

## Topic and Challenges

The aim of this project consists in applying **nonlinear probabilistic constraints** to optimization problems in gas transportation assuming the underlying random parameter obeys a **multivariate** and **continuous** distribution. Robustness in the sense of probabilistic network design shall be facilitated.

- ▷ Modeling of uncertain parameters as random vectors with multivariate distribution, taking network node correlations into consideration
- ▷ Using continuous distributions for higher efficiency compared with discretization of the random vector
- ▷ Optimization in gas transport networks requires non-linear and even implicit probabilistic constraints
- ▷ There are no analytical representations for both function values and gradients of the probability function

## Probabilistic Constraints

Stochastic optimization problem with probabilistic constraints:

$$\min\{f(x) \mid \varphi(x) \geq p, x \in X\}$$

Probability function:  $\varphi(x) := \mathbb{P}(g(x, \xi) \leq 0)$

In general, both values and gradients are needed for  $\varphi(\cdot)$ :

**Spheric-Radial Decomposition:**  $\xi \in \mathcal{N}(0, \Sigma)$  with  $\Sigma = LL^T$

If  $g(x, \cdot)$  continuous, convex and  $x$  such that  $g(x, 0) \leq 0$ . Then

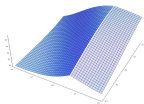
$$\varphi(x) = \int_{v \in \mathbb{S}^{n-1}} \chi_{\text{cdf}}(\rho(x, v)) d\mu_{\eta}(v),$$

where  $\rho(x, v) := \sup\{r \geq 0 \mid g(x, rLv) \leq 0\}$ .

Additionally, if  $g : \mathbb{R}^s \times \mathbb{R}^n \rightarrow \mathbb{R}$  continuously differentiable, then

$$\nabla \varphi(x) = \int_{v \in \mathbb{S}^{n-1}} -\frac{\chi_{\text{pdf}}(\rho(x, v))}{\langle \nabla_{\xi} g(x, \rho(x, v)Lv), Lv \rangle} \nabla_x g(x, \rho(x, v)Lv) d\mu_{\eta}(v)$$

In general: Smooth  $g, \xi$  do not imply smooth probability functions

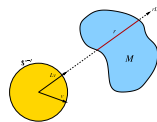


⇒ Derivatives (subdifferential) in terms of **Clarke or Mordukhovich**

## Spheric-Radial Decomposition

Let be  $\xi \sim \mathcal{N}(0, \Sigma)$   $n$ -dimensional Gaussian random vector with covariance  $\Sigma = LL^T$ . Then it holds:

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



where  $\mathbb{S}^{n-1}$  is the unit sphere in  $\mathbb{R}^n$ ,  $\mu_{\eta}$  the law of uniform distribution on it.  $\chi$  is the law of chi-distribution with  $n$  degree of freedom.

## Stationary Gas Networks

Feasibility of **exit load nomination**  $b$  for pressure bounds  $p^{\min/\max}$

$$\begin{aligned} \exists z : A_N^T g(b, z) &= \Phi_N |z|z \\ \min_{k=1, \dots, |V|} [(p_k^{\max})^2 + g_k(b, z)] &\geq \max_{k=1, \dots, |V|} [(p_k^{\min})^2 + g_k(b, z)] \\ (p_0^{\min})^2 &\leq \min_{k=1, \dots, |V|} [(p_k^{\max})^2 + g_k(b, z)] \\ (p_0^{\max})^2 &\geq \max_{k=1, \dots, |V|} [(p_k^{\min})^2 + g_k(b, z)] \end{aligned}$$

Definition:  $g(u, v) := (A_B^T)^{-1} \Phi_B |A_B^{-1}(u - A_N v)| A_B^{-1}(u - A_N v)$   
 $A = (A_B | A_N)$  incidence matrix,  $\Phi = (\Phi_B | \Phi_N)$  frictional coefficients

**Uncertainty:** Nomination  $b$  assumed to be of Gaussian type

## Joint Robust/Probabilistic Approach

Two different characters of uncertainty:

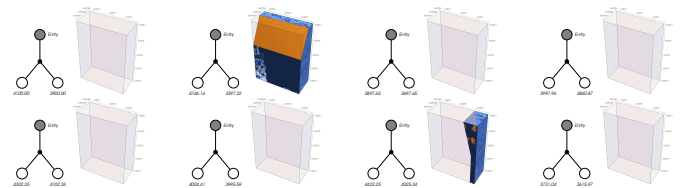
1. **Gas demand** (nominations) ⇒ Distribution available
2. **Friction coefficients** ⇒ No statistical information available

Find maximum uncertainty allowed for friction coefficients while guaranteeing demand satisfaction at high probability:

$$\max \{f(\delta) \mid \mathbb{P}(g(\Phi, b) \leq 0 \quad \forall \Phi \in U_{\delta}) \geq p\}$$

$U_{\delta}$  ... uncertainty set (e.g. rectangle, ellipsoid)

$\delta$  ... certain shape parameter (e.g. edge length, axis)



Out-of-sample constraint violation ( $p = 0.80$ ) for fixed uncertainty set

## References

- [1] W.Ackooij, R.Henrion: Gradient formulae for nonlinear probabilistic constraints with Gaussian-like distributions, SIAM Journal on Optimization 24 (2014), 1864-1889.
- [2] C.Gotzes, H.Heitsch, R.Henrion, R.Schultz: Feasibility of nominations in stationary networks with random load, to appear in MMOR (2016).
- [3] H.Heitsch, H.Leövey and W.Römisch: Are Quasi-Monte Carlo algorithms efficient for two-stage stochastic programs?, COAP (2016), DOI 10.1007/s10589-016-9843-z.