

An a posteriori Probabilistic Robustness Check for Deterministic Optimal Controls

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Uncertainty in Dynamical Systems



Medicine &
Epidemiology

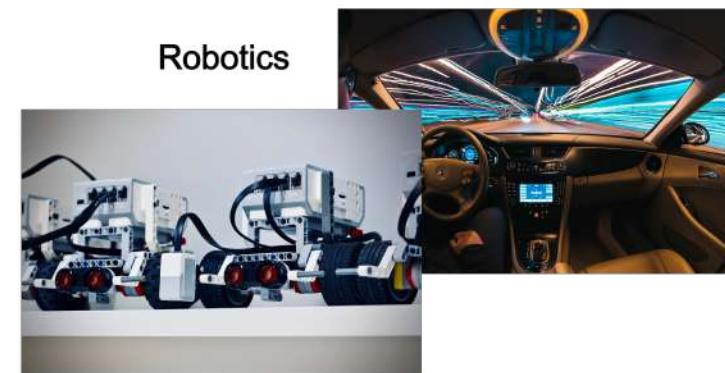


Aerospace
Engineering

Uncertainty often plays a significant role in dynamical systems!



Energy Systems



Robotics

Pictures from <https://unsplash.com/de>

Robust vs Probabilistic

Robust Optimization:

Consider the optimization problem

$$\begin{aligned} \min \quad & f(x) \\ \text{s.t.} \quad & g(x, u) \leq 0 \quad \forall u \in \mathcal{U} \end{aligned}$$

with objective function f , constraint g , decision vector x , parameter u and uncertainty set \mathcal{U} .

Probabilistic Constrained Optimization:

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 ξ and probability level α .

Gas Network Optimization

Mathematical Modelling

p gas pressure
 ρ gas density

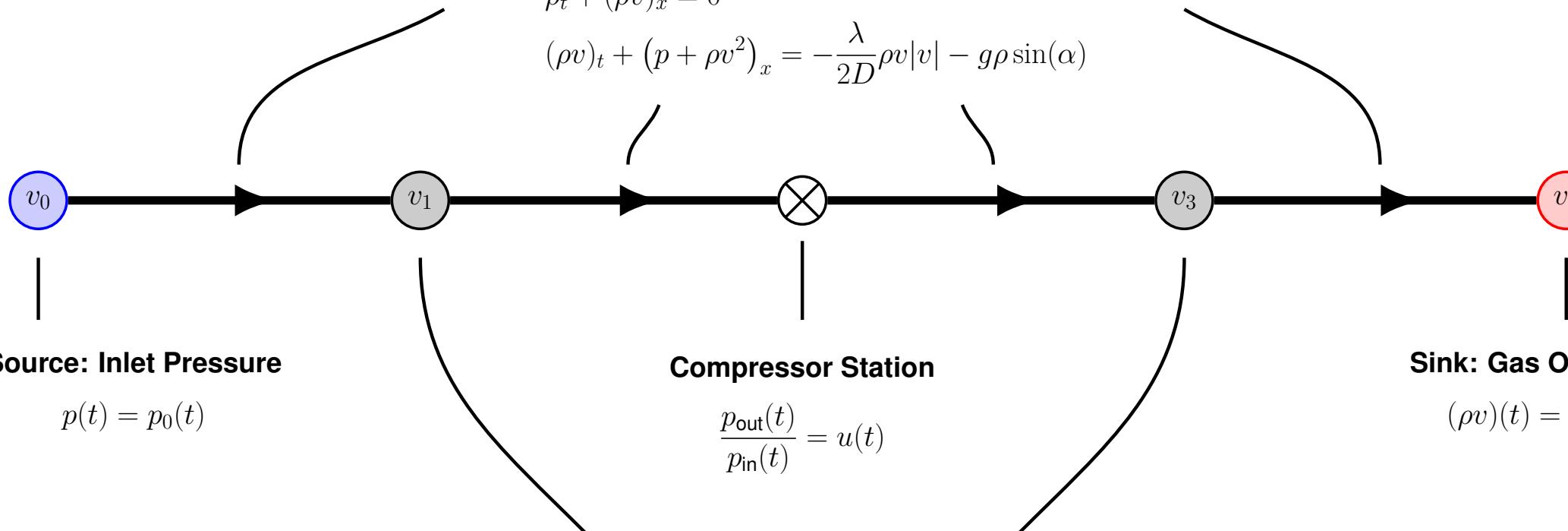
v gas velocity
 λ/D pipe friction

g gravitational constant
 α pipe slope

Isothermal Euler Equations

$$\rho_t + (\rho v)_x = 0$$

$$(\rho v)_t + (p + \rho v^2)_x = -\frac{\lambda}{2D}\rho v|v| - g\rho \sin(\alpha)$$



Source: Inlet Pressure

$$p(t) = p_0(t)$$

Compressor Station

$$\frac{p_{\text{out}}(t)}{p_{\text{in}}(t)} = u(t)$$

Sink: Gas Outflow

$$(\rho v)(t) = b(t)$$

Coupling Conditions

$$\text{Conservation of Mass: } \sum(\rho v)_{\text{in}}(t) = \sum(\rho v)_{\text{out}}(t), \quad \text{Continuity in Pressure: } p_{\text{in}} = p_{\text{out}}$$

The Optimal Control System

Let bounds for the pressures $0 < p_{\min} < p_{\max}$ be given at every node. Consider the optimal control problem

$$\min_{u \in L^2(0,T)} f(u)$$

$$\rho_t + (\rho v)_x = 0$$

$$\text{s.t. } (\rho v)_t + (p + \rho v^2)_x = -\frac{\lambda}{2D} \rho v |v| - g \rho \sin(\alpha) \quad \text{on every edge}$$

$$p(t) = p_0(t)$$

$$(\rho v)(t) = b(t)$$

$$\sum (\rho v)_{\text{in}}(t) = \sum (\rho v)_{\text{out}}(t)$$

$$p_{\text{in}} = p_{\text{out}}$$

$$\frac{p_{\text{out}}(t)}{p_{\text{in}}(t)} = u(t)$$

$$p(t) \in [p_{\min}, p_{\max}] \quad \forall t \in [0, T]$$

on every source node

on every sink node

on every inner node

for every compressor

on every node

Uncertainty and Probabilistic Robustness

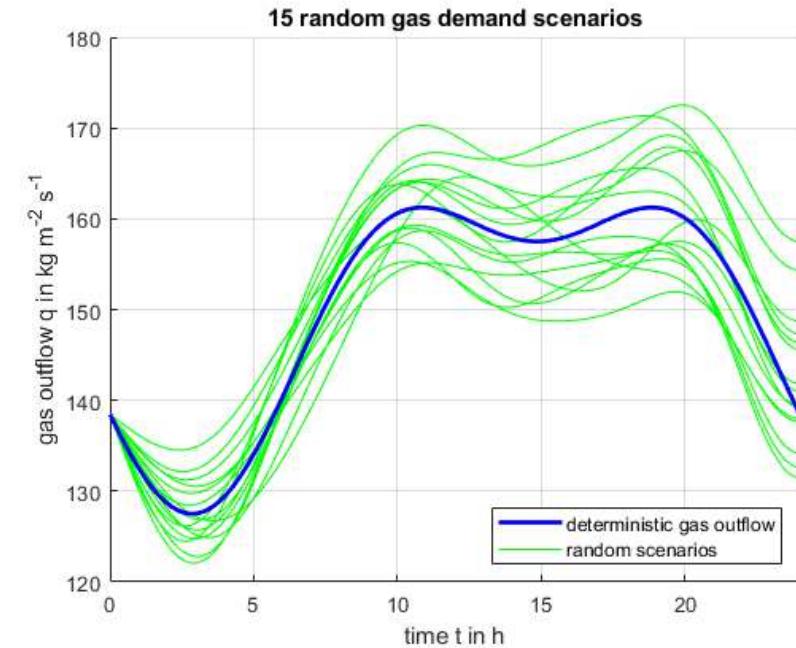
We a posteriori assume that the consumers gas demand $b(t)$ is random:

- Write boundary condition $b(t)$ as Fourier series

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

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

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



Probabilistic Robustness

For a control u^* , the probability

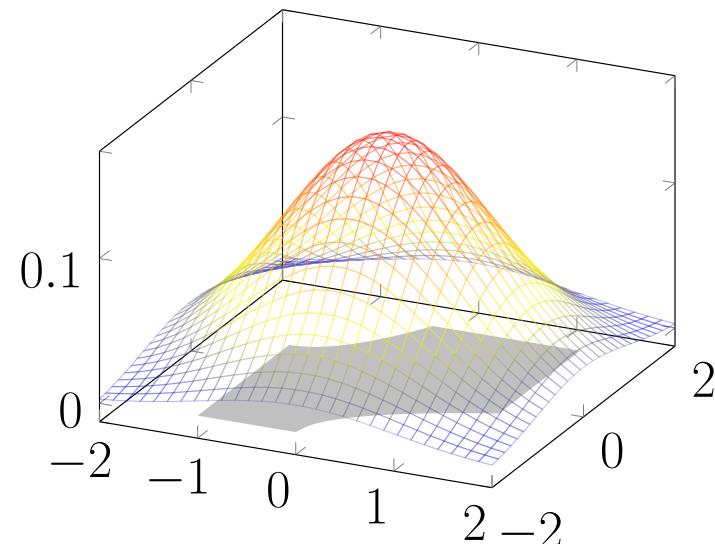
$$\mathbb{P}(b^\omega \in M(u^*, t) \quad \forall t \in [0, T])$$

is called probabilistic robustness of u^* , where $M(u^*, t)$ contains all constraints of the optimal control problem.

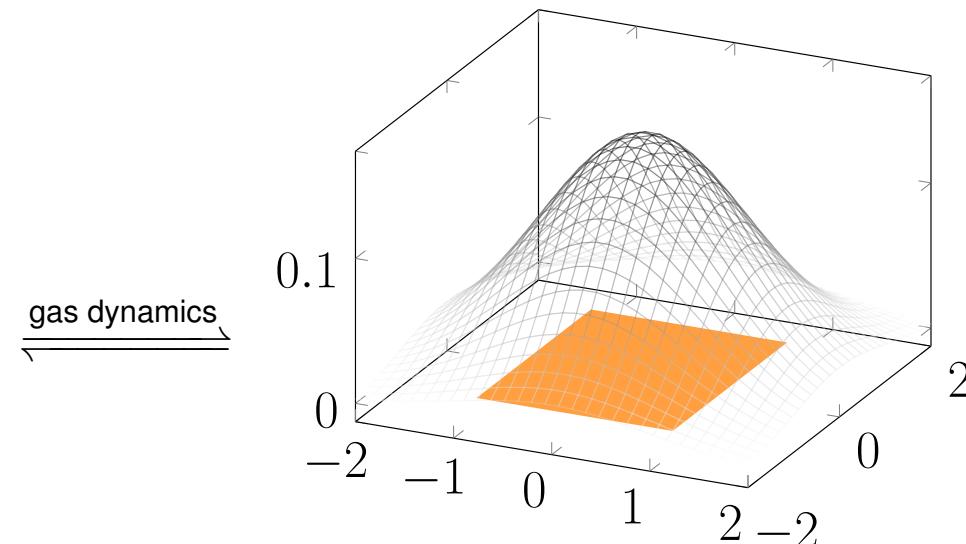
Gas Network Optimization

Uncertainty and Probabilistic Robustness

$$\mathbb{P}(b^\omega \in M(u^*, t) \quad \forall t \in [0, T]) = \mathbb{P}(p^\omega(t) \in [p_{\min}, p_{\max}] \quad \forall t \in [0, T])$$



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



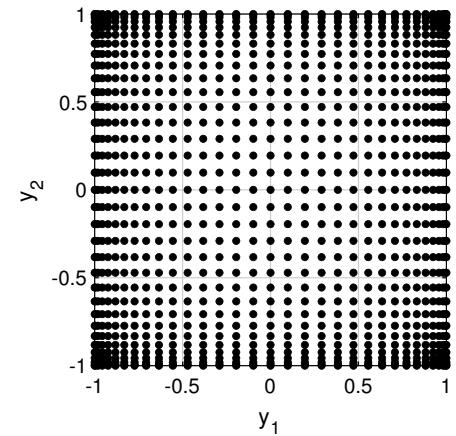
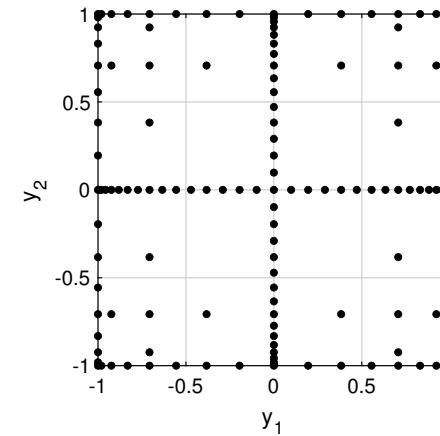
(b) Unknown distribution (grey), well-known set of feasible pressures (orange)

Stochastic Collocation

- Let an optimal control $u(t)$, inlet pressures $p_0(x)$ and a n_d -dimensional random gas outflow be given
- We approximate the pressure $p(t, x, b^\omega)$ in the stochastic space by stochastic collocation on a *Smolyak sparse grid* with *Clenshaw-Curtis* nodes

- For a multi-index $\mathbf{i} \in \mathbb{N}^{n_S}$ and a natural number $k \in \mathbb{N}$ we define the constant

$$c_{\mathbf{i}} = (-1)^{k+n_S-|\mathbf{i}|} \binom{n_S - 1}{k + n_S - |\mathbf{i}|}.$$



- The approximated pressures are given by the Smolyak formula with level $k > 0$

$$S_k[p(t, x, \cdot)] = \sum_{\substack{\mathbf{i} \in \mathbb{N}^{n_S} \\ k+1 \leq \mathbf{i} \leq k+n_S}} c_{\mathbf{i}} \left(\mathcal{U}^{(i_1)} \otimes \cdots \otimes \mathcal{U}^{(i_{n_S})} \right) [p(t, x, \cdot)],$$

where the $\mathcal{U}^{(i_m)}$ for $m = 1, \dots, n_S$ are the interpolation operators on one dimension.

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 $\mathcal{P}_{\mathcal{B}} = \{ p(t; b^{S,1}), \dots, p(t; b^{S,N_{\text{KDE}}}) \}$ be the corresponding densities at the end of the pipe (given by the approximation of the solution in the stochastic space)

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

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

Kernel density estimator with Gaussian kernels for bandwidths h^{\min} and h^{\max}

$$\varrho_{p,N_{\text{KDE}}}(z) = \frac{1}{N_{\text{KDE}}} \frac{1}{\prod_{j=1}^d h_j^{\min} h_j^{\max}} \frac{1}{(2\pi)^d} \sum_{i=1}^{N_{\text{KDE}}} \prod_{j=1}^d \exp\left(-\frac{1}{2} \left(\frac{z_{1,j} - \underline{p}_j(b_i)}{h_j^{\min}}\right)^2\right) \cdot \exp\left(-\frac{1}{2} \left(\frac{z_{2,j} - \bar{p}_j(b_i)}{h_j^{\max}}\right)^2\right)$$

Kernel Density Estimation

$$\begin{aligned} \mathbb{P}(p^\omega(t) \in [p_{\min}, p_{\max}] \quad \forall t \in [0, T]) &= \int_{[p_{\min}, p_{\max}]^d} \varrho_{p, N_{\text{KDE}}}(z) \, dz \\ &= \int_{[p_{\min}, p_{\max}]^d} \frac{1}{N_{\text{KDE}}} \frac{1}{\prod_{j=1}^d h_j^{\min} h_j^{\max}} \frac{1}{(2\pi)^d} \sum_{i=1}^{N_{\text{KDE}}} \prod_{j=1}^d \exp \left(- \left(\frac{z_{1,j} - \underline{p}_j(b_i)}{\sqrt{2} h_j^{\min}} \right)^2 \right) \cdot \exp \left(- \left(\frac{z_{2,j} - \bar{p}_j(b_i)}{\sqrt{2} h_j^{\max}} \right)^2 \right) \, dz \end{aligned}$$

Kernel Density Estimation

$$\begin{aligned}
 \mathbb{P}(p^\omega(t) \in [p_{\min}, p_{\max}] \quad \forall t \in [0, T]) &= \int_{[p_{\min}, p_{\max}]^d} \varrho_{p, N_{\text{KDE}}}(z) \, dz \\
 &= \int_{[p_{\min}, p_{\max}]^d} \frac{1}{N_{\text{KDE}}} \frac{1}{\prod_{j=1}^d h_j^{\min} h_j^{\max}} \frac{1}{(2\pi)^d} \sum_{i=1}^{N_{\text{KDE}}} \prod_{j=1}^d \exp \left(- \left(\frac{z_{1,j} - \underline{p}_j(b_i)}{\sqrt{2} h_j^{\min}} \right)^2 \right) \cdot \exp \left(- \left(\frac{z_{2,j} - \bar{p}_j(b_i)}{\sqrt{2} h_j^{\max}} \right)^2 \right) \, dz \\
 &= \frac{1}{N_{\text{KDE}}} \frac{1}{\prod_{j=1}^d h_j^{\min} h_j^{\max}} \frac{1}{(2\pi)^d} \sum_{i=1}^{N_{\text{KDE}}} \prod_{j=1}^d \int_{p_{\min}}^{p_{\max}} \exp \left(- \left(\frac{z_{1,j} - \underline{p}_j(b_i)}{\sqrt{2} h_j^{\min}} \right)^2 \right) \, dz_{1,j} \cdot \int_{p_{\min}}^{p_{\max}} \exp \left(- \left(\frac{z_{2,j} - \bar{p}_j(b_i)}{\sqrt{2} h_j^{\max}} \right)^2 \right) \, dz_{2,j}
 \end{aligned}$$

Kernel Density Estimation

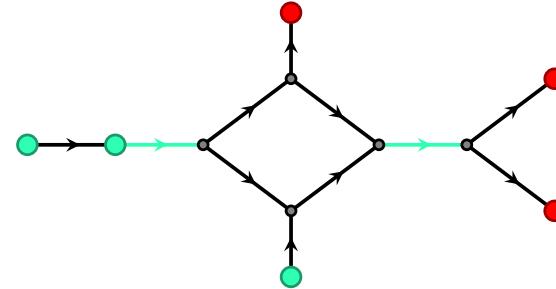
$$\begin{aligned}
 \mathbb{P}(p^\omega(t) \in [p_{\min}, p_{\max}] \quad \forall t \in [0, T]) &= \int_{[p_{\min}, p_{\max}]^d} \varrho_{p, N_{\text{KDE}}}(z) \, dz \\
 &= \int_{[p_{\min}, p_{\max}]^d} \frac{1}{N_{\text{KDE}}} \frac{1}{\prod_{j=1}^d h_j^{\min} h_j^{\max}} \frac{1}{(2\pi)^d} \sum_{i=1}^{N_{\text{KDE}}} \prod_{j=1}^d \exp \left(- \left(\frac{z_{1,j} - \underline{p}_j(b_i)}{\sqrt{2} h_j^{\min}} \right)^2 \right) \cdot \exp \left(- \left(\frac{z_{2,j} - \bar{p}_j(b_i)}{\sqrt{2} h_j^{\max}} \right)^2 \right) \, dz \\
 &= \frac{1}{N_{\text{KDE}}} \frac{1}{\prod_{j=1}^d h_j^{\min} h_j^{\max}} \frac{1}{(2\pi)^d} \sum_{i=1}^{N_{\text{KDE}}} \prod_{j=1}^d \int_{p_{\min}}^{p_{\max}} \exp \left(- \left(\frac{z_{1,j} - \underline{p}_j(b_i)}{\sqrt{2} h_j^{\min}} \right)^2 \right) \, dz_{1,j} \cdot \int_{p_{\min}}^{p_{\max}} \exp \left(- \left(\frac{z_{2,j} - \bar{p}_j(b_i)}{\sqrt{2} h_j^{\max}} \right)^2 \right) \, dz_{2,j} \\
 &= \frac{1}{N_{\text{KDE}} 4^d} \sum_{i=1}^{N_{\text{KDE}}} \prod_{j=1}^d \left[\operatorname{erf} \left(\frac{p_{\max} - \underline{p}_j(b_i)}{\sqrt{2} h_j^{\min}} \right) - \operatorname{erf} \left(\frac{p_{\min} - \underline{p}_j(b_i)}{\sqrt{2} h_j^{\min}} \right) \right] \cdot \left[\operatorname{erf} \left(\frac{p_{\max} - \bar{p}_j(b_i)}{\sqrt{2} h_j^{\min}} \right) - \operatorname{erf} \left(\frac{p_{\min} - \bar{p}_j(b_i)}{\sqrt{2} h_j^{\min}} \right) \right]
 \end{aligned}$$

Let bounds for the pressures $0 < p_{\min} < p_{\max}$ be given at every node. For $\varepsilon > 0$ consider the optimal control problem

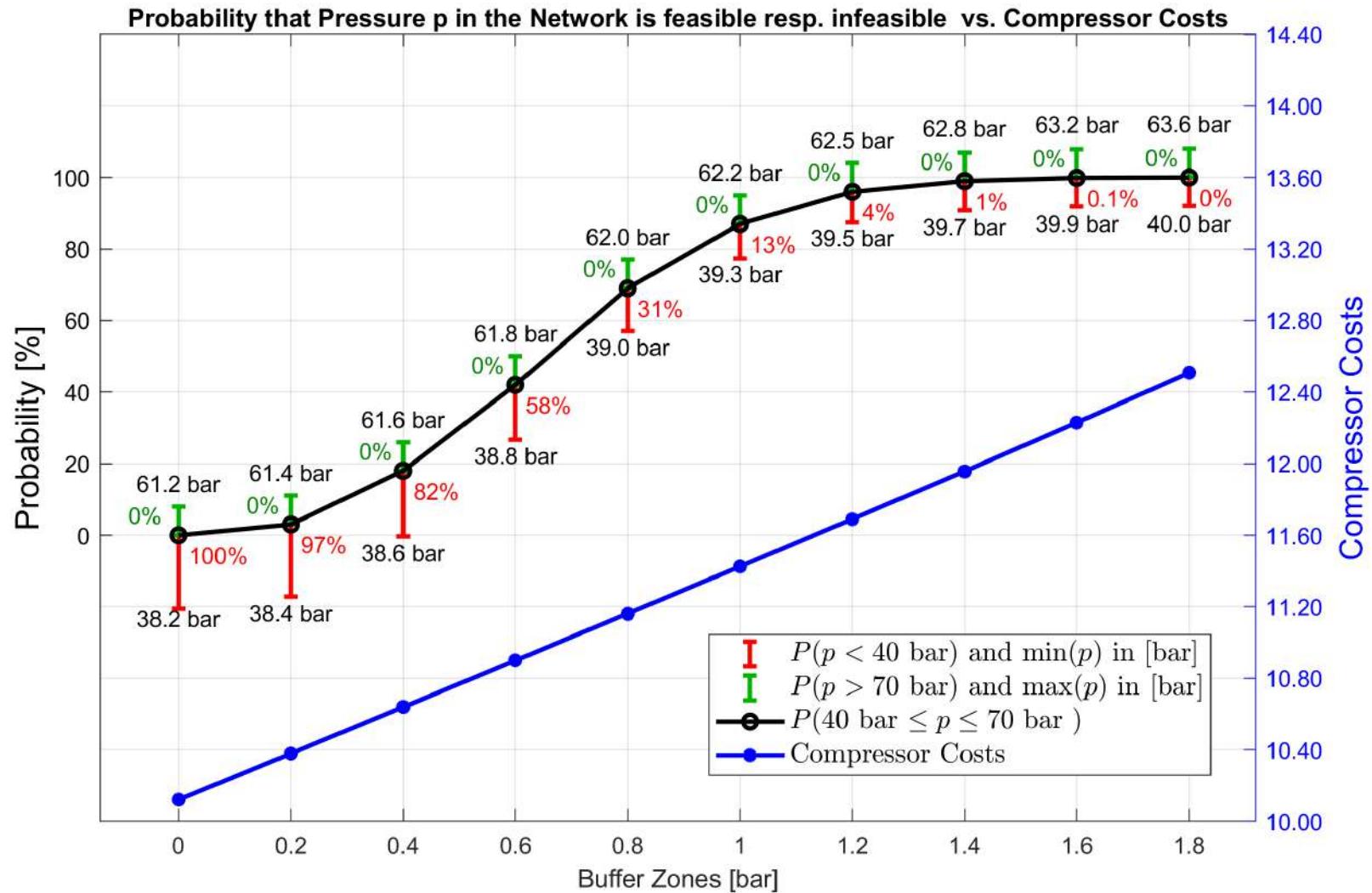
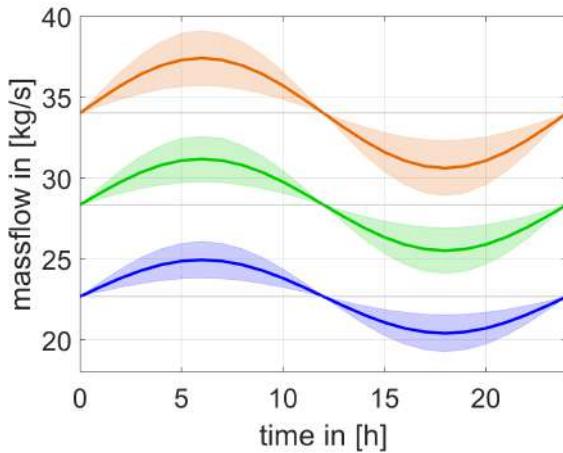
$$\begin{array}{ll}\min_{u \in L^2(0,T)} & f(u) \\ \text{s.t.} & \rho_t + (\rho v)_x = 0 \quad \text{on every edge} \\ & (\rho v)_t + (p + \rho v^2)_x = -\frac{\lambda}{2D} \rho v |v| - g \rho \sin(\alpha) \\ & p(t) = p_0(t) \quad \text{on every source node} \\ & (\rho v)(t) = b(t) \quad \text{on every sink node} \\ & \sum (\rho v)_{\text{in}}(t) = \sum (\rho v)_{\text{out}}(t) \quad \text{on every inner node} \\ & p_{\text{in}} = p_{\text{out}} \\ & \frac{p_{\text{out}}(t)}{p_{\text{in}}(t)} = u(t) \quad \text{for every compressor} \\ & p(t) \in [p_{\min} + \varepsilon, p_{\max} - \varepsilon] \quad \forall t \in [0, T] \quad \text{on every node}\end{array}$$

Numerical Example

Result for GasLib-11



● source ● junction → compr.
● sink — pipe station



A posteriori Probabilistic Robustness Check for Deterministic Controls



[Schuster, Strauch, Lang, Gugat, 2023]: *An a posteriori Probabilistic Robustness Check for Deterministic Optimal Controls*. Preprint

[Schuster, 2021]: *Nodal Control and Probabilistic Constrained Optimization using the Example of Gas Networks*. Dissertation at FAU Erlangen-Nürnberg

[Strauch, 2023]: *Adaptive Multi-Level Monte Carlo and Stochastic Collocation Methods for Hyperbolic Partial Differential Equations with Random Data on Networks*. Dissertation at TU Darmstadt