

# Probabilistic Constrained Optimization on Gas Networks

**Michael Schuster (FAU), Martin Gugat (FAU), Rüdiger Schultz (UDE)**

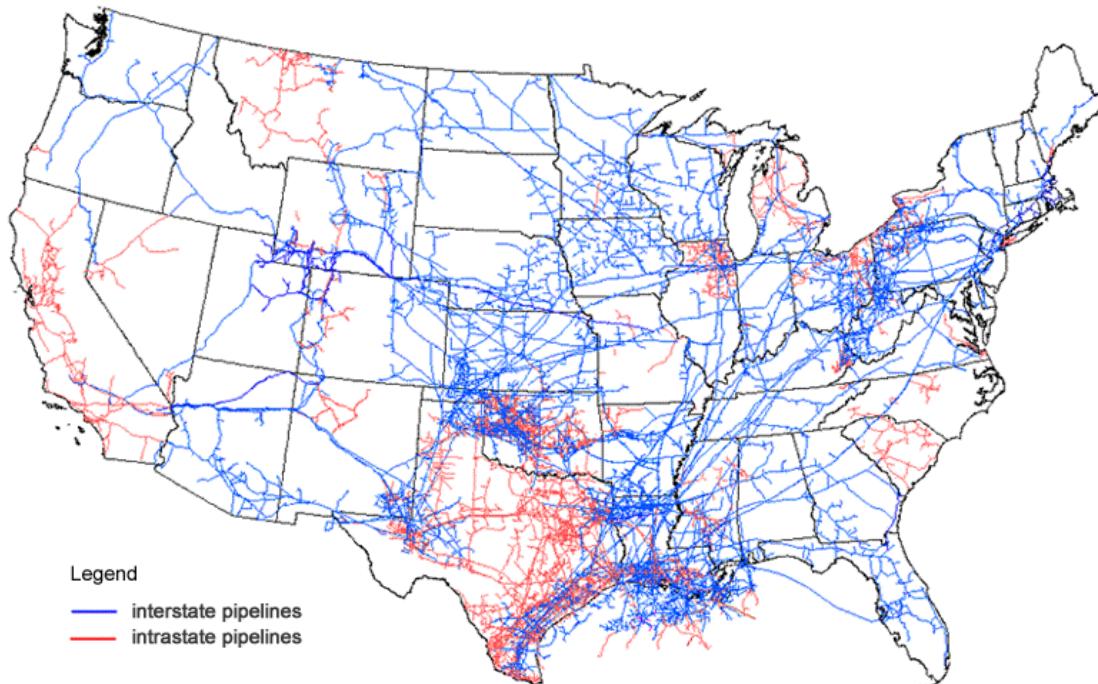
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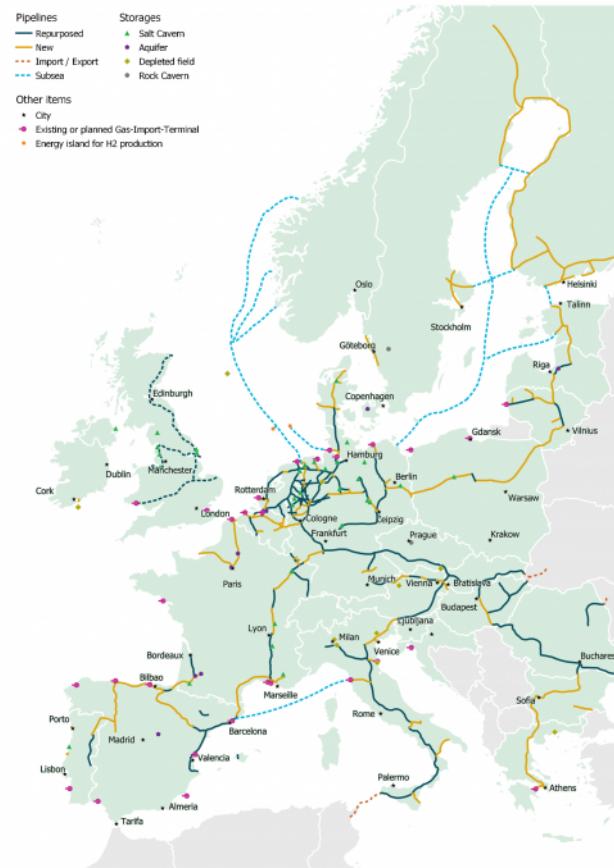
# Motivation

## Natural Gas Transport

Map of U.S. interstate and intrastate natural gas pipelines



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## Probabilistic Constraints

Consider the optimization problem

$$\begin{aligned} \min \quad & f(x) \\ \text{s.t.} \quad & \mathbb{P}(g(x, \xi) \leq 0) \geq \alpha \end{aligned}$$

with objective function  $f$ , constraint  $g$ , decision vector  $x$ , random variable  $\xi$  (with probability distribution and density function) and probability level  $\alpha$ .

$$\mathbb{P}(g(x, \xi) \leq 0) = \int_{M(x)} \varrho_{g_\xi}(z) dz,$$

with

$$M(x) = \{\omega \in \Omega \mid g(x, \xi(\omega)) \leq 0\}.$$

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Is there a „better“ way to compute this probability?

## Mathematical Modelling on Networks

- Consider a connected, directed graph  $\mathcal{G} = (\mathcal{V}, \mathcal{E})$  with vertex set  $\mathcal{V}$  and set of edges  $\mathcal{E} \subseteq \mathcal{V} \times \mathcal{V}$
- We consider the stationary model (ISO4) for ideal gases on every edge  $e \in \mathcal{E}$

### (ISO4) for ideal gases

$$q_x = 0, \quad p_x = -\frac{c^2 \lambda^F}{2D} \frac{q|q|}{p}$$

### solution of (ISO4)

$$q(x) = \text{const.}, \quad p^2(x) = p(0)^2 - \frac{c^2 \lambda^F}{2D} q|q| x$$

Coupling conditions at the nodes:

### Conservation of mass

$$\sum_{e \in \mathcal{E}_-(v)} q^e \left( \frac{D^e}{2} \right)^2 \pi = b^v + \sum_{e \in \mathcal{E}_+(v)} q^e \left( \frac{D^e}{2} \right)^2 \pi \quad \forall v \in \mathcal{V} \setminus \mathcal{V}_0.$$

### Continuity in pressure

$$p^{e_1}(L^{e_1}) = p^{e_2}(0) \quad \forall e_1 \in \mathcal{E}_-(v), e_2 \in \mathcal{E}_+(v).$$

### Boundary Conditions:

#### Inlet pressure

$$p^e(0) = p_0 \in \mathbb{R}_{\geq 0} \quad \forall e \in \mathcal{E}_+(v_0)$$

#### Gas outflow

$$q^e(L^e) = b^v \in \mathbb{R}_{\geq 0} \quad \forall e \in \mathcal{E}_-(v)$$

$b^v$  represents the consumers gas demand

- Let  $p \in \mathbb{R}^n$  be the vector of pressures at the nodes  $v_1, \dots, v_n$
- We assume box constraints for the pressures at the nodes:  $p_i \in [p_i^{\min}, p_i^{\max}]$

#### Set of feasible loads

$$M := \left\{ b \in \mathbb{R}_{\geq 0}^n \mid \begin{array}{l} (p, q) \in \mathbb{R}^n \times \mathbb{R}^n \text{ satisfies:} \\ \bullet \text{ stationary semilinear isothermal Euler equations,} \\ \bullet \text{ inlet pressure and gas outflow,} \\ \bullet \text{ conservation of mass and continuity in pressure,} \\ \bullet \text{ pressure bounds.} \end{array} \right\}$$

[Gugat, Hante, Hirsch-Dick, Leugering, 2015]: *Stationary states in gas networks*. Netw. Heterog. Media, 10(2): 295–320.

Assume that the consumers gas demand is random in the sense, that there is a random variable

$$\xi_b \sim \mathcal{N}(\mu, \Sigma),$$

on an appropriate probability space. We identify  $b$  with the image  $\xi_b(\omega)$  for  $\omega \in \Omega$ .

*For a given inlet pressure, can we guarantee, that every consumer receives their demanded gas, s.t. the gas pressure in the network is neither too high nor too low, in at least  $\alpha\%$  of all scenarios?*

$$\mathbb{P}(\omega \in \Omega \mid \xi_b(\omega) \in M) \geq \alpha$$

# Stationary Gas Transport

## Gas Networks under Uncertainty

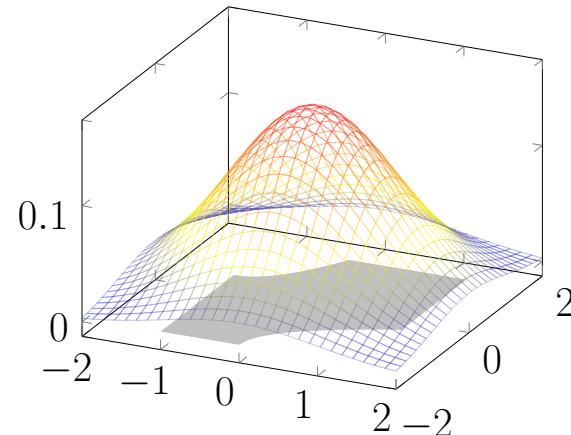
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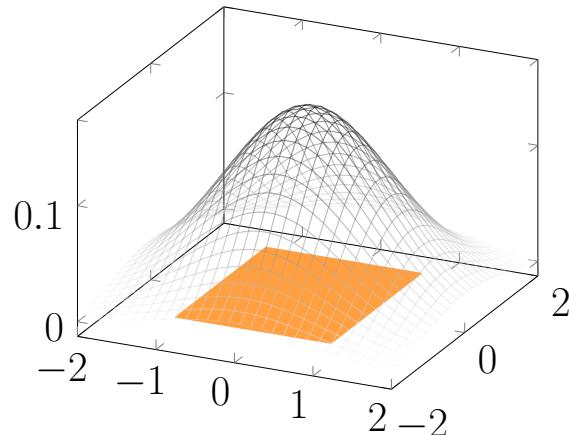
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(a) Well-known distribution (colored),  
unknown set of feasible loads (grey)

gas dynamics



(b) Unknown distribution (grey), well-known  
set of feasible pressures (orange)

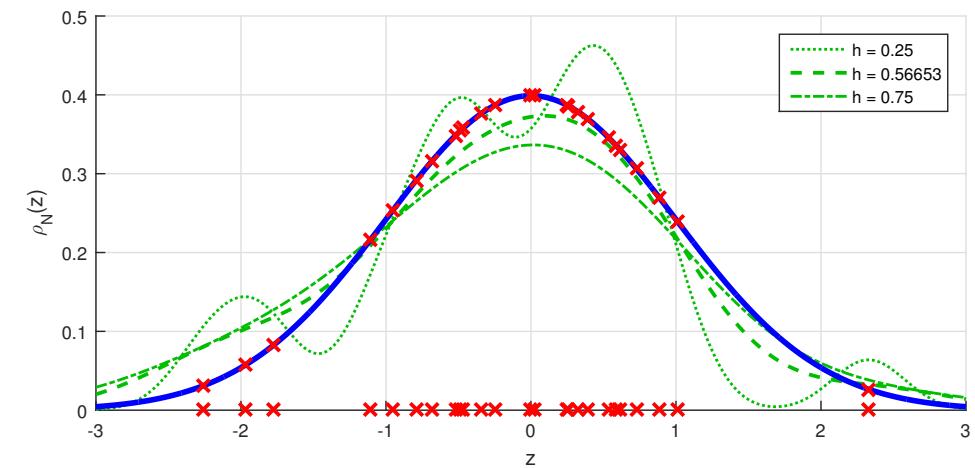
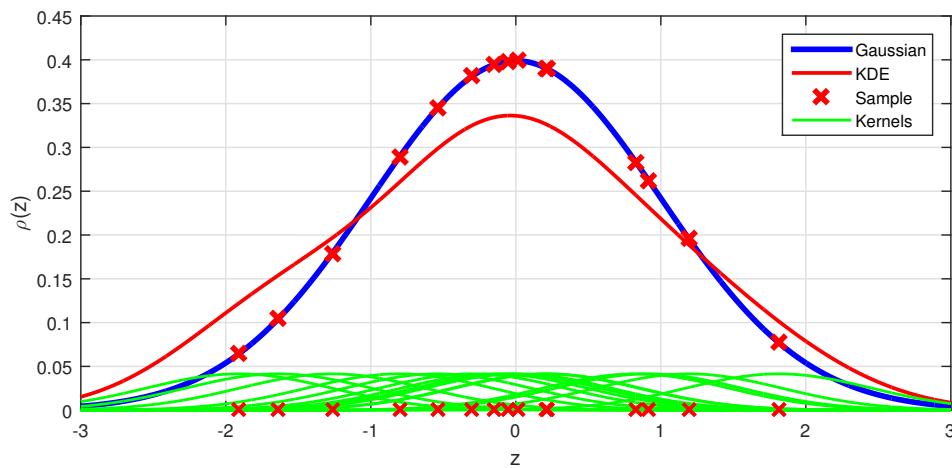
## Kernel Density Estimation

### Definition: Kernel Density Estimator

Let  $\mathcal{Y} = \{y_1, \dots, y_N\} \subseteq \mathbb{R}^n$  be i.i.d. samples of the random variable  $Y$ , which has an absolutely continuous distribution function with probability density function  $\varrho$ . Let  $K$  be a kernel function.

Then the kernel density estimator  $\varrho_N$  corresponding to the bandwidth  $h \in (0, \infty)$  is defined as

$$\varrho_N(z) = \frac{1}{Nh} \sum_{i=1}^N K\left(\frac{z - y_i}{h}\right).$$



[Gramacki 2018]: Nonparametric Kernel Density Estimation and its Computational Aspects. Springer International Publishing

## Application of Kernel Density Estimation

- Let  $\mathcal{B} = \{ b^{S,1}, \dots, b^{S,N_{\text{KDE}}} \} \subseteq \mathbb{R}_{\geq 0}^n$  be independent and identically distributed samples of the random variable  $\xi_b$
- Let  $\mathcal{P}_{\mathcal{B}} = \{ p(b^{S,1}), \dots, p(b^{S,N_{\text{KDE}}}) \} \subseteq \mathbb{R}^n$  be the corresponding pressures at the nodes (also independent and identically distributed)

### Gaussian kernel

$$K(x) = \prod_{j=1}^n \frac{1}{\sqrt{2\pi}} \exp\left(-\frac{1}{2}x_j^2\right)$$

### bandwidth matrix

$$H_{i,i} = h^2 (\Sigma_{N_{\text{KDE}}})_{i,i}$$
$$h = \left(\frac{4}{(n+2)N_{\text{KDE}}}\right)^{\frac{1}{n+4}}$$

### kernel density estimator

$$\varrho_{p,N_{\text{KDE}}}(z) = \frac{1}{N_{\text{KDE}} \det \sqrt{H_{j,j}}} \sum_{i=1}^{N_{\text{KDE}}} \prod_{j=1}^n \frac{1}{\sqrt{2\pi}} \exp\left(-\frac{1}{2} \left(\frac{z_j - p_j(b^{S,i})}{\sqrt{H_{j,j}}}\right)^2\right)$$

[Schuster, Strauch, Gugat, Lang, 2022]: *Probabilistic Constrained Optimization on Flow Networks*. Optim. Eng. 23: 1–50

## Application of Kernel Density Estimation

$$\begin{aligned}\mathbb{P}_{N_{\text{KDE}}}(p \in P_{\min}^{\max}) &= \int_{P_{\min}^{\max}} \varrho_{p, N_{\text{KDE}}}(z) \, dz \\ &= \int_{P_{\min}^{\max}} \frac{1}{N_{\text{KDE}} \prod_{j=1}^n h_j} \sum_{i=1}^{N_{\text{KDE}}} \prod_{j=1}^n \frac{1}{\sqrt{2\pi}} \exp \left( -\frac{1}{2} \left( \frac{z_j - p_j(b^{S,i})}{h_j} \right)^2 \right) \, dz \\ &= \frac{1}{N_{\text{KDE}} \prod_{j=1}^n h_j} \sum_{i=1}^{N_{\text{KDE}}} \prod_{j=1}^n \int_{p_j^{\min}}^{p_j^{\max}} \frac{1}{\sqrt{2\pi}} \exp \left( -\frac{1}{2} \left( \frac{z_j - p_j(b^{S,i})}{h_j} \right)^2 \right) \, dz_j\end{aligned}$$

## Application of Kernel Density Estimation

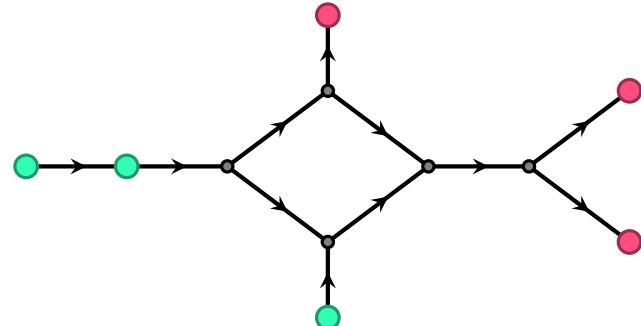
$$\begin{aligned}
 \mathbb{P}_{N_{\text{KDE}}}(p \in P_{\min}^{\max}) &= \int_{P_{\min}^{\max}} \varrho_{p, N_{\text{KDE}}}(z) \, dz \\
 &= \int_{P_{\min}^{\max}} \frac{1}{N_{\text{KDE}} \prod_{j=1}^n h_j} \sum_{i=1}^{N_{\text{KDE}}} \prod_{j=1}^n \frac{1}{\sqrt{2\pi}} \exp \left( -\frac{1}{2} \left( \frac{z_j - p_j(b^{S,i})}{h_j} \right)^2 \right) \, dz \\
 &= \frac{1}{N_{\text{KDE}} \prod_{j=1}^n h_j} \sum_{i=1}^{N_{\text{KDE}}} \prod_{j=1}^n \int_{p_j^{\min}}^{p_j^{\max}} \frac{1}{\sqrt{2\pi}} \exp \left( -\frac{1}{2} \left( \frac{z_j - p_j(b^{S,i})}{h_j} \right)^2 \right) \, dz_j
 \end{aligned}$$

**Gauss error function:**  $\text{erf}(x) = \frac{2}{\sqrt{\pi}} \int_0^x \exp(-t^2) \, dt$

### probability via KDE

$$\mathbb{P}_{N_{\text{KDE}}}(p \in P_{\min}^{\max}) = \frac{1}{N_{\text{KDE}} 2^n} \sum_{i=1}^{N_{\text{KDE}}} \prod_{j=1}^n \left[ \text{erf} \left( \frac{p^{\max} - p_j(b^{S,i})}{\sqrt{2} h_j} \right) - \text{erf} \left( \frac{p^{\min} - p_j(b^{S,i})}{\sqrt{2} h_j} \right) \right]$$

## A Numerical Example



### Deterministic optimization

$$\begin{array}{ll} \min_{p_{\text{det}}^{\max}} & \sum p_{\text{det}}^{\max}, \\ \text{s.t.} & p_i \in [p_i^{\min}, p_{\text{det},i}^{\max}]. \end{array} \Rightarrow p_{\text{det}}^{\max} = \begin{pmatrix} 46.10 \\ 52.04 \\ 51.08 \end{pmatrix}$$

### Probabilistic optimization

$$\begin{array}{ll} \min_{p_{\text{prob}}^{\max}} & \sum p_{\text{prob}}^{\max}, \\ \text{s.t.} & \mathbb{P}(p_i \in [p_i^{\min}, p_{\text{prob},i}^{\max}]) \geq 0.75. \end{array} \Rightarrow p_{\text{prob}}^{\max} = \begin{pmatrix} 47.52 \\ 53.34 \\ 52.45 \end{pmatrix}$$

$p_0$	$p^{\min}$	outflow	covariance	$\alpha$
$\begin{pmatrix} 60 \\ 58 \\ 60 \end{pmatrix}$	$\begin{pmatrix} 40 \\ 40 \\ 40 \end{pmatrix}$	$\begin{pmatrix} 20 \\ 15 \\ 18 \end{pmatrix}$	$\begin{pmatrix} 2 & 0 & 0 \\ 0 & 2 & 0 \\ 0 & 0 & 2 \end{pmatrix}$	75%

How good is the optimal deterministic solution in the probabilistic setting?

$$\mathbb{P}(b \in M(p_{\text{det}}^{\max})) \approx 35.4\%$$

<https://gaslib.zib.de/>

## The Isothermal Euler Equations

The isothermal Euler equations for ideal gases:

(ISO)

$$\begin{aligned}\rho_t + q_x &= 0, \\ q_t + \left( c^2 p + \frac{q^2}{\rho} \right)_x &= -\frac{\lambda^F}{2D} \frac{q|q|}{\rho}.\end{aligned}$$

Inlet density & Gas outflow

$$\begin{aligned}\rho(t, 0) &= \rho_0(t), \\ q(t, L) &= b(t).\end{aligned}$$

Initial condition

$$\begin{aligned}\rho(0, x) &= \rho_{\text{ini}}(x), \\ q(0, x) &= q_{\text{ini}}(x).\end{aligned}$$

see Gugat and Ulbrich (2018): *Lipschitz solutions of initial boundary value problems for balance laws*. Math. Models Methods Appl. Sci., 28(5): 921–951

## Time Dependent Uncertainty

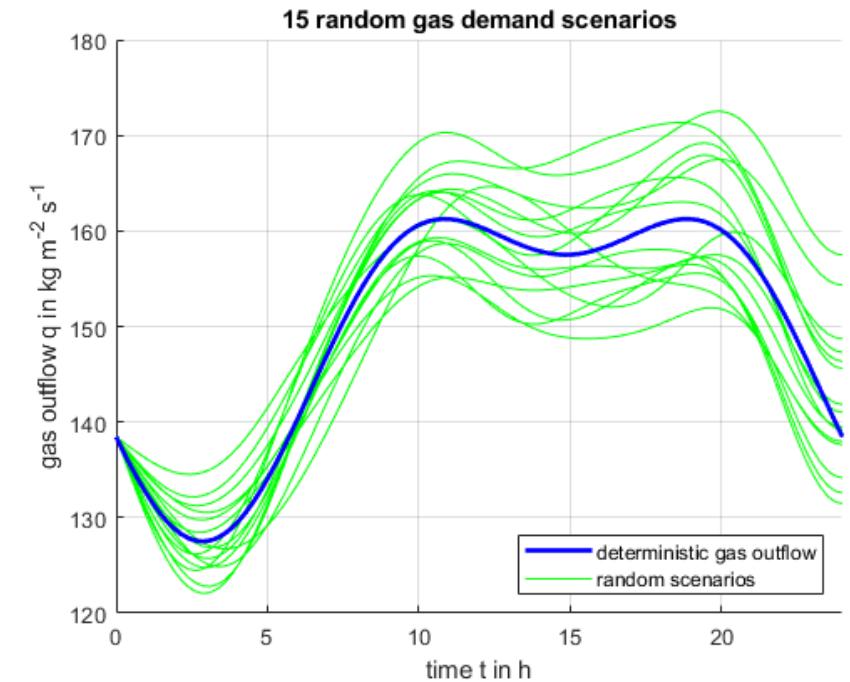
### Random Boundary Functions

- Write a function  $f$  as Fourier series

$$f(t) = \sum_{m=0}^{\infty} a_m^0(f) \psi_m(t)$$

- For random variables  $\xi_m \sim \mathcal{N}(1, \sigma)$  define

$$f^\omega(t) = \sum_{m=0}^{\infty} \xi_m(\omega) a_m^0(f) \psi_m(t)$$



## Time Dependent Uncertainty

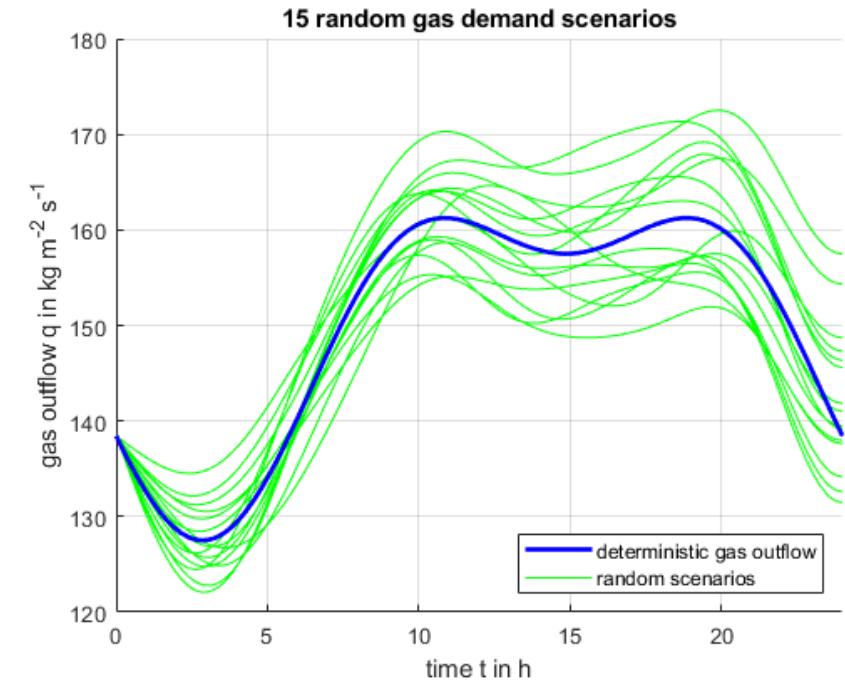
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### Time dependent probabilistic constraint

$$\mathbb{P}( f^\omega \in M(t) \quad \forall t \in [0, T] ) \geq \alpha$$

„We want to guarantee that a percentage  $\alpha$  of all possible random scenarios is feasible in every point in time  $t \in [0, T]$ .“

## Application of Kernel Density Estimation

- Let  $\mathcal{B} = \{ b^{S,1}(t), \dots, b^{S,N_{\text{KDE}}}(t) \}$  be independent and identically distributed random boundary functions
- Let  $\mathcal{P}_{\mathcal{B}} = \{ \rho(t; b^{S,1}), \dots, \rho(t; b^{S,N_{\text{KDE}}}) \}$  be the corresponding densities at the end of the pipe

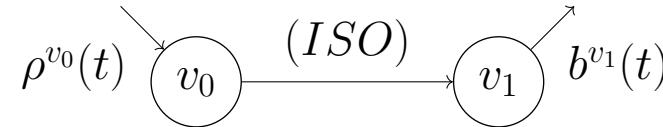
$$\mathbb{P} \left( \rho(t, L) \in [\rho^{\min}, \rho^{\max}] \quad \forall t \in [0, T] \right) = \mathbb{P} \left( \begin{array}{l} \min_{t \in [0, T]} \rho(t, L) \in [\rho^{\min}, \rho^{\max}] \\ \max_{t \in [0, T]} \rho(t, L) \in [\rho^{\min}, \rho^{\max}] \end{array} \right)$$

- Let  $\left\{ \begin{array}{l} \underline{\rho}(b_1) := \min_{t \in [0, T]} \rho(t; b^{S,1}) \\ \bar{\rho}(b_1) := \max_{t \in [0, T]} \rho(t; b^{S,1}) \end{array} \right\}, \dots, \left\{ \begin{array}{l} \underline{\rho}(b_{N_{\text{KDE}}}) := \min_{t \in [0, T]} \rho(t; b^{S,N_{\text{KDE}}}) \\ \bar{\rho}(b_{N_{\text{KDE}}}) := \max_{t \in [0, T]} \rho(t; b^{S,N_{\text{KDE}}}) \end{array} \right\} \subseteq \mathbb{R}^2$  be a sample of the minimal and maximal densities in  $[0, T]$

### Kernel density estimator for bandwidths $h^{\min}$ and $h^{\max}$

$$\varrho_{p, N_{\text{KDE}}}(z) = \frac{1}{N_{\text{KDE}} h^{\min} h^{\max}} \sum_{i=1}^{N_{\text{KDE}}} \frac{1}{\sqrt{2\pi}} \exp \left( -\frac{1}{2} \left( \frac{z - \underline{\rho}(b_i)}{h^{\min}} \right)^2 \right) \cdot \frac{1}{\sqrt{2\pi}} \exp \left( -\frac{1}{2} \left( \frac{z - \bar{\rho}(b_i)}{h^{\max}} \right)^2 \right)$$

## A Numerical Example



$\rho_0(t)$	$\rho^{\min}$	$c$	$\lambda^F$	$D$	$L$	$T$	$\alpha$
46.75 kg/m <sup>3</sup>	34 kg/m <sup>3</sup>	343 m/s	0.1	0.5 m	30 km	24 h	90%

### Deterministic Optimization

$$\begin{aligned}
 & \min_{\rho_{\text{det}}^{\max}} \rho_{\text{det}}^{\max}, \\
 \text{s.t.} \quad & \rho(t, L) \in [\rho^{\min}, \rho_{\text{det}}^{\max}], \\
 \Rightarrow \quad & \rho_{\text{det}}^{*,\max} = 42.15 \text{ kg/m}^3
 \end{aligned}$$

### Probabilistic Optimization

$$\begin{aligned}
 & \min_{\rho_{\text{prob}}^{\max}} \rho_{\text{prob}}^{\max}, \\
 \text{s.t.} \quad & \mathbb{P}(\rho(t, L) \in [\rho^{\min}, \rho_{\text{prob}}^{\max}] \ \forall t \in [0, T]) \geq 0.9. \\
 \Rightarrow \quad & \rho_{\text{prob}}^{*,\max} = 42.49 \text{ kg/m}^3
 \end{aligned}$$

How good is the optimal deterministic solution in the probabilistic setting?

$$\mathbb{P}(b(t) \in M(t; p_{\text{det}}^{\max}) \ \forall t \in [0, T]) \approx 50\%$$

## References

- M. Gugat, R. Schultz, M. Schuster: *Convexity and Starshapedness of Feasible Sets in Stationary Flow Networks*. Netw. Heterog. Media 15(2), pp. 171–195, 2020
- M. Schuster: *Nodal Control and Probabilistic Constrained Optimization*. PhD thesis, FAU Erlangen-Nürnberg, Germany, 2021, <https://opus4.kobv.de/opus4-trr154/frontdoor/index/index/searchtype/latest/docId/410/start/2/rows/10>
- M. Schuster, E. Strauch, M. Gugat, J. Lang: *Probabilistic Constrained Optimization on Flow Networks*. Optim. Eng. 23, 1–50, 2022

