

Motivation

The modeling of stationary/time-dependent subsurface and fractured porous media flows by elliptic/parabolic equations, where:

- Random advection- and diffusion coefficients account for uncertain permeability and insufficient measurements.
- Random discontinuities in the coefficients are incorporated to model heterogeneous media and fractures in ground layers.

Advection-Diffusion Problem with Jump Coefficients

Let $(\Omega, \mathcal{A}, \mathbb{P})$ be a complete probability space, $\mathcal{D} \subset \mathbb{R}^d$ be a bounded and convex spatial domain for some $d \in \mathbb{N}$ and $\mathbb{T} = [0, T]$ with $T > 0$ be a finite time interval. We consider the random parabolic problem to find $u : \Omega \times \mathcal{D} \times \mathbb{T} \rightarrow \mathbb{R}$ such that

$$\partial_t u(\omega, \mathbf{x}, t) + \mathbf{A}(\omega, \mathbf{x})u(\omega, \mathbf{x}, t) = \mathbf{f}(\omega, \mathbf{x}, t), \quad \text{in } \Omega \times \mathcal{D} \times \mathbb{T},$$

subject suitable boundary conditions on $\partial\mathcal{D}$ and initial data u_0 . In the above equation, $\mathbf{A}(\omega, \mathbf{x}) : H^1(\mathcal{D}) \rightarrow H^{-1}(\mathcal{D})$ is a linear, elliptic differential operator of second order and \mathbf{f} is a given source term.

To model uncertain permeability and fractured media, the advection and diffusion coefficients in $\mathbf{A} := \nabla \cdot (\mathbf{a}\nabla) + \mathbf{b}\nabla \cdot$ admit the structure

$$\mathbf{a}(\omega, \mathbf{x}), \mathbf{b}(\omega, \mathbf{x}) \simeq \exp(\mathbf{W}(\omega, \mathbf{x})) + \mathbf{P}(\omega, \mathbf{x}),$$

where

- $\mathbf{W} : \Omega \times \mathcal{D} \rightarrow \mathbb{R}$ is a continuous Gaussian random field associated to a non-negative, symmetric trace class operator and
- $\mathbf{P} : \Omega \times \mathcal{D} \rightarrow \mathbb{R}_{\geq 0}$ is a discontinuous jump random field which partitions the domain \mathcal{D} into non-empty subsets.

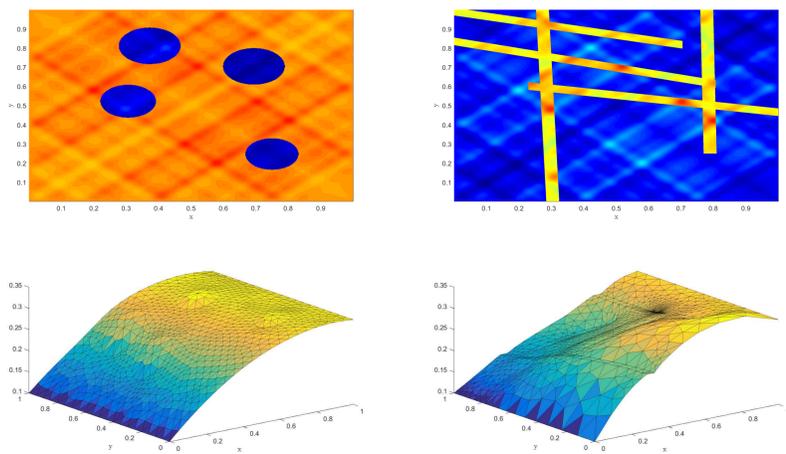


Figure 1: Samples of different diffusion coefficients (top) and corresponding pathwise solutions u (bottom).

Adaptive Numerical Schemes

In general, for fixed $\omega \in \Omega$, the exact pathwise solution $u(\omega)$ for a given sample $\mathbf{A}(\omega, \cdot)$ will be out of reach. To obtain approximate samples of u , we need to employ several numerical techniques:

- The advection and diffusion coefficients have to be replaced by analytically tractable random fields, i.e. with truncated KL expansions, circulant embedding methods and Fourier inversion.
- A spatial discretization of $H^1(\mathcal{D})$ using finite dimensional subspaces is necessary, for instance by the Finite Element (FE) method.
- If the problem is time-dependent, we need to employ a stable time-stepping scheme.

Especially the spatial discretization involves difficulties since $u(\omega)$ has low regularity due to the jumps in the random field \mathbf{P} . To this end, we align the FE mesh pathwise for each ω to the discontinuities in the sample $\mathbf{P}(\omega, \cdot)$. This pathwise adaptive FE approach is then combined with suitable approximations of \mathbf{a}, \mathbf{b} and an implicit time stepping scheme to approximate the samples $u(\omega)$ with increased order of convergence.

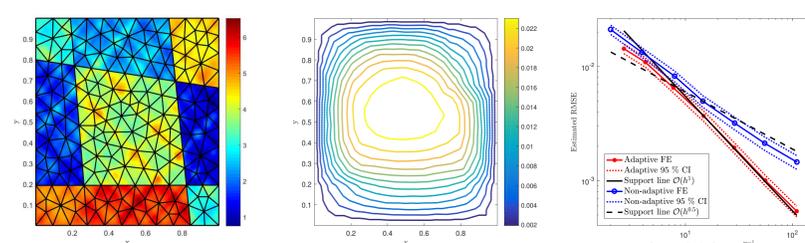


Figure 2: Sample of a diffusion/advection coefficient with adaptive FE grid (right), contour of the FE approximation to a corresponding parabolic problem (center) and convergence rates in the $L^2(\mathbb{T}; H^1(\mathcal{D}))$ -norm (left). The error curves are estimated based on 100 independent samples.

Multilevel Monte Carlo Moment Estimation

For practical applications, the aim is often to estimate moments of u rather than only generating pathwise approximations. Based on each sample of \mathbf{A} , the adaptive FE approach yields a strictly decreasing sequence of stochastic refinement parameters $(h_\ell(\omega), \ell \in \mathbb{N}_0) \subset \mathbb{R}_{>0}$. If $u_\ell(\omega)$ denotes the semi-discrete FE approximation of $u(\omega)$, it holds that

$$\|u(\omega) - u_\ell(\omega)\| \leq C_1 h_\ell(\omega)^\alpha \leq C_1 \bar{h}_\ell^\alpha, \quad \ell \in \mathbb{N}_0.$$

Above, the constants $C_1, \alpha, \bar{h}_\ell$ are independent of ω , $h_\ell(\omega) \leq \bar{h}_\ell$ holds almost surely and $\bar{h}_\ell \rightarrow 0$ as $\ell \rightarrow \infty$. The other error contributions, i.e. the approximation of \mathbf{a}, \mathbf{b} and the temporal discretization, are now equilibrated to the spatial approximation error of order \bar{h}_ℓ and we denote by \bar{u}_ℓ the full approximation of u for each $\ell \in \mathbb{N}_0$. We then fix a (maximum) level $L \in \mathbb{N}$ and estimate $\mathbb{E}(u)$ by the *multilevel Monte Carlo estimator*

$$E^L(u_L) := \sum_{i=0}^L \frac{1}{M_i} \sum_{j=1}^{M_i} \bar{u}_\ell^{(j)} - \bar{u}_{\ell-1}^{(j)},$$

of $\mathbb{E}(\bar{u}_L)$, where $M_0 > \dots > M_L$ are the decreasing numbers of sampled differences and $\bar{u}_\ell^{(j)} - \bar{u}_{\ell-1}^{(j)}$ are generated independently in j on each level ℓ . The number of samples on each level may now be chosen such that the mean-squared estimation error is bounded by

$$\mathbb{E} \left(\int_0^T \|\mathbb{E}(u) - E^L(\bar{u}_L)\|^2 dt \right)^{1/2} \leq C_2 h_L^\alpha,$$

where $C_2 > 0$ is independent of h_L and α .

⇒ Combining the MLMC estimator with adaptive pathwise schemes leads to increased convergence rates and produces a lower error for any computational budget, see Figure 3 and Figure 4.

⇒ The algorithm can be further enhanced by *bootstrapping* (BS), meaning the simulated quantities $u_\ell^{(j)}$ are "recycled" on the next level $\ell + 1$.

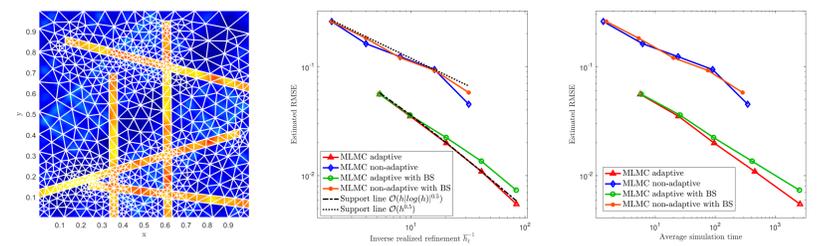


Figure 3: Coefficient for a fractured porous medium and adaptive FE grid (left), convergence plot in the $H^1(\mathcal{D})$ -norm (center), Time-to-error plot (right).

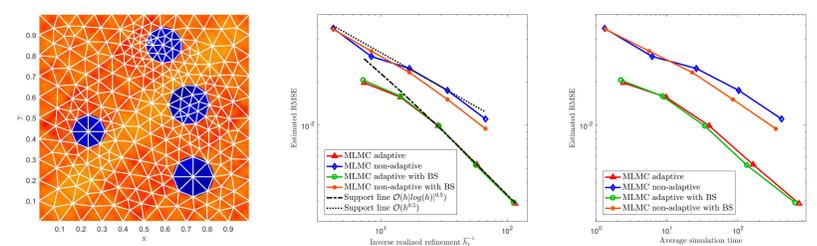


Figure 4: Coefficient for a medium with inclusions and adaptive FE grid (left), convergence plot in the $H^1(\mathcal{D})$ -norm (center), Time-to-error plot (right).

References

- [1] A. Barth and A. Stein. An adaptive multilevel Monte Carlo algorithm for advection-diffusion PDEs with random discontinuous coefficients. Preprint, submitted to *Proceedings of the 13th International Conference in Monte Carlo & Quasi-Monte Carlo Methods in Scientific Computing*, 2018.
- [2] A. Barth and A. Stein. Approximation and simulation of infinite-dimensional Lévy processes. *Stochastics and Partial Differential Equations: Analysis and Computations*, 6(2):286–334, June 2018.
- [3] A. Barth and A. Stein. Numerical analysis of time-dependent advection-diffusion problems with random discontinuous coefficients. Preprint, submitted to *SIAM Journal on Numerical Analysis*, 2018.
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