based on stochastic subgradient λ_i

Convex quadratic approximation (SHACV)	$\hat{Q}^0(x) = ax^2 + bx$
Adaptive certainty equivalent (SHACE)	Add certainty equivalent to first stage
Extrema equivalent – new (SHAXE)	Add extreme scenarios to first stage

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3. Obtain **stochastic subgradient $\boldsymbol{\lambda_i}$** and update the approximation:

$$\overline{\lambda}_i^{(\nu+1)} = \overline{\lambda}_i^{(\nu)} + \alpha^{(\nu)}\left(\lambda_i^{(\nu)} - \left(\hat{q}_{0i}^{(\nu)} + \overline{\lambda}_i^{(\nu)}\right)\right)$$

Step size
$\alpha = \rho/\nu$

Derivative of initial
approximation $d\hat{Q}_0/dx$
at solution x_i

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Provably convergent for convex problems.

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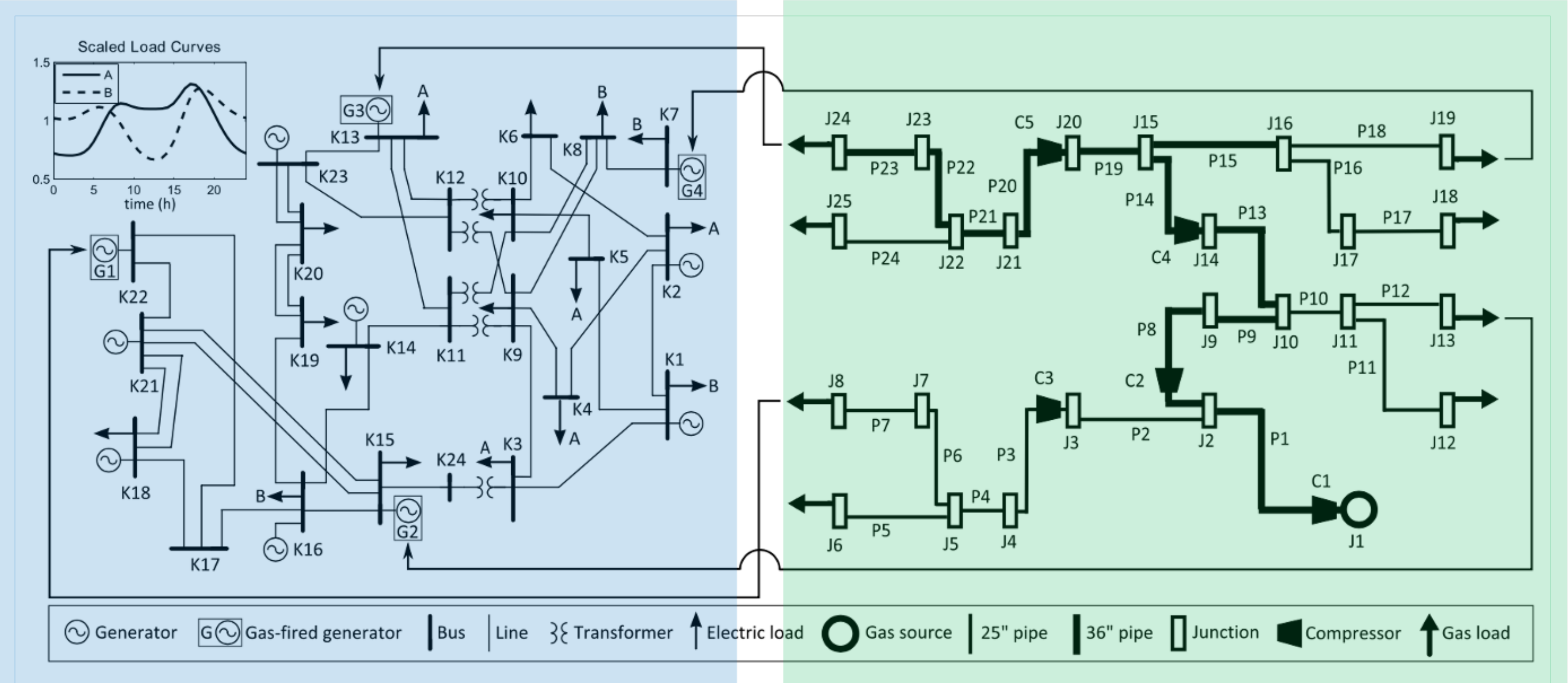
4. Evaluate the solution as an **average across multiple iterations:** $\overline{x}_n^{(\nu)} = \frac{\sum_{i=i_0}^{\nu} x^{(i)}/\alpha^{(i)}}{\sum_{i=i_0}^{\nu} 1/\alpha^{(i)}}$
5. Repeat the process until **solution convergence or time limit**

Provably convergent for convex problems. **But not here…**

Numerical results

Electric grid Gas-fired generation **Gas system**



- 24 nodes (meshed)
- 33 Generators (18 Gas Generators - 5300 MW)
- Peak Load = 2850 MW
- 100 wind scenarios (average = 500 MW)

- 30 nodes (radial)
- 1 Supply and 5 Compressors
- Peak Load (no generators) = 7600 MW

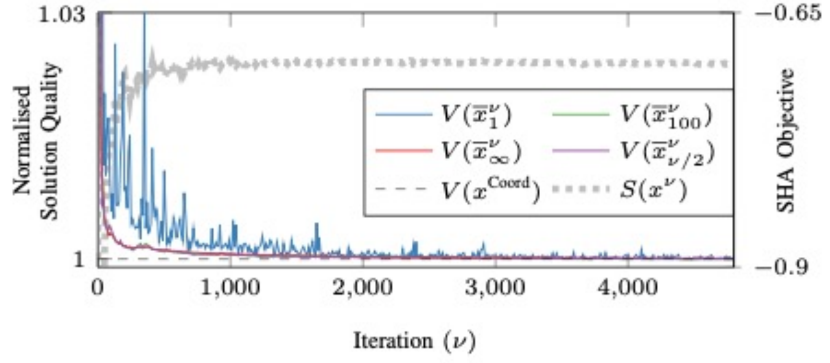
- **Stressed** system conditions
- **Correlated** wind uncertainty

Notes on solving the problem

Not easy to know when to stop!

- Solutions are noisy
- It is expensive to evaluate the true objective value of the solution

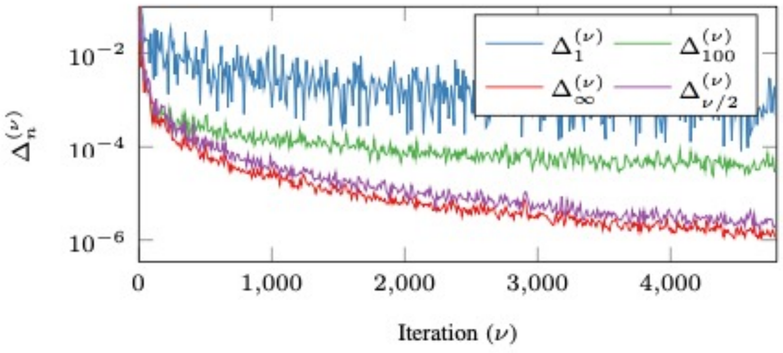
Stop when **averaged** solution stops changing



(a) Solution quality for different window lengths

Limited number of samples

- Reuse samples multiple times
- Continues to improve solution quality



(b) Solution update for different window lengths

Notes on solving the problem

Benchmarking

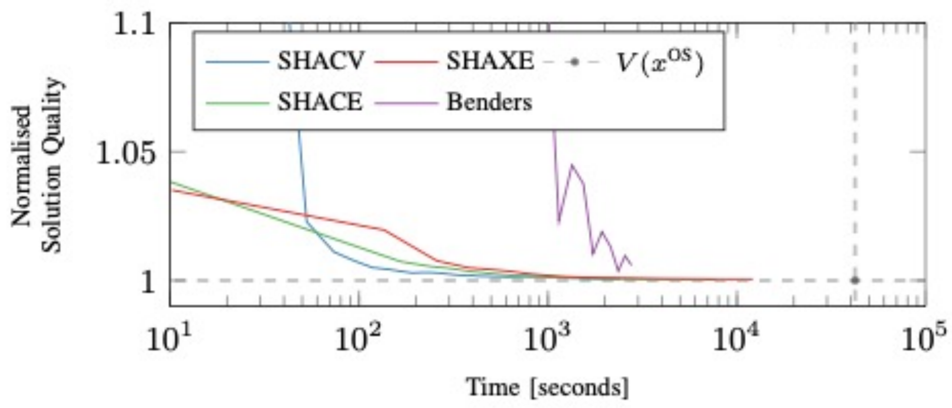
- Generalized Benders algorithm
- Different approximations

Convex quadratic approximation (SHACV)
Adaptive certainty equivalent (SHACE)
Extrema equivalent – new (SHAXE)

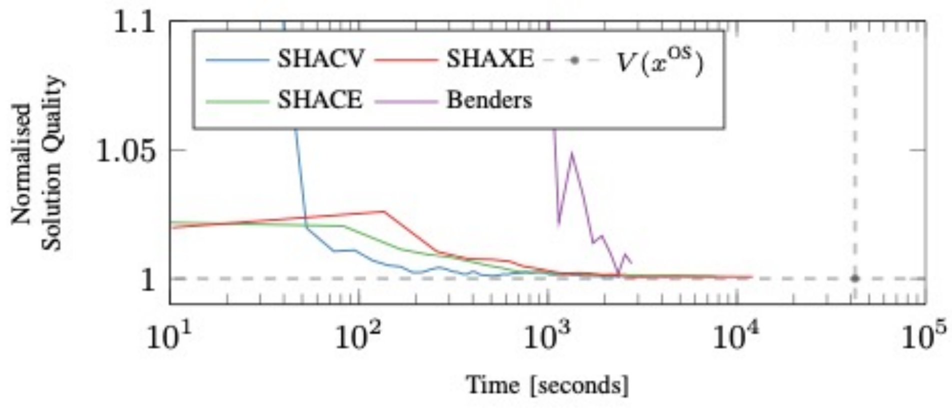
Outcomes

- Stochastic approximations find high quality solutions faster
- Convex quadratic approximation (SHACV) is best, but requires most tuning

Training data set (used for optimization)



Testing data set (used to check solution quality)



Do we need to **co-optimize** gas and grid?

Yes, co-optimization that considers both the electric grid and the gas system

- Avoids load shedding
- Lowers cost

TABLE II
EXPECTED MITIGATION ACTIONS (TOP) AND TOTAL SYSTEM COSTS (BOTTOM) GIVEN FIRST STAGE OPF AND OPGF RESULTS.

Average Value	x OPF			x OPGF		
	Mean	Max.	Min.	Mean	Max.	Min.
Wind Spill [%]	25.4	41.86	1.95	25.39	42.16	2.19
Elec. Load Shed [%]	0.95	4.99	0	0.01	0.52	0
Gas Load Shed [%]	14.95	15.81	14.46	0	0	0

Cost [Million CHF]	x OPF			x OPGF		
	Mean	Max.	Min.	Mean	Max.	Min.
1^{st} Stage Elec.	0.95	-	-	1.09	-	-
2^{nd} Stage Elec.	0.57	3.17	-0.12	-0.07	0.55	-0.15
2^{nd} Stage Gas	10.51	11.05	10.19	0.94	0.97	0.89

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With co-optimization: **No load shed**

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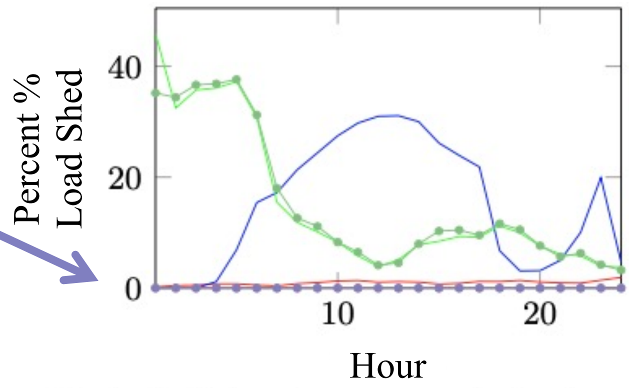

Wind spill
Gas load shed **without** co-optimization
Gas load shed **with** co-optimization

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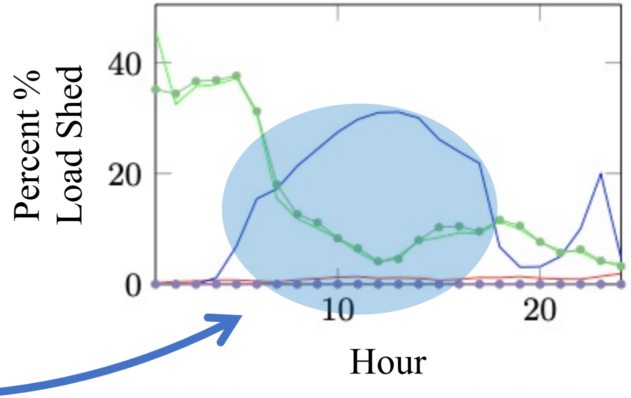
With co-optimization: **No load shed**

Without co-optimization: **30 % reduction** in natural gas deliveries!

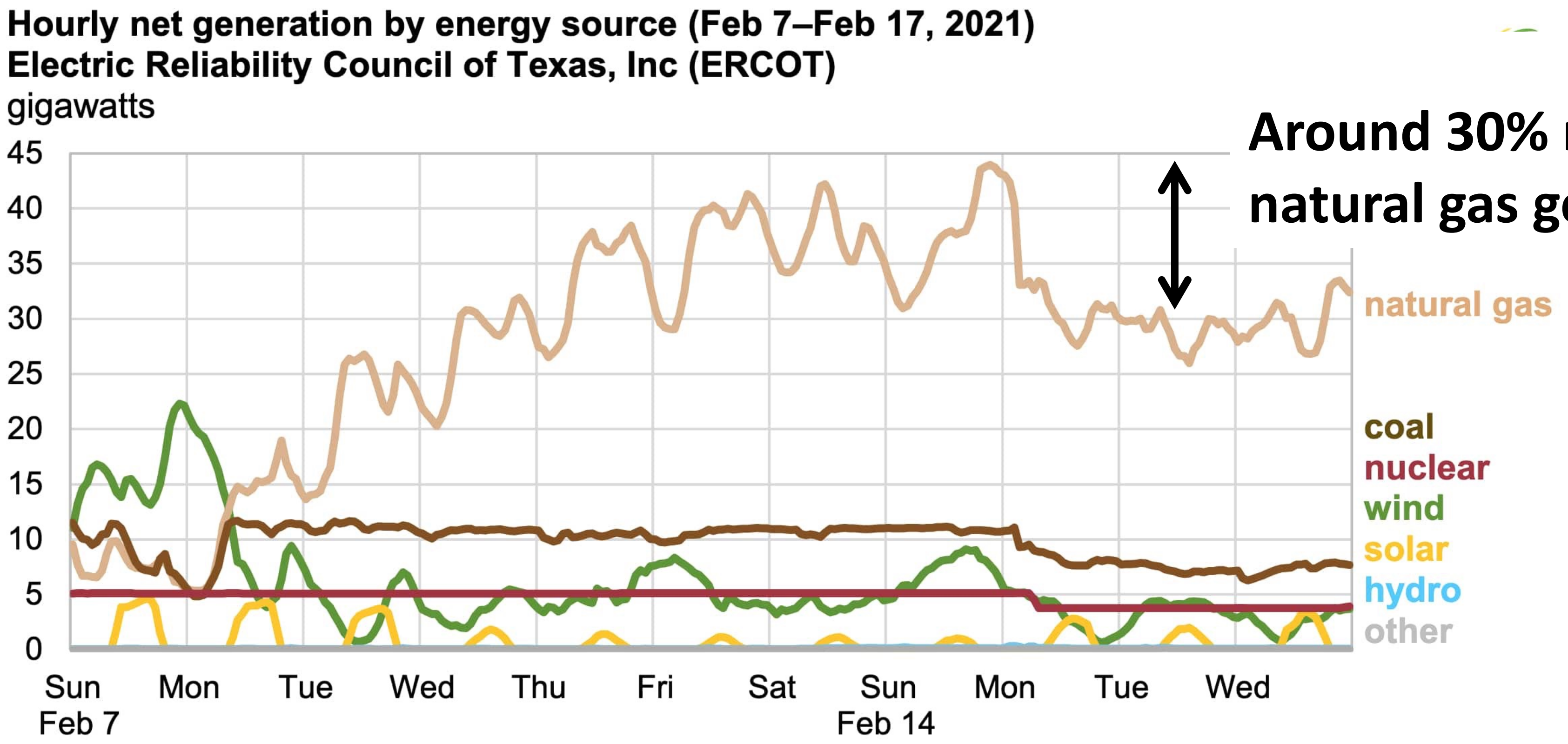


Wind spill

Gas load shed **without** co-optimization

Gas load shed **with** co-optimization

Do we need to **co-optimize** gas and grid?



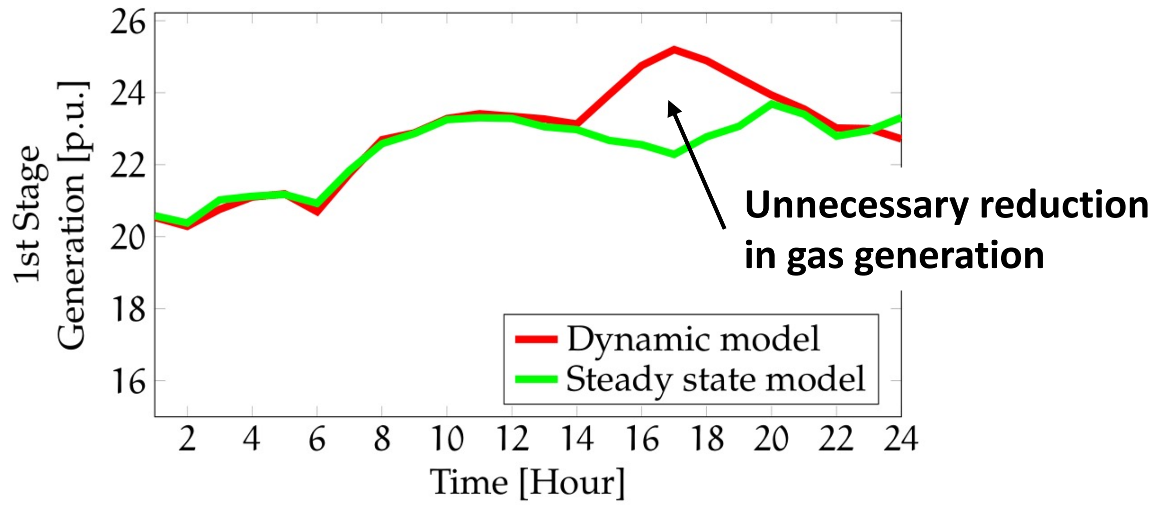
Around 30% reduction in natural gas generation

https://en.wikipedia.org/wiki/2021_Texas_power_crisis#/media/File:ERCOT_generation_2021_power_crisis_US_Energy_Information_Administration.jpg

Do we need to consider a **dynamic** gas model?

- Yes!

- Steady-state model **fails to leverage** the inherent gas system storage, leading to **costly** solutions

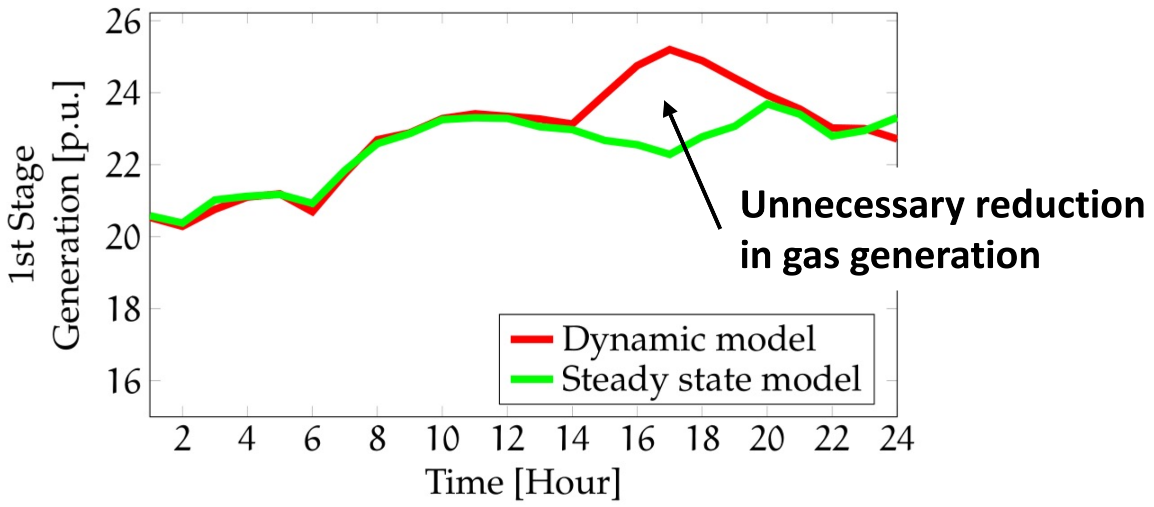


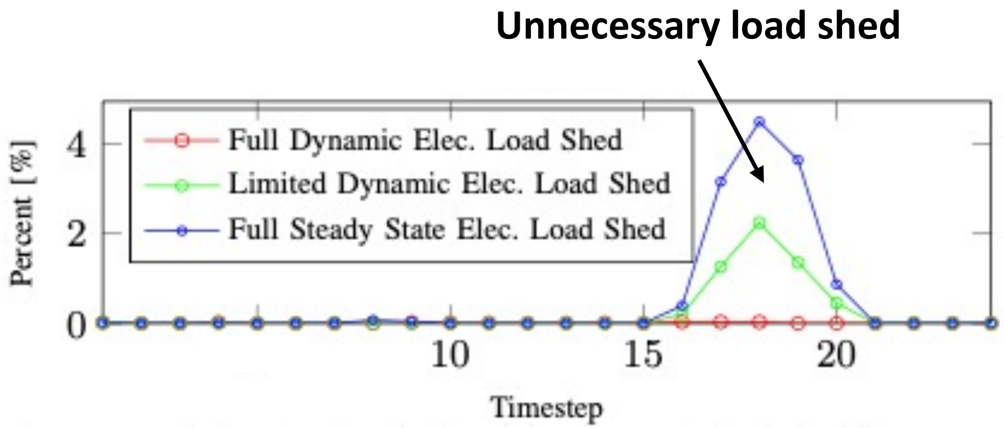
Do we need to consider a **dynamic** gas model?

- Yes!

- Steady-state model **fails to leverage** the inherent gas system storage, leading to **costly** solutions

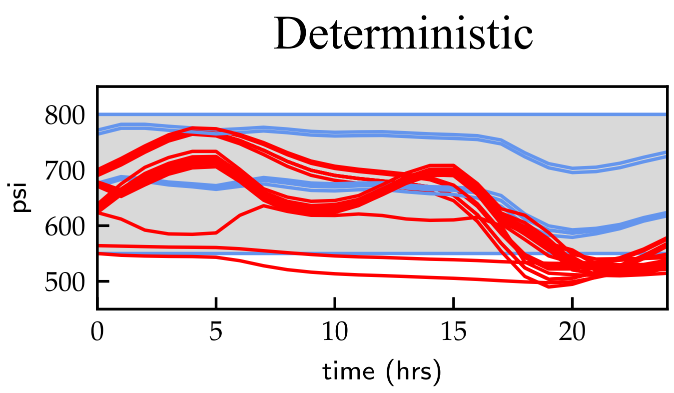
- Steady-state models **unnecessarily** predict a need for **load shedding**

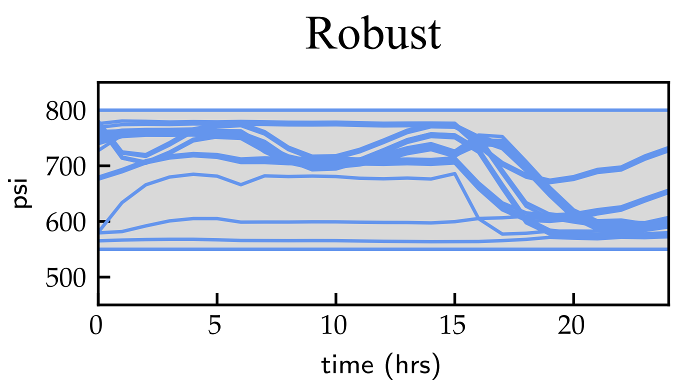




Do we need to consider **uncertainty**?

Pressure profiles at maximum withdrawal:
Robust solution is safe
Deterministic solution gives big violations





L. Roald, K. Sundar, A. Zlotnik, S. Misra and G. Andersson, "An Uncertainty Management Framework for Integrated Gas-Electric Energy Systems," in *Proceedings of the IEEE*, Sep. 2020

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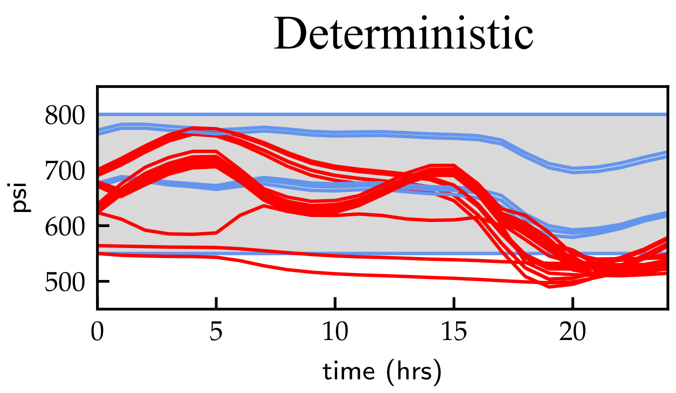
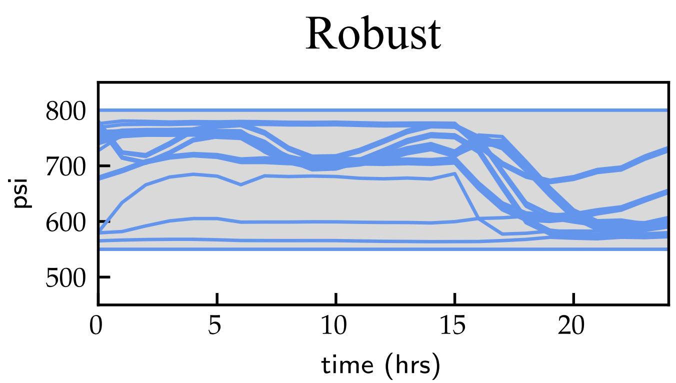
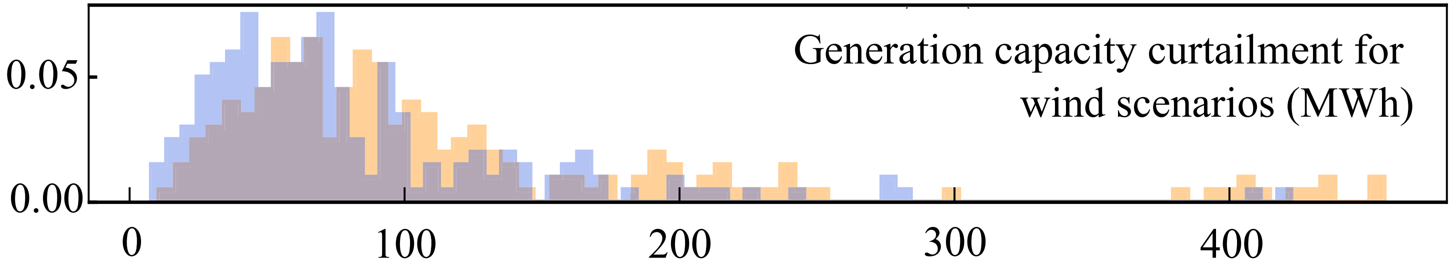




Requires **generation curtailment** to guarantee secure gas system operation



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Conclusions and Outlook

- **Capturing system interdependence, uncertainty and gas system dynamics is worth the hassle!**

Particularly important during stressed system conditions!

Proposed method: Stochastic hybrid approximation

- Start from a simple approximation and add information from one uncertain scenario at the time.
- Using one scenario at the time improves tractability.
- Converges fast to a good solution in our application.
- No guarantees on optimality, but this is anyways a large-scale non-linear, non-convex problem!

Winter freeze in Texas (Eli Hartman, AP)

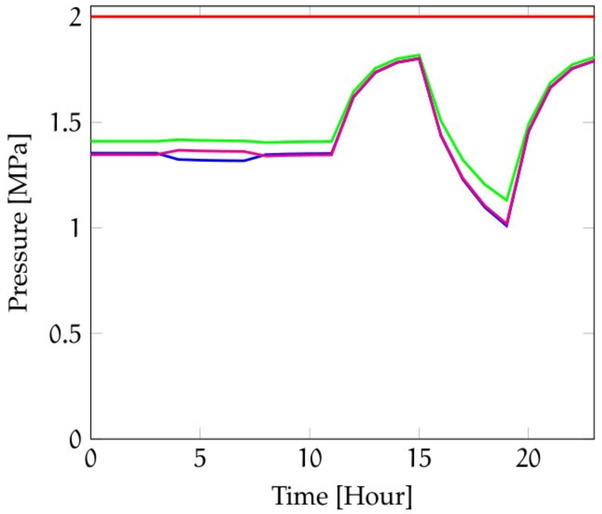
Gas leak in Aliso Canyon (EDF)

Conclusions and Outlook

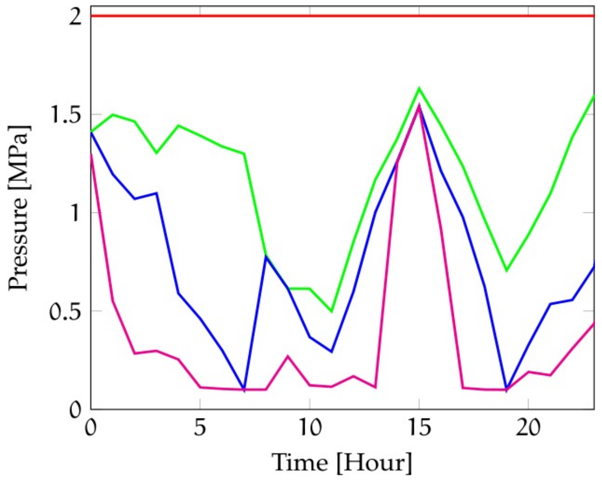
Chasing better solutions…

- Large-scale, non-convex optimization is numerically challenging and we have no guarantees on optimality
- Worth noting (from C. O'Malley, ETH PhD thesis)
  - Local methods seem to find global solutions
  - Relaxations often provide bad solutions!
- Other open questions: Global solutions or bounds? Scalability? Performance with other uncertainty data/distributions? Stopping criterion? …

Interior Point Solution



MISOCP Solution



Thank you!

Line A. Roald
roald@wisc.edu