

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

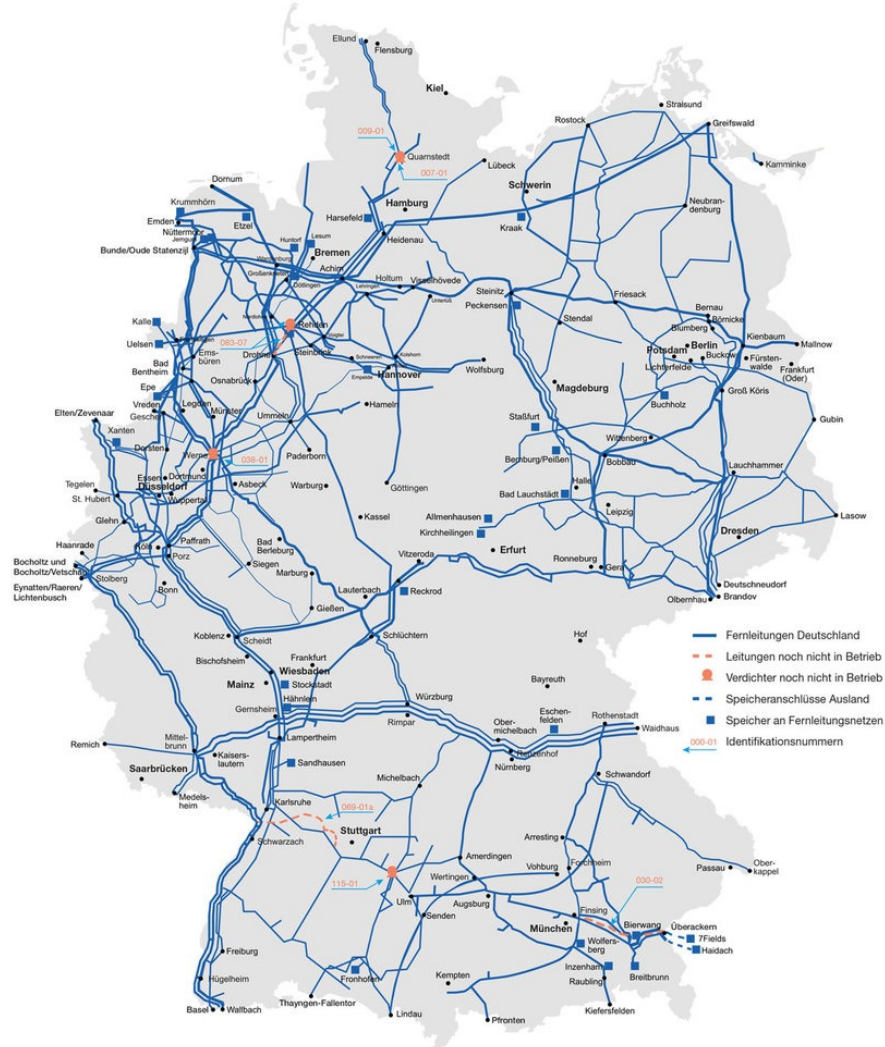
**Michael Schuster**

2023 May 09, Erlangen

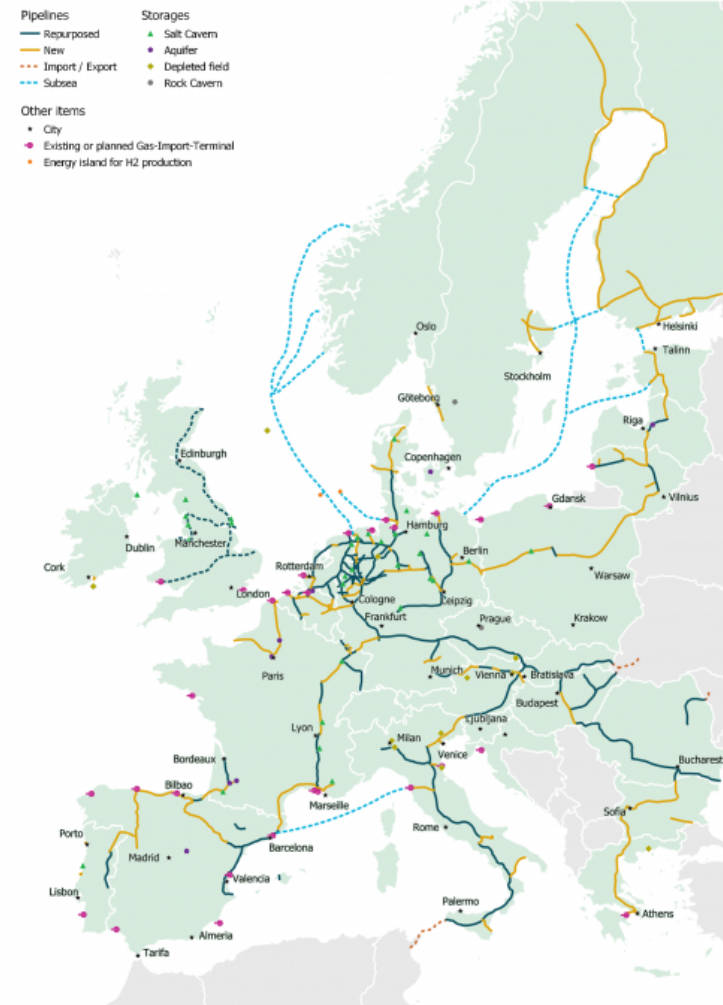
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Department of Mathematics

# Motivation

## Gas Transport Networks



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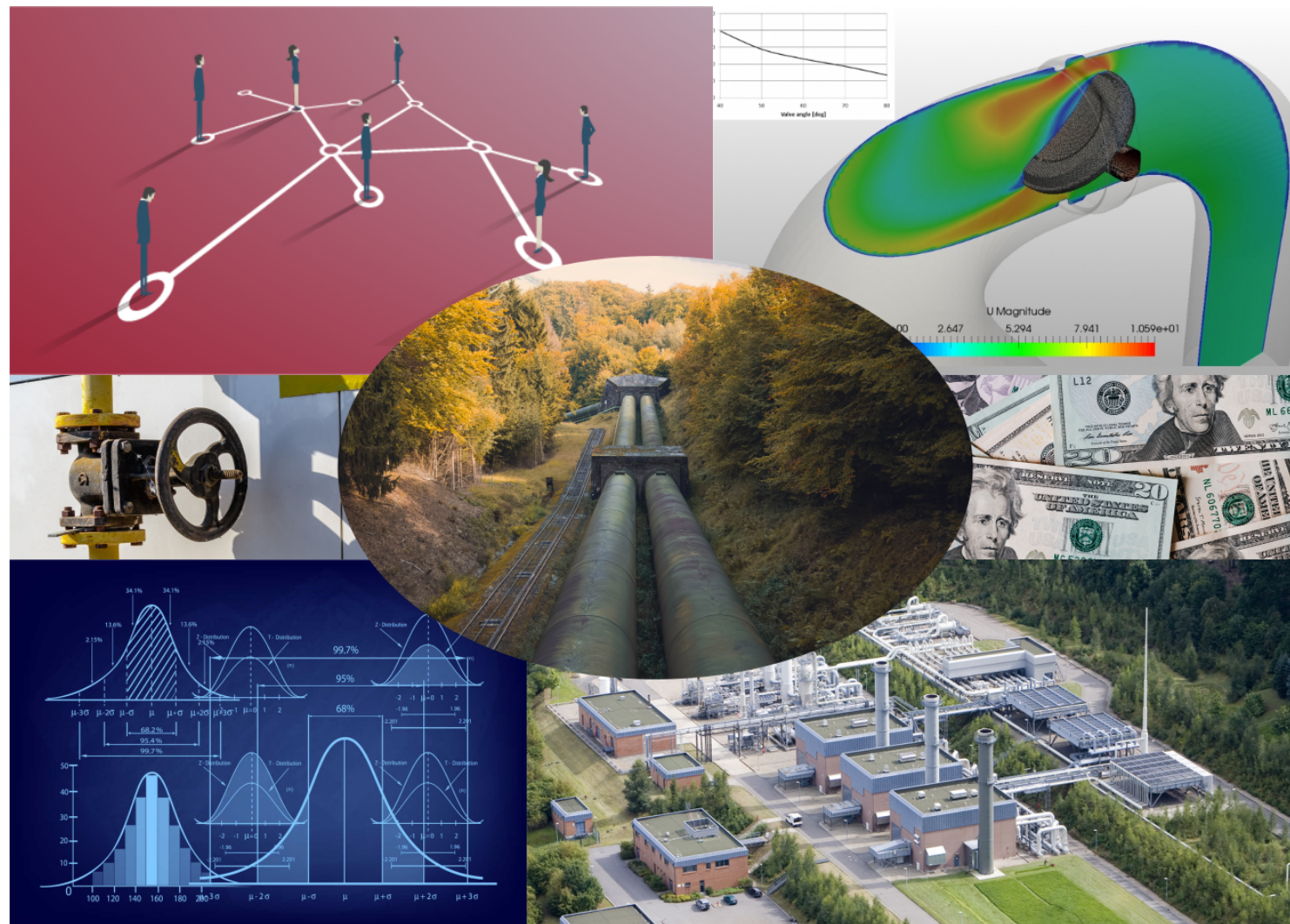


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# Motivation

## Mathematical Gas Transport



For constant temperature the gas flow in pipelines is modeled by the isothermal Euler equations:

**(ISO1)**

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

Variable	Letter	Unit	Range
density	$\rho$	$\text{kg m}^{-3}$	$\mathbb{R}_{\geq 0}$
flow	$q$	$\text{kg s}^{-1} \text{m}^{-2}$	$\mathbb{R}$
pressure	$p$	Pa	$\mathbb{R}_{\geq 0}$
sound speed in the gas	$c$	$\text{m s}^{-1}$	$\mathbb{R}_{\geq 0}$
pipe friction coefficient	$\lambda^F$		$\mathbb{R}_{\geq 0}$
pipe diameter	$D$	m	$\mathbb{R}_+$

**Inlet density & Gas outflow**

$$\rho(t, 0) = \rho_0(t),$$
$$q(t, L) = b(t).$$

**Initial condition**

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

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

# Mathematical Gas Transport

## Gas Transport in Pipeline Networks

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### (ISO1) - quasilinear model

$$\rho_t + q_x = 0$$
$$q_t + \left( p + \frac{q^2}{\rho} \right)_x = -\frac{\lambda^F}{2D} \frac{q|q|}{\rho}$$

### (ISO2) - semilinear model

$$\rho_t + q_x = 0$$
$$q_t + p_x = -\frac{\lambda^F}{2D} \frac{q|q|}{\rho}$$

### (ISO4) - stationary model

$$q_x = 0$$
$$p_x = -\frac{\lambda^F}{2D} \frac{q|q|}{\rho}$$

subsonic flow:  $|v| = \left| \frac{q}{\rho} \right| \ll c$

stationary flow:  $\frac{\partial}{\partial t} \equiv 0$

## Stationary Gas Transport in Pipeline 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

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

## Stationary Gas Transport in Pipeline Networks

### 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.



## Stationary Gas Transport in Pipeline Networks

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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?*

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

## Stationary Gas Transport in Pipeline Networks

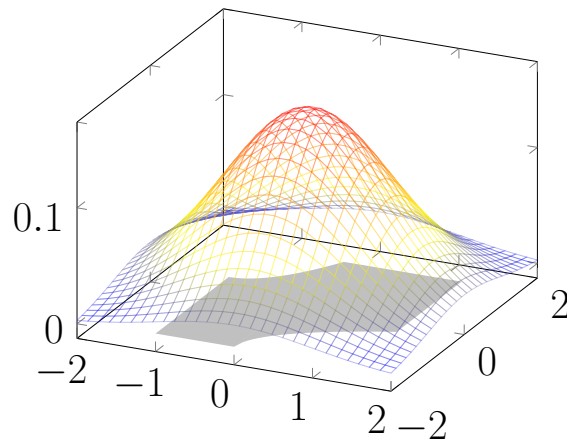
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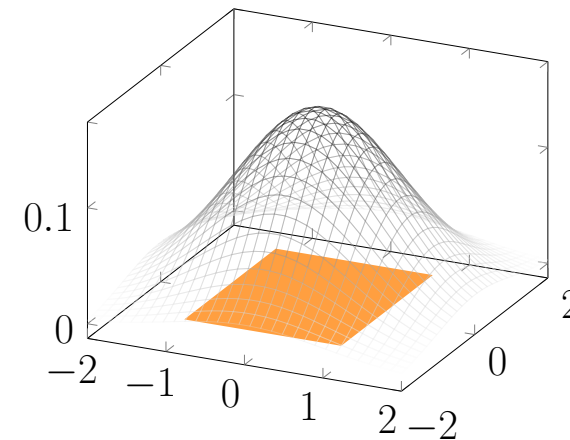
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(a) Well-known distribution (colored), unknown set of feasible loads (grey)

gas dynamics  
↔



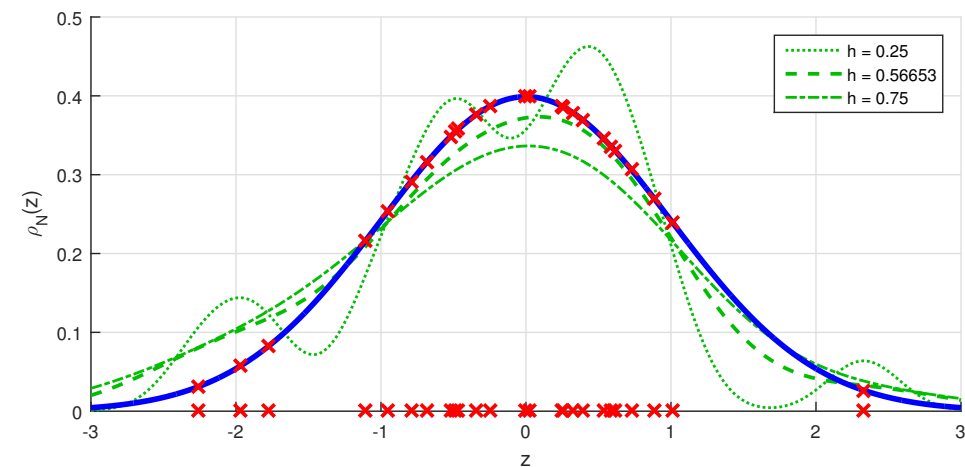
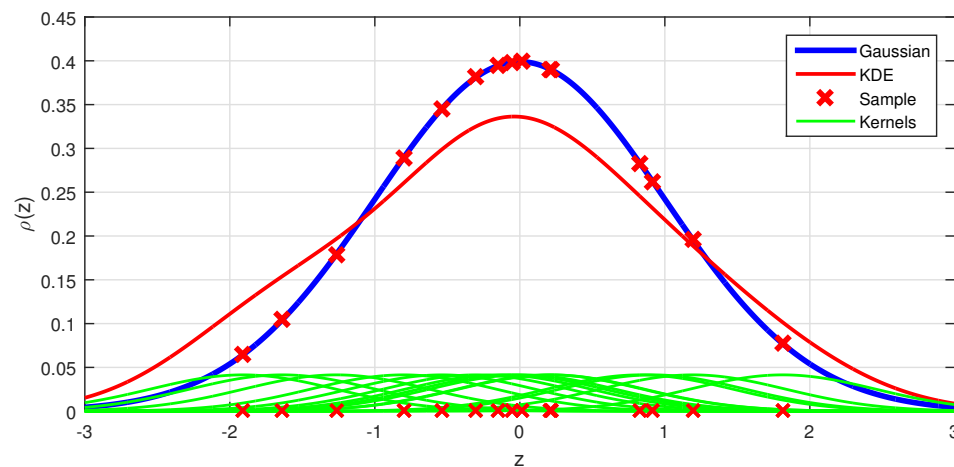
(b) Unknown distribution (grey), well-known set of feasible pressures (orange)

### 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*

## Stationary Gas Transport in Pipeline Networks

- 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

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

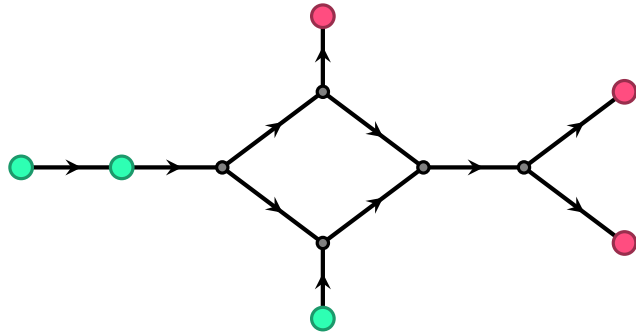


$$\begin{aligned}
 \mathbb{P}_{N_{\text{KDE}}}(p \in P_{\min}^{\max}) &= \int_{P_{\min}^{\max}} \varrho_{p, N_{\text{KDE}}}(z) dz \\
 &= \int_{P_{\min}^{\max}} \frac{1}{N_{\text{KDE}} \prod_{j=1}^n h_j} \sum_{i=1}^{N_{\text{KDE}}} \prod_{j=1}^n \frac{1}{\sqrt{2\pi}} \exp\left(-\frac{1}{2} \left(\frac{z_j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

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

### probability via KDE

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



$p_0$	$p^{\min}$	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%

### Deterministic optimization

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

### Probabilistic optimization

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

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

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

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

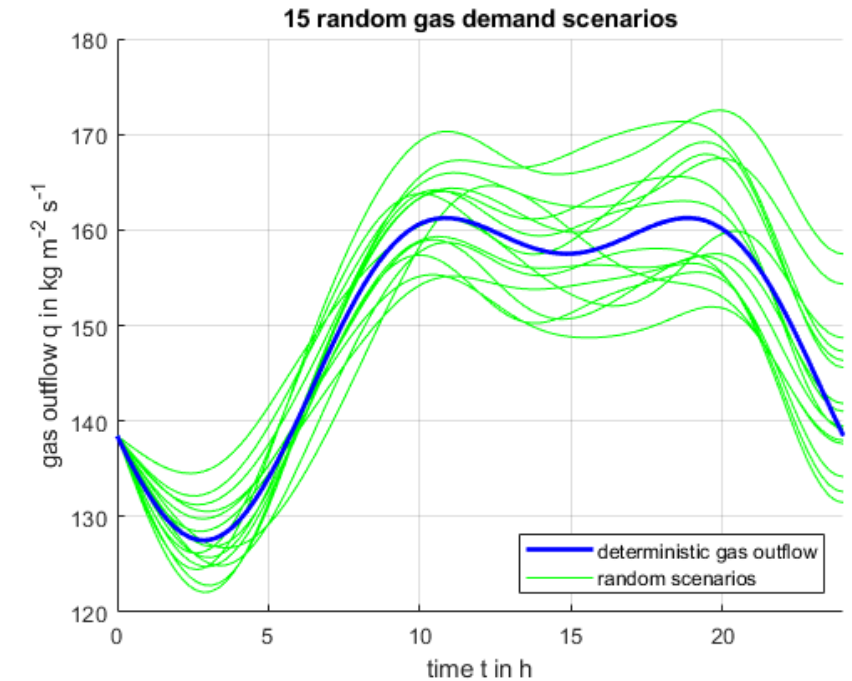
### Random Boundary Functions

- 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

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



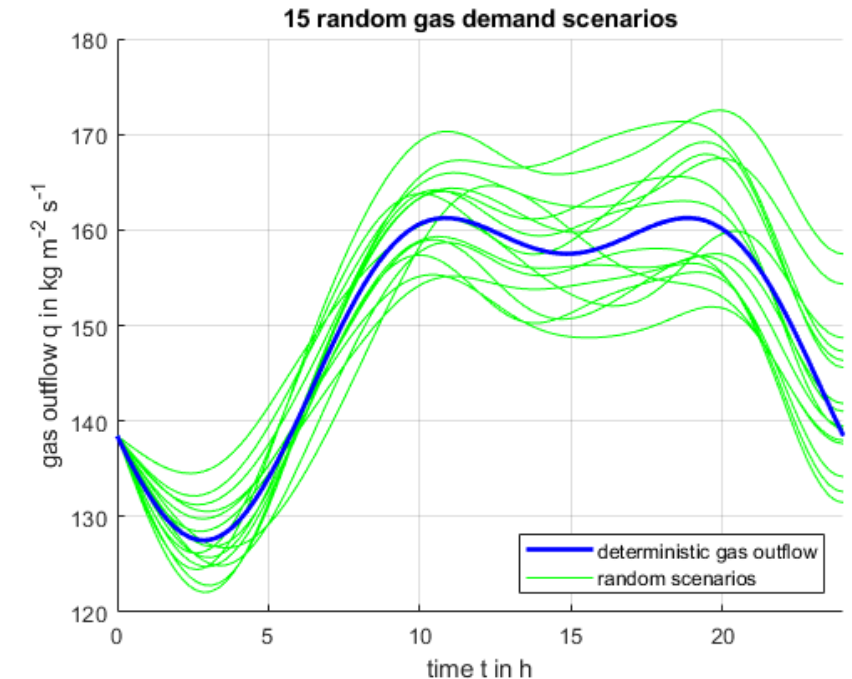
### Random Boundary Functions

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### Time dependent probabilistic constraint

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

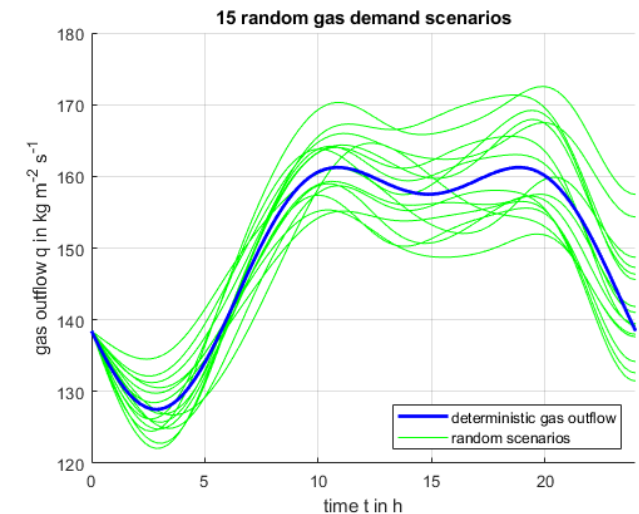
„We want to guarantee that a percentage  $\alpha$  of all possible random scenarios is feasible in every point in time  $t \in [0, T]$ .“

For  $(t, x) \in [0, T] \times [0, L]$ ,  $\rho = \rho(t, x)$  and  $q = q(t, x)$  consider the isothermal Euler equations for ideal gases:

### The isothermal Euler equations

$\rho$  density  
 $q$  flow  
 $c$  sound speed  
 $\lambda$  friction  
 $D$  diameter

$$\begin{aligned}\rho_t + q_x &= 0, \\ q_t + \left( c^2 \rho + \frac{q^2}{\rho} \right)_x &= \frac{\lambda}{2D} \frac{q|q|}{\rho}, \\ \rho(t, 0) &= \rho_0(t), \\ q(t, L) &= b(t)\end{aligned}$$



- For suitable initial and boundary conditions there exists a unique solution
- We consider random boundary flow by using randomized Fourier series
- We define the set of feasible loads as  $M(t) := \{ \rho(\cdot, L) \mid \rho^{\min} \leq \rho(t, L) \leq \rho^{\max} \}$
- We want to compute the probability  $\mathbb{P}(\omega \in \Omega \mid \rho^\omega(\cdot, L) \in M(t) \quad \forall t \in [0, T])$

[Gugat and Ulbrich, 2017]: *Lipschitz solutions of initial boundary value problems for balance laws*. Math. Models Methods Appl. Sci., 28(5): 921–951.



# Mathematical Gas Transport

## Dynamic Gas Transport in Pipeline Networks

- 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

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

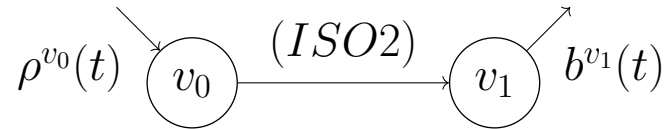
- Let  $\left\{ \left[ \begin{array}{l} \underline{\rho}(b_1) := \min_{t \in [0, T]} \rho(t; b^{S,1}) \\ \bar{\rho}(b_1) := \max_{t \in [0, T]} \rho(t; b^{S,1}) \end{array} \right], \dots, \left[ \begin{array}{l} \underline{\rho}(b_{N_{\text{KDE}}}) := \min_{t \in [0, T]} \rho(t; b^{S,N_{\text{KDE}}})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

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

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

[Schuster 2021]: *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>



$\rho_0(t)$	$\rho^{\min}$	$c$	$\lambda^F$	$D$	$L$	$T$	$\alpha$
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

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

### Probabilistic Optimization

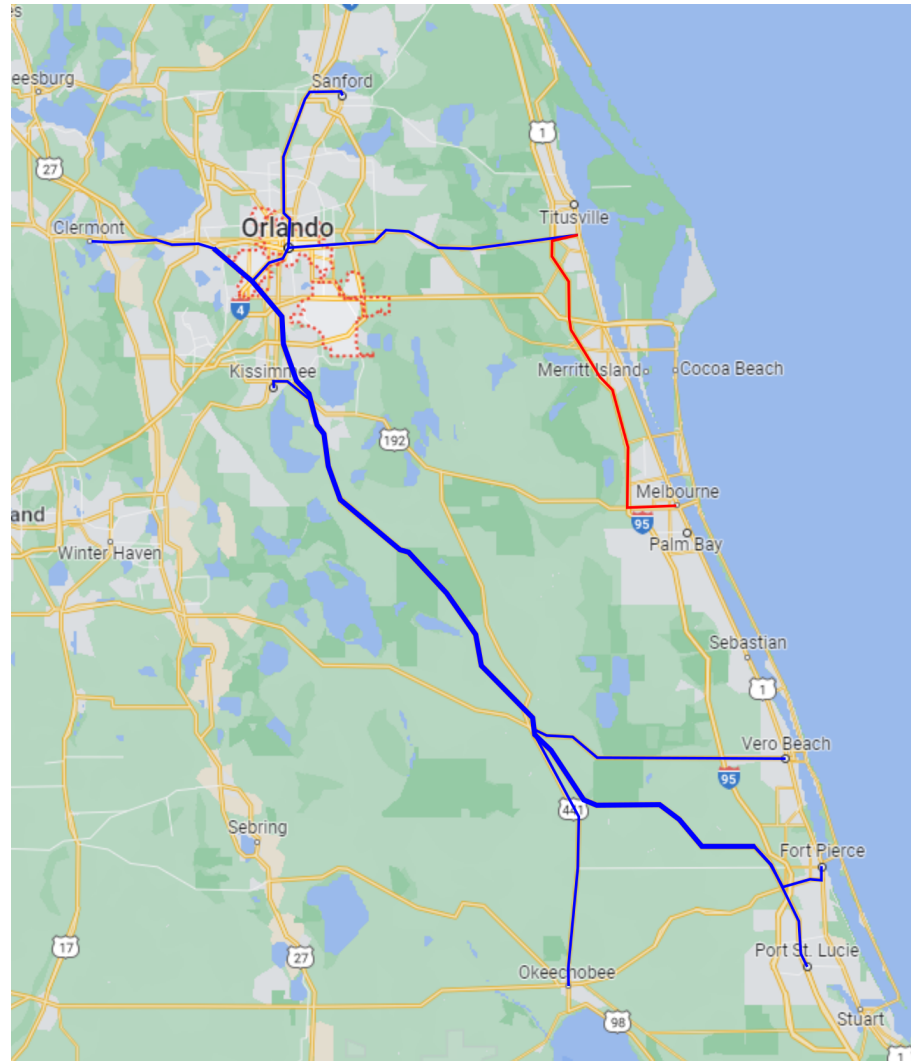
$$\begin{aligned} & \min_{\rho_{\text{prob}}^{\max}} \rho_{\text{prob}}^{\max}, \\ & \text{s.t. } \mathbb{P}(\rho(t, L) \in [\rho^{\min}, \rho_{\text{prob}}^{\max}] \forall t \in [0, T]) \geq 0.9. \\ & \Rightarrow \rho_{\text{prob}}^{*, \max} = 42.49 \text{ kg/m}^3 \end{aligned}$$

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

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

# Nodal Control under Uncertainty

## A Turnpike Result for the Transport Equation



- There is a fastest route between any two points and if the origin and destination are close together and far from the turnpike, the best route may not touch the turnpike.
- But if origin and destination are far enough apart, it will always pay to get on to the turnpike and cover distance at the best rate of travel, even if this means adding a little mileage at either end.

[Dorfman, Samuelson, Solow, 1958]: Linear Programming and Economic Analysis. *New York: McGraw-Hill*

## Stationary Gas Transport in Pipeline Networks

For  $c > 0$  consider the transport equation in one dimension

$$r_t(t, x) + c r_x(t, x) = m r(t, x),$$

with initial condition and boundary control

$$r(0, x) = r_{\text{ini}}(x) \quad \text{and} \quad r(t, 0) = u(t).$$

For convex functions  $f$  and  $g$  consider the optimal control problems

### Dynamic Optimal Control Problem

$$\begin{aligned} \min_{u \in L^2(0, T)} \quad & J_T(u) = \int_0^T f(u(t)) + g(r(t, L)) \, dt \\ \text{s.t.} \quad & r_t(t, x) + c r_x(t, x) = m r(t, x), \\ & r(0, x) = r_{\text{ini}}(x), \\ & r(t, 0) = u(t). \end{aligned}$$

### Static Optimal Control Problem

$$\begin{aligned} \min_{u \in \mathbb{R}} \quad & J(u) = f(u) + g(r(L)) \\ \text{s.t.} \quad & c r_x(x) = m r(x), \\ & r(0) = u. \end{aligned}$$

**(A1)** For  $\varepsilon > 0$  let functions  $f$  and  $g$  satisfy  $(f'(x_1) - f'(x_2))(x_1 - x_2) + (g'(y_1) - g'(y_2))(y_1 - y_2) \geq \varepsilon \|x_1 - x_2\|_2^2$ .

**(A2)** Let the derivative of  $g$  be Lipschitz continuous with Lipschitz constant  $L_k$ , i.e.,  $\|g'(y_1) - g'(y_2)\|_2 \leq L_k \|y_1 - y_2\|_2$ .

# Nodal Control under Uncertainty

## A Turnpike Result for the Transport Equation

We consider the deterministic case first.

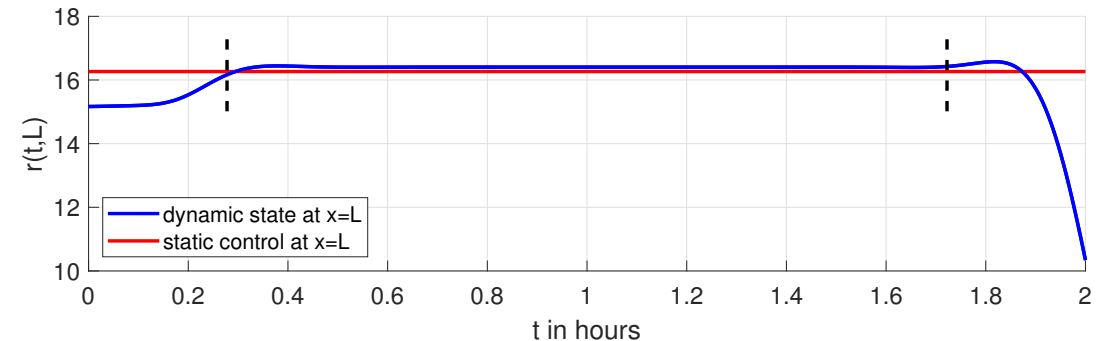
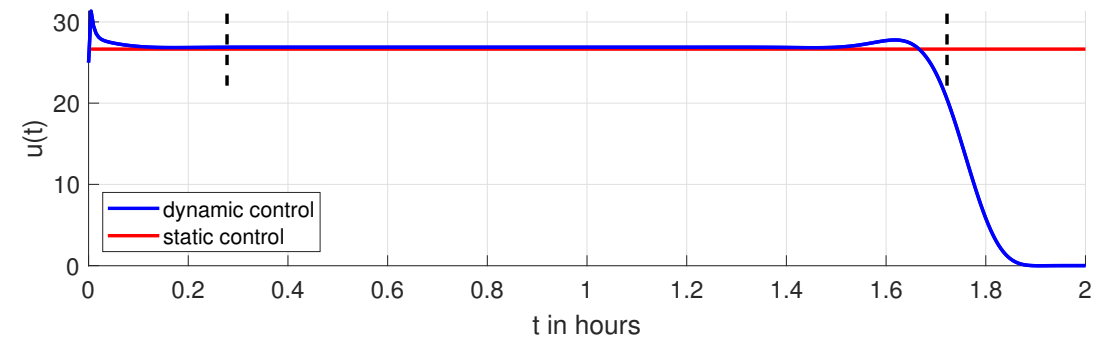
### Deterministic Turnpike

The optimal solution  $u^\delta(t)$  of the dynamic optimal control problem

$$\begin{aligned} \min_{u \in L^2(0,T)} \quad & J_T(u) = \int_0^T f(u(t)) + g(r(t, L)) dt \\ \text{s.t.} \quad & r_t(t, x) + cr_x(t, x) = m r(t, x), \\ & r(0, x) = r_{\text{ini}}(x), \\ & r(t, 0) = u(t). \end{aligned}$$

and the optimal solution  $u^\sigma$  of the corresponding static problem satisfy the integral turnpike property

$$\int_0^T \|u^\delta(t) - u^\sigma\|_2^2 dt \leq \mathcal{C}.$$



[Sakamoto and Schuster, 2023]: *A Turnpike Result for Optimal Boundary Control Problems with the Transport Equation under Uncertainty*. Preprint



# Nodal Control under Uncertainty

## A Turnpike Result for the Transport Equation

We randomize the initial state using a Wiener process:  $r_{\text{ini}}^\omega(x) = r_{\text{ini}}(x) + W_x$

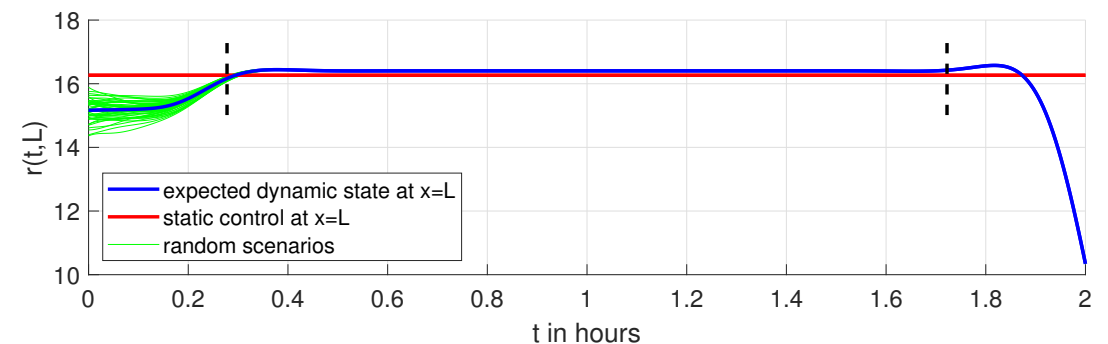
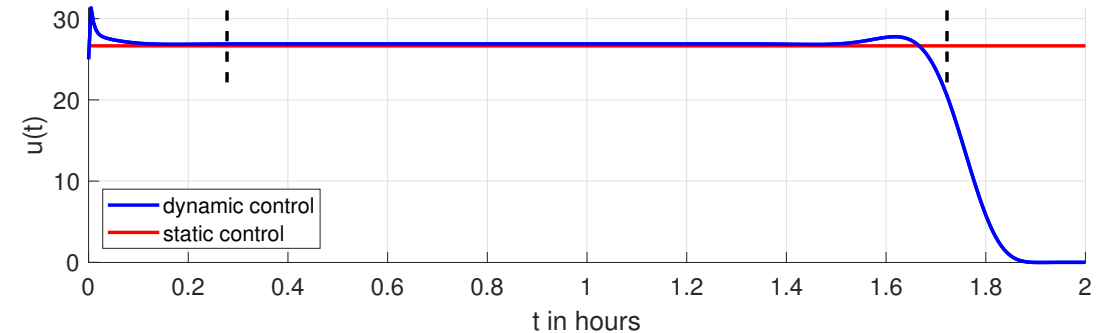
### Deterministic Turnpike

The optimal solution  $u^\delta(t)$  of the dynamic optimal control problem

$$\begin{aligned} \min_{u \in L^2(0,T)} \quad & J_T(u) = \int_0^T f(u(t)) + g(\mathbb{E}[r(t, L)]) dt \\ \text{s.t.} \quad & r_t(t, x) + cr_x(t, x) = m r(t, x), \\ & r(0, x) = r_{\text{ini}}^\omega(x), \\ & r(t, 0) = u(t). \end{aligned}$$

and the optimal solution  $u^\sigma$  of the corresponding static problem satisfy the integral turnpike property

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[Sakamoto and Schuster, 2023]: *A Turnpike Result for Optimal Boundary Control Problems with the Transport Equation under Uncertainty*. Preprint

# Nodal Control under Uncertainty

## A Turnpike Result for the Transport Equation

We randomize the source term by a Gaussian distribution:  $m^\omega = m(\omega) \sim \mathcal{N}(\mu, \sigma)$

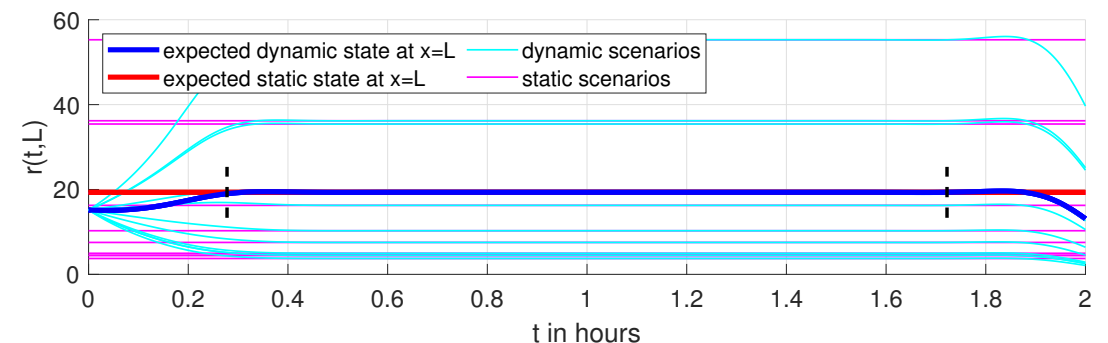
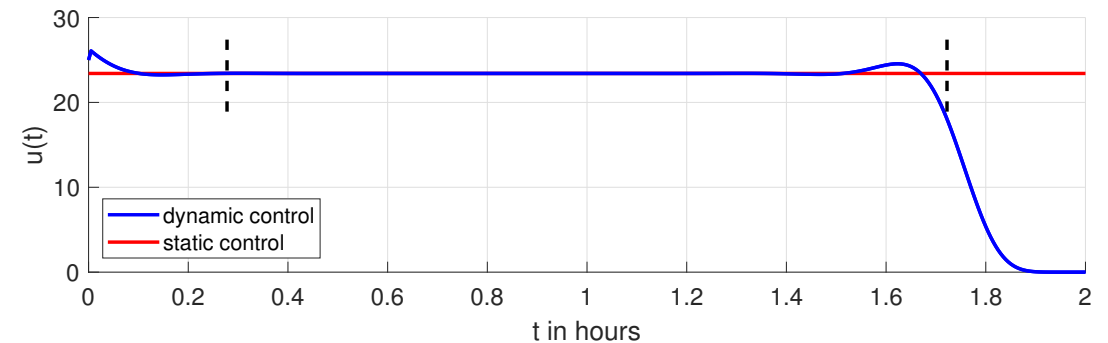
### Deterministic Turnpike

The optimal solution  $u^\delta(t)$  of the dynamic optimal control problem

$$\begin{aligned} \min_{u \in L^2(0,T)} \quad & J_T(u) = \int_0^T f(u(t)) + g(\mathbb{E}[r(t, L)]) dt \\ \text{s.t.} \quad & r_t(t, x) + cr_x(t, x) = m^\omega r(t, x), \\ & r(0, x) = r_{\text{ini}}(x), \\ & r(t, 0) = u(t). \end{aligned}$$

and the optimal solution  $u^\sigma$  of the corresponding static problem satisfy the integral turnpike property

$$\int_0^T \|u^\delta(t) - u^\sigma\|_2^2 dt \leq \mathcal{C}.$$



[Sakamoto and Schuster, 2023]: *A Turnpike Result for Optimal Boundary Control Problems with the Transport Equation under Uncertainty*. Preprint

# Nodal Control and Probabilistic Constrained Optimization



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