

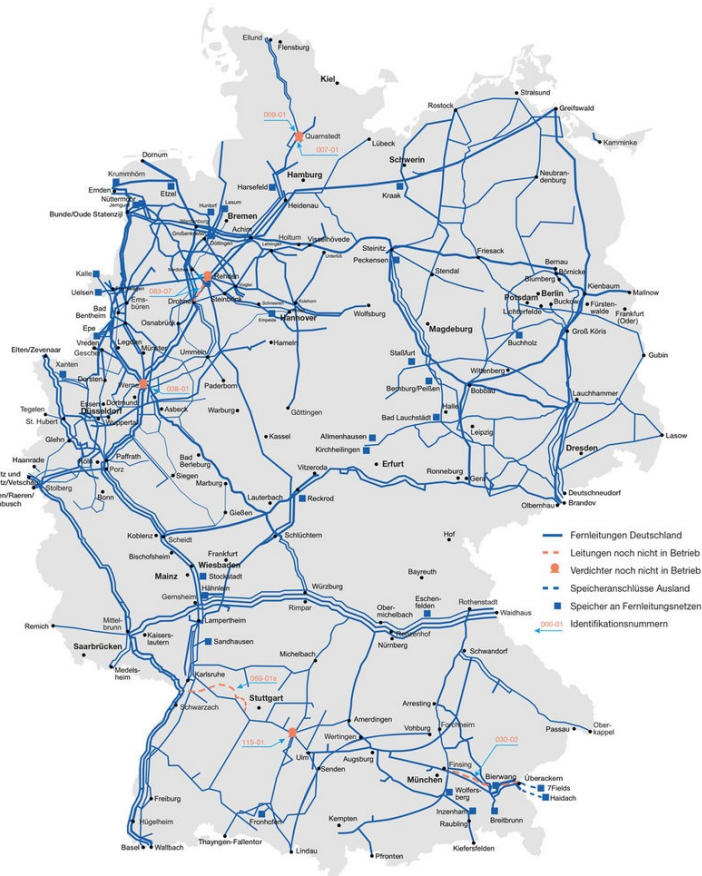
# Nodal Control and Probabilistic Constrained Optimization using the Example of Gas Networks

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# Motivation



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# Motivation

Consider the optimization problem

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

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

We have:

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

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?

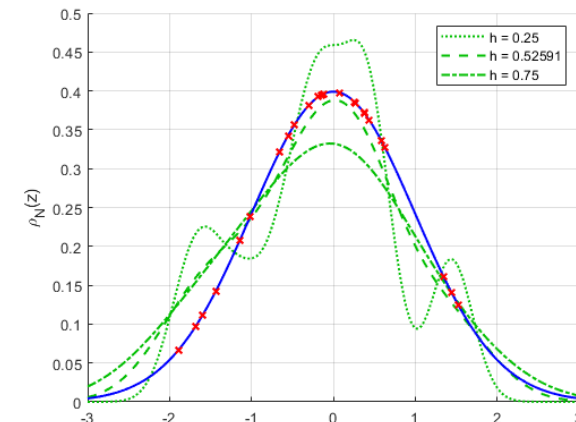
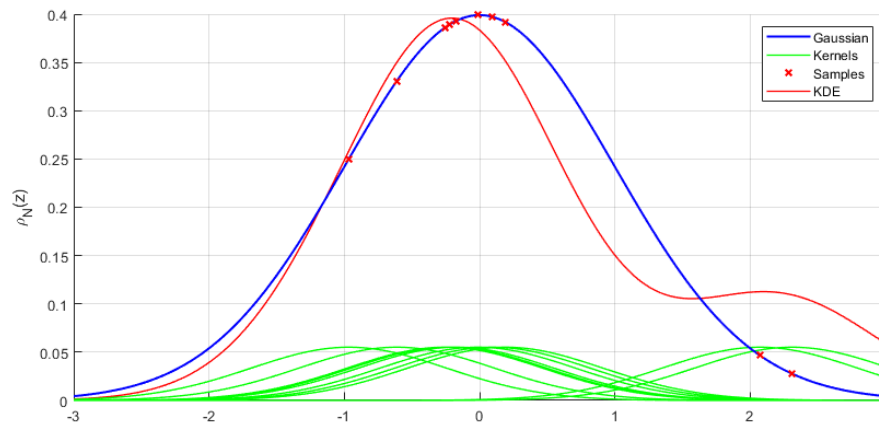
# Mathematical Background

## Definition: kernel density estimator

Let  $\mathcal{Y} = \{y_1, \dots, y_N\} \subseteq \mathbb{R}^n$  be independent and identically distributed 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

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



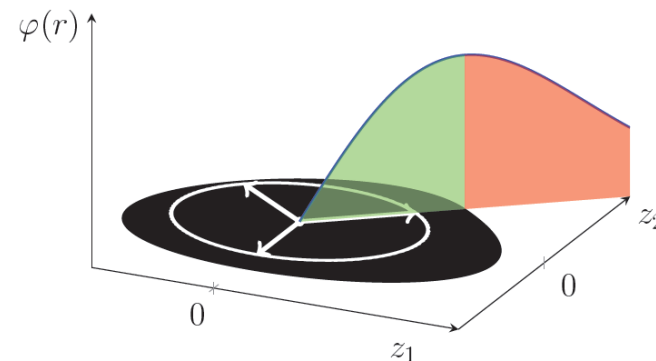
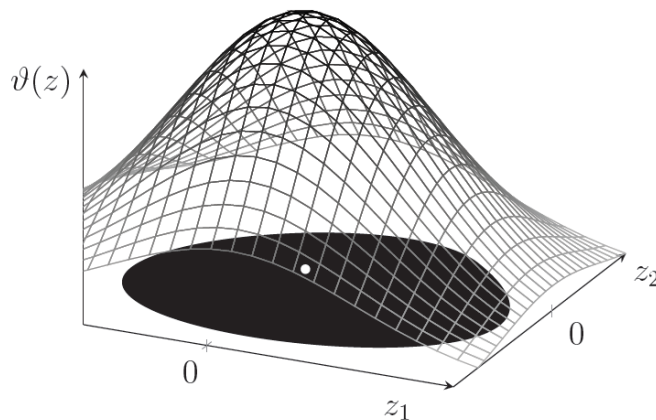
# Mathematical Background

## Theorem: Spheric radial decomposition (SRD)

Let  $\xi \sim \mathcal{N}(0, R)$  be the  $n$ -dimensional standard Gaussian distribution with zero mean and positive definite correlation matrix  $R$ . Then, for any Borel measurable subset  $M \subseteq \mathbb{R}^n$  it holds that

$$\mathbb{P}(\xi \in M) = \int_{\mathbb{S}^{n-1}} \mu_\chi\{r \geq 0 \mid rLv \in M\} d\mu_\eta(v),$$

where  $\mathbb{S}^{n-1}$  is the  $(n-1)$ -dimensional sphere in  $\mathbb{R}^n$ ,  $\mu_\eta$  is the uniform distribution on  $\mathbb{S}^{n-1}$ ,  $\mu_\chi$  denotes the  $\chi$ -distribution with  $n$  degrees of freedom and  $L$  is s.t.  $R = LL^T$ .



# Outline

- 1) Probabilistic Constrained Optimization on Stationary Gas Networks**
- 2) Probabilistic Constrained Optimization on Dynamic Gas Networks

# Stationary Gas Networks: Mathematical Modelling

- Consider a connected, directed, tree-structured graph  $\mathcal{G} = (\mathcal{V}, \mathcal{E})$  with vertex set  $\mathcal{V}$  and set of edges  $\mathcal{E} \subseteq \mathcal{V} \times \mathcal{V}$
- From the root the graph is numbered using breadth-first search or depth-first search

The stationary isothermal Euler equations for ideal gases:

**quasilinear**

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

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**semilinear**

$$\begin{aligned}
 q_x &= 0, \\
 c^2 \rho_x &= -\frac{\lambda^F}{2D} \frac{q|q|}{\rho}.
 \end{aligned}$$

**solution**

$$\begin{aligned}
 q(x) &= k_1 \\
 p^2(x) &= -\frac{\lambda^F}{c^2 D} (R_S T)^2 q(x) |q(x)| x + k_2, \\
 k_1, k_2 &\in \mathbb{R}.
 \end{aligned}$$

# Stationary Gas Networks: Mathematical Modelling

## Boundary Conditions:

### Inlet pressure

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

### Gas outflow

$b_i \in \mathbb{R}_{\geq 0}$  represents the consumers gas demand at node  $v_i$   
 $(i = 1, \dots, n)$

## 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

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

# Stationary Gas Networks: Mathematical Modelling

- 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

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

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

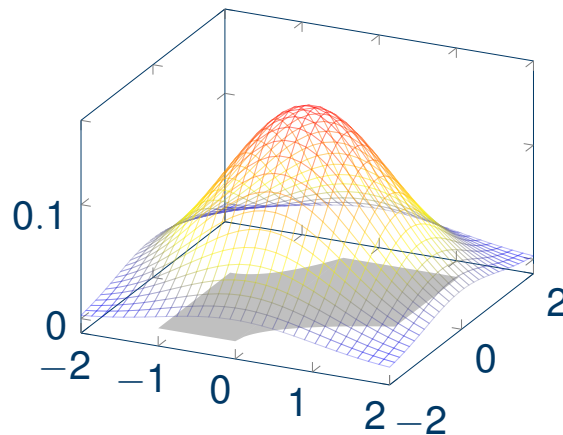
$$\xi_b \sim \mathcal{N}(\mu, \Sigma),$$

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?*

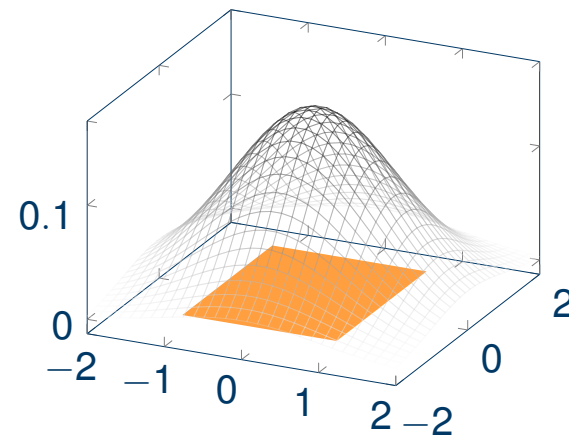
# Stationary Gas Networks: SRD vs KDE

Define  $P_{\min}^{\max} := \otimes_{i=1}^n [p_i^{\min}, p_i^{\max}]$ . Then we have  $\mathbb{P}(b \in M) = \mathbb{P}(p \in P_{\min}^{\max})$ .



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

gas dynamics



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

Figure: Scheme of the SRD vs. scheme of the KDE

# Stationary Gas Networks: Application of the SRD

Define a function  $g : \mathbb{R}^n \rightarrow \mathbb{R}^n$ , where  $g_i(b)$  states the pressure loss from the root to node  $v_i$ .

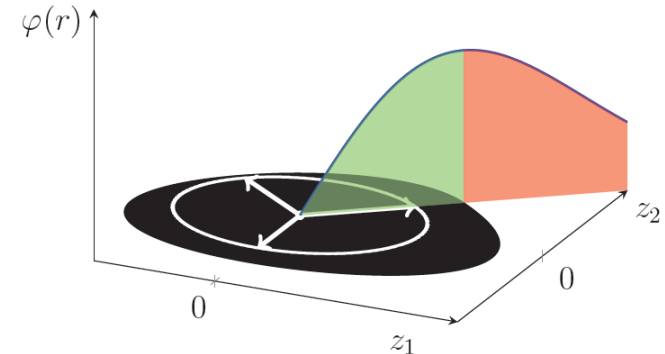
## Lemma 1

A load vector  $b \in \mathbb{R}_{\geq 0}^n$  is feasible, i.e.  $b \in M$ , iff the following system of inequalities hold:

$$\begin{aligned}
 p_0^2 &\leq \min_{k=1, \dots, n} [(p_k^{\max})^2 + g_k(b)] , \\
 p_0^2 &\geq \max_{k=1, \dots, n} [(p_k^{\min})^2 + g_k(b)] .
 \end{aligned}$$

# Stationary Gas Networks: Application of the SRD

- Let  $\mathcal{S} = \{ v_1, \dots, v_{N_{\text{SRD}}} \}$  be a uniformly distributed sample of the unit sphere  $\mathbb{S}^{n-1}$
- For  $v \in \mathcal{S}$  identify the load vector with the one dimensional rays:  $b_v(r) = rLv + \mu$
- Define the regular range:  
 $R_{v,\text{reg}} := \{ r \geq 0 \mid b_v(r) \geq 0 \}$
- Use *Lemma 1* to compute the one dimensional sets  $M_v = \bigcup_{j=1}^{\ell_v} [\underline{a}_{v,j}, \bar{a}_{v,j}]$
- Evaluate the  $\chi$ -distribution:  $\mu_\chi(M_v) = \sum_{j=1}^{\ell_v} F_\chi(\bar{a}_{v,j}) - F_\chi(\underline{a}_{v,j})$



## probability via SRD

$$\mathbb{P}_{N_{\text{SRD}}}(b \in M) = \frac{1}{N_{\text{SRD}}} \sum_{v \in \mathcal{S}} \sum_{j=1}^{\ell_v} F_\chi(\bar{a}_{v,j}) - F_\chi(\underline{a}_{v,j})$$



# Stationary Gas Networks: Application of the KDE

- 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 ( $h_j^2 := H_{j,j}$ )

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

# Stationary Gas Networks: Application of the KDE

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

# Stationary Gas Networks: Application of the KDE



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 \mathbb{P}_{N_{\text{KDE}}}(\boldsymbol{p} \in \boldsymbol{P}_{\min}^{\max}) &= \int_{\boldsymbol{P}_{\min}^{\max}} \varrho_{\boldsymbol{p}, N_{\text{KDE}}}(z) dz \\
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 \end{aligned}$$

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

## probability via KDE

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

# SRD vs KDE: Advantages and Disadvantages

		
<b>SRD</b>	<ul style="list-style-type: none"> <li>• Powerful tool</li> <li>• Reduces dimension of integration</li> </ul>	<ul style="list-style-type: none"> <li>• Analytical solution required</li> </ul>
<b>KDE</b>	<ul style="list-style-type: none"> <li>• Almost always applicable</li> </ul>	<ul style="list-style-type: none"> <li>• Almost surely convergence</li> <li>• Curse of dimensionality</li> </ul>

# Stationary Gas Networks: Optimization

For  $f : \mathbb{R}^n \rightarrow \mathbb{R}$ ,  $p^{\max} \mapsto f(p^{\max})$  convex and  $\alpha \in (0, 1)$  consider

$$(O) \quad \begin{cases} \min_{p^{\max} \in \mathbb{R}^n} & f(p^{\max}) \\ \text{s.t.} & \mathbb{P}(b \in M(p^{\max})) \geq \alpha \\ & p^{\max} \geq p^{\min} \end{cases} \quad (OA) \quad \begin{cases} \min_{p^{\max} \in \mathbb{R}^n} & f(p^{\max}) \\ \text{s.t.} & \mathbb{P}_{N_{\text{KDE}}}(b \in M(p^{\max})) \geq \alpha \\ & p^{\max} \geq p^{\min} \end{cases}$$

## Lemma 2

- Assume that the set of admissible upper pressure bounds for (O) and (OA) is nonempty
- Assume that  $f$  is strictly monotonous increasing

Then there exists a solution  $p^{*,\max}$  of (O) and  $p_{N_{\text{KDE}}}^{*,\max}$  of (OA), s.t.

$$\begin{aligned} \mathbb{P}(b \in M(p^{*,\max})) &= \alpha, \\ \mathbb{P}_{N_{\text{KDE}}}(b \in M(p_{N_{\text{KDE}}}^{*,\max})) &= \alpha. \end{aligned}$$

# Stationary Gas Networks: Optimization

Define  $g^\alpha(p^{\max})$  and  $\mathcal{Z}$  ( $g_{N_{\text{KDE}}}^\alpha$ ,  $\mathcal{Z}_{N_{\text{KDE}}}$  analog) as

$$\begin{aligned}
 g^\alpha(p^{\max}) &:= \alpha - \mathbb{P}(b \in M(p^{\max})), \\
 \mathcal{Z} &:= \{x \in \mathbb{R}^n \mid x \geq p^{\min} \text{ and } g^\alpha(x) = 0\}.
 \end{aligned}$$

## Theorem 3 part 1

Let a probability level  $\alpha \in (0, 1)$ , an inlet pressure  $p_0$  and a lower pressure bound  $p^{\min}$  be given.

- Assume that the set of admissible upper pressure bounds for (O) and (OA) is nonempty
- Assume that  $f$  is strictly monotonous increasing

Let  $p^{*,\max}$  be a solution of (O).

# Stationary Gas Networks: Optimization

Define  $g^\alpha(p^{\max})$  and  $\mathcal{Z}$  ( $g_{N_{\text{KDE}}}^\alpha$ ,  $\mathcal{Z}_{N_{\text{KDE}}}$  analog) as

$$g^\alpha(p^{\max}) := \alpha - \mathbb{P}(b \in M(p^{\max})),$$

$$\mathcal{Z} := \{x \in \mathbb{R}^n \mid x \geq p^{\min} \text{ and } g^\alpha(x) = 0\}.$$

## Theorem 3

Let  $p^{*,\max}$  be a solution of (O).

- Assume that  $p^{*,\max}$  is unique
- Assume that for all  $x \in \mathcal{Z}$  there exist  $d_1, d_2 \in \mathbb{R}^n \setminus \{0_n\}$  s.t. for all  $\tau \in (0, 1)$ :

$$g^\alpha(x + \tau d_1) < 0 \quad \text{and} \quad g^\alpha(x + \tau d_2) > 0.$$

- Assume that there exist  $\delta, \epsilon > 0$ , s.t. for  $p \in \mathcal{Z}$  with

$$\|p^{*,\max} - p\| > \delta/2 \quad \text{it holds} \quad |f(p^{*,\max}) - f(p)| > \epsilon$$

Then there exists  $N_{\text{KDE}}$  sufficiently large, s.t. the solution  $p_{N_{\text{KDE}}}^{*,\max}$  of (OA) is close to  $p^{*,\max}$ , i.e.

$$\|p^{*,\max} - p_{N_{\text{KDE}}}^{*,\max}\| < \delta \quad \text{a.s.}$$

# Outline

- 1) Probabilistic Constrained Optimization on Stationary Gas Networks
- 2) Probabilistic Constrained Optimization on Dynamic Gas Networks**



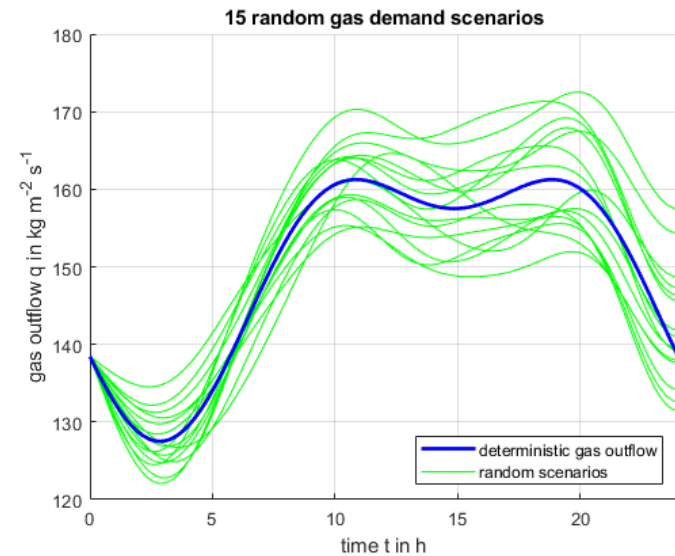
# Time dependent Uncertainty

- 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

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



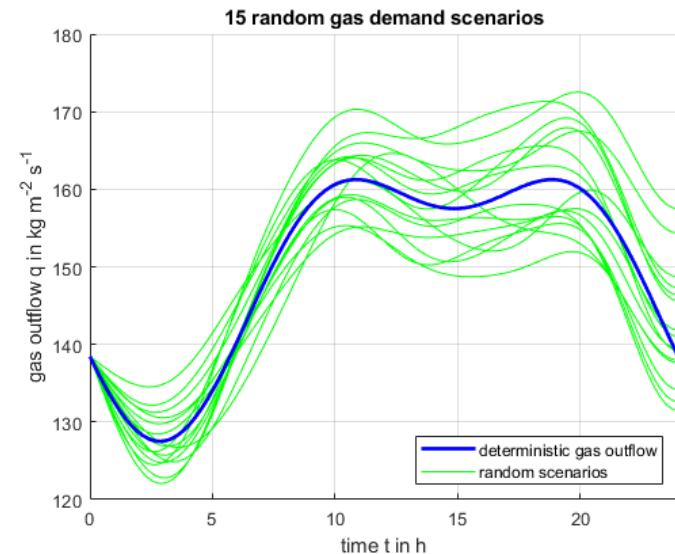
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## Time dependent probabilistic constraint

$$\mathbb{P}( b \in M(t) \forall t \in [0, T] ) \geq \alpha$$

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

# Dynamic Gas Networks: Mathematical Modelling

- Consider a connected, directed graph  $\mathcal{G} = (\mathcal{V}, \mathcal{E})$  with vertex set  $\mathcal{V}$  and set of edges  $\mathcal{E} \subseteq \mathcal{V} \times \mathcal{V}$ .

## isothermal Euler equations (for ideal gas)

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

## set of feasible loads

$$M(t^*) := \left\{ \begin{array}{l} b : [0, T] \rightarrow \mathbb{R}^n \\ b_i \in \text{Lip}([0, T]) \end{array} \right\} \left. \begin{array}{l} \text{The solution of (ISO) with} \\ \bullet \text{ initial conditions,} \\ \bullet \text{ inlet density and gas outflow,} \\ \bullet \text{ conservation of mass,} \\ \bullet \text{ continuity in pressure,} \\ \text{satisfies box constraints for the density in } t^*. \end{array} \right\}$$

# Dynamic Gas Networks: Application of the KDE

- Consider a sequence of random variables  $(\xi_m)_{m \geq 0}$  with  $\xi_m \sim \mathcal{N}(\mu, \Sigma)$
- For  $m \geq 0$  let  $\mathcal{A}_m = \{ \mathbf{a}_m^{\omega,1}, \dots, \mathbf{a}_m^{\omega, N_{\text{KDE}}} \}$  be an independent and identically distributed sampling of the random variable  $\xi_m$
- Let  $\mathcal{B}_{\mathcal{A}} = \{ \mathbf{b}^{\omega,1}(t), \dots, \mathbf{b}^{\omega, N_{\text{KDE}}}(t) \}$  be the corresponding sampling of the random boundary functions (also independent and identically distributed)
- Let  $\mathcal{P}_{\mathcal{B}} = \{ \rho_{\text{out}}(t, \mathbf{b}^{\omega,1}), \dots, \rho_{\text{out}}(t, \mathbf{b}^{\omega, N_{\text{KDE}}}) \}$  be the corresponding sampling of densities at the outflow nodes

$$\rho_{\text{out}}(t, \cdot) \in \mathcal{P}_{\min}^{\max} \quad \forall t \in [0, T] \quad \Leftrightarrow \quad \min_{t \in [0, T]} \rho_{\text{out}}(t, \cdot), \max_{t \in [0, T]} \rho_{\text{out}}(t, \cdot) \in \mathcal{P}_{\min}^{\max}$$

- For  $i = 1, \dots, N_{\text{KDE}}$  let  $\bar{\mathcal{P}}_{\mathcal{B}} = \left[ \left( \underline{\rho}_{\text{out}}(\mathbf{b}^{\omega,i}), \bar{\rho}_{\text{out}}(\mathbf{b}^{\omega,i}) \right)^{\top} \right]$  be the sampling of minimal and maximal densities.

## probability via KDE

Apply KDE as in the stationary case to  $2n$ -dimensional sample

# Dynamic Gas Networks: Application of the KDE

## probability via kde

$$\begin{aligned}
 \mathbb{P}(\rho_{\text{out}}(t) \in \mathcal{P}_{\text{min}}^{\text{max}} \forall t \in [0, T]) &= \\
 &= \frac{1}{N_{\text{KDE}} 2^{2n}} \sum_{i=1}^{N_{\text{KDE}}} \prod_{j=1}^n \left[ \text{erf} \left( \frac{\rho_j^{\text{max}} - \rho_{j,\text{out}}(b^{\omega,i})}{\sqrt{2} h_j^{\text{min}}} \right) - \text{erf} \left( \frac{\rho_j^{\text{min}} - \rho_{j,\text{out}}(b^{\omega,i})}{\sqrt{2} h_j^{\text{min}}} \right) \right] \\
 &\quad \cdot \left[ \text{erf} \left( \frac{\rho_j^{\text{max}} - \bar{\rho}_{j,\text{out}}(b^{\omega,i})}{\sqrt{2} h_j^{\text{max}}} \right) - \text{erf} \left( \frac{\rho_j^{\text{min}} - \bar{\rho}_{j,\text{out}}(b^{\omega,i})}{\sqrt{2} h_j^{\text{max}}} \right) \right]
 \end{aligned}$$

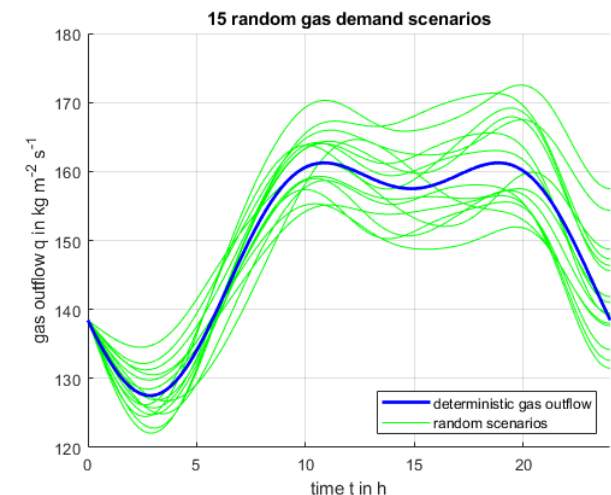
**Optimization analog to the stationary case!**

# Dynamic Gas Networks: A Numerical Example

Consider (ISO) on a single edge:



Variable	Letter	Value	Unit
lower density bound	$\rho^{\min}$	34	kg/m <sup>3</sup>
speed of sound in the gas	$c$	343	m/s
pipe friction coefficient	$\lambda^F$	0.1	
pipe diameter	$D$	0.5	m
pipe length	$L$	30	km
final time	$T$	24	h



# Dynamic Gas Networks: A Numerical Example

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$$\min_{\rho_{\text{det}}^{\text{max}}} w f(\rho_{\text{det}}^{\text{max}})$$

$$\text{s.t. } \rho^{v_1}(t) \in [\rho^{\text{min}}, \rho_{\text{det}}^{\text{max}}] \quad \forall t \in [0, T]$$

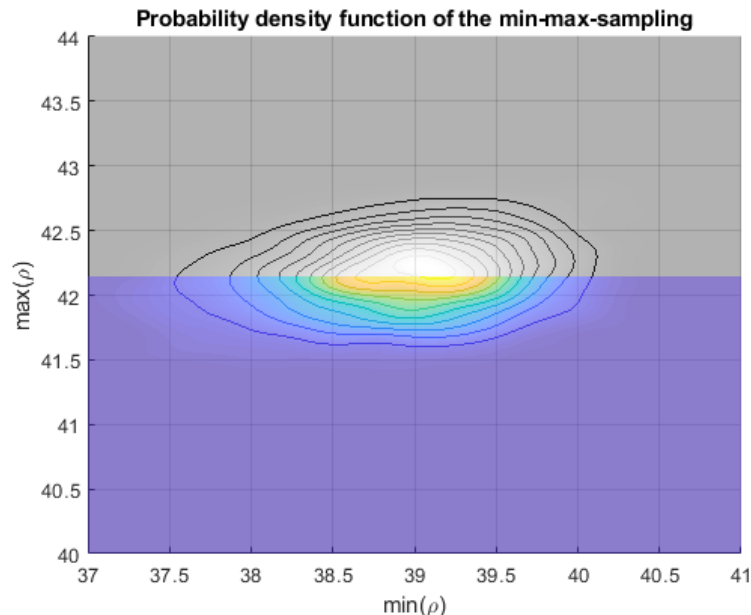
$$\rho_{\text{det}}^{\text{max}} \geq \rho^{\text{min}}$$

$$\min_{\rho_{\text{prob}}^{\text{max}}} w f(\rho_{\text{prob}}^{\text{max}})$$

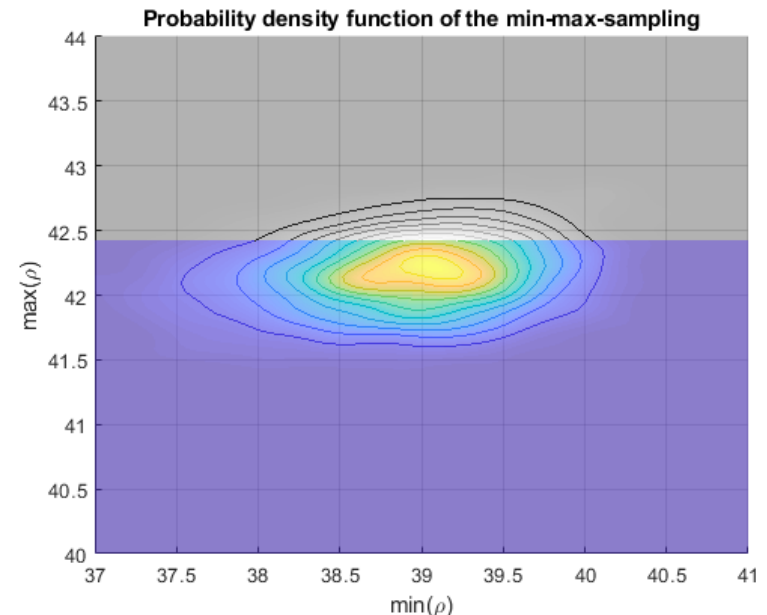
$$\text{s.t. } \mathbb{P}(\rho^{v_1}(t) \in [\rho^{\text{min}}, \rho_{\text{prob}}^{\text{max}}] \quad \forall t \in [0, T]) \geq 0.9$$

$$\rho_{\text{prob}}^{\text{max}} \geq \rho^{\text{min}}$$

$$\rho_{\text{det}}^{*,\text{max}} = 42.15 \frac{\text{kg}}{\text{m}^3}$$



$$\rho_{\text{prob}}^{*,\text{max}} = 42.49 \frac{\text{kg}}{\text{m}^3}$$





# Summary

- We introduced the SRD and the KDE
- We computed the probability for a random load vector to be feasible using SRD and KDE respectively
- We discussed the advantages and disadvantages of both methods
- We showed the existence of optimal solutions for a certain probabilistic constrained optimization problem
- We showed that the optimal solution of the approximated problem is close to the optimal solution of the exact problem
- We extended the KDE approach to a dynamic setting

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