

The solution of high dimensional elliptic PDEs with random data

Ivan Graham, University of Bath, UK.

Joint work with:

Frances Kuo, Ian Sloan (New South Wales)

Dirk Nuyens (Leuven)

Rob Scheichl (Bath)

CUHK April 2016

High dimensional Problems: PDE with random data

- Many problems involve **PDEs** with spatially varying **data** which is subject to **uncertainty**.

Example: groundwater flow in rock underground.

- **Uncertainty** enters the PDE through its coefficients. (**random fields**). The **quantity of interest**: is a random number or field derived from the PDE solution.

Examples: (i) pressure in medium, (ii) effective permeability, (iii) breakthrough time of a pollution plume .

- Typical Computational Goal: **expected value of quantity of interest**.

This is the **Forward problem of uncertainty quantification**

Some ingredients

PDE Problem:

$$-\nabla \cdot k \nabla p = f \quad \text{with} \quad k(\mathbf{x}, \omega) = \exp(Z(\mathbf{x}, \omega)), \quad \text{lognormal}$$

Random field $Z(\mathbf{x}, \omega)$ Gaussian at each \mathbf{x}
specified mean (= 0 here) and (rough) covariance.

no uniform ellipticity, Low regularity,
high contrast, high stochastic dimension,

Computational goal: Functionals of p , e.g.

$$\mathbb{E}(p(\mathbf{x}, \omega)) = \int_{\Omega} p(\mathbf{x}, \omega) d\mathbb{P}(\omega) \quad \text{high dimensional}$$

Classical method: Monte-Carlo

- random sampling of Z (how to do it?)
- Finite element method for p
- convergence $\mathcal{O}(1/\sqrt{N})$ ($N = \# \text{ samples}$) + FE Error.

Outline of talk

Part I: Algorithm: circulant embedding with Quasi-Monte Carlo

IGG, Kuo, Nuyens, Scheichl, Sloan JCP 2011

Part II: Rigorous error estimates

IGG, Kuo, Nicholls, Scheichl, Schwab, Sloan

Numer Math 2014

IGG, Scheichl, Ullmann

Stochastic PDE: Analysis and Computation 2014

IGG, Kuo, Nuyens, Scheichl, Sloan in preparation 2016

Gaussian Random Fields (more generally)

PDE Problem:

$$-\nabla \cdot k \nabla p = f \quad + \text{Boundary conditions} \quad k = \exp(Z)$$

Covariance function: (centred) stationary field:

$$\mathbb{E}[Z(\mathbf{x}, \cdot)Z(\mathbf{y}, \cdot)] = \rho(\mathbf{x} - \mathbf{y}), \quad \rho \text{ positive definite}$$

Examples:

$$\rho(\mathbf{x} - \mathbf{y}) = \sigma^2 \exp\left(-\|\mathbf{x} - \mathbf{y}\|/\lambda\right) \quad \text{“exponential”}.$$

$$\rho(\mathbf{x} - \mathbf{y}) = \sigma^2 \exp\left(-\|\mathbf{x} - \mathbf{y}\|^2/\lambda\right) \quad \text{“Gaussian”}.$$

$\sigma^2 = \text{variance}$, $\lambda = \text{lengthscale}$

The Matérn family: $\rho = \rho_\beta$, $\beta \in [1/2, \infty)$.

Limiting cases: exponential ($\beta = 1/2$), Gaussian ($\beta = \infty$).

Gaussian Random Fields (more generally)

Loss of uniform ellipticity and boundedness: for all $\epsilon > 0$:

$$\min[\mathbb{P}(k(\mathbf{x}, \cdot) < \epsilon), \mathbb{P}(k(\mathbf{x}, \cdot) > \epsilon^{-1})] > 0$$

Mild smoothness condition on $\rho(\mathbf{0})$:

Karhunen-Loeve (KL) Expansion: (a.s. convergence)

$$Z(\mathbf{x}, \omega) = \sum_{j=1}^{\infty} \sqrt{\mu_j} \xi_j(\mathbf{x}) Y_j(\omega) \quad Y_j \sim N(0, 1)$$

(ξ_j, μ_j) eigenpairs of **covariance operator** with kernel $\rho(\mathbf{x} - \mathbf{y})$.

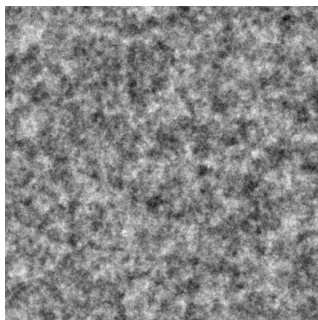
Kolmogorov's theorem: With probability 1,

$k(\mathbf{x}, \omega) \in C^t(D)$, with $t \in [0, \beta)$

In fact, for all $q \in (1, \infty)$,

- $k \in L^q(\Omega, C^t(D))$,
- and $\|p\|_{L^q(\Omega, H_0^1(D))} \leq \|a_{\min}^{-1}\|_{L^q(\Omega)} \|f\|_{H^{-1}}$ (**Dirichlet problem**).

Non-smooth fields : a typical realization (**exponential**)



λ - “frequency”: **Finite element accuracy** requires $h \approx \lambda/10$

σ^2 - “amplitude”:

$$\frac{\max_x k(\mathbf{x}, \omega)}{\min_x k(\mathbf{x}, \omega)} \sim \exp(\sigma) \quad \text{high contrast}$$

Mixed FEM ($f = 0$ mixed BCs)

$$\begin{aligned} \mathbf{q} + k\nabla p &= 0, & \mathbf{q}\cdot\mathbf{n} &= 0 \quad \text{on } \partial D_1 \\ \nabla\cdot\mathbf{q} &= 0 & p &= g \quad \text{on } \partial D_2 \end{aligned}$$

Mixed formulation $(q, p) \in H(\text{div}, D) \times L_2(D)$:

$$\begin{aligned} \int_D k^{-1}\mathbf{q}\cdot\mathbf{v} - \int_D p\nabla\cdot\mathbf{v} &= - \int_{\partial D_2} g\mathbf{v}\cdot\mathbf{n}, \\ - \int_D w\nabla\cdot\mathbf{q} &= 0 & \text{for all } (\mathbf{v}, w). \end{aligned}$$

Mixed FEM ($f = 0$ mixed BCs)

$$\begin{aligned} \mathbf{q} + k\nabla p &= 0, & \mathbf{q} \cdot \mathbf{n} &= 0 \quad \text{on } \partial D_1 \\ \nabla \cdot \mathbf{q} &= 0 & p &= g \quad \text{on } \partial D_2 \end{aligned}$$

Mixed formulation $(\mathbf{q}, p) \in H(\text{div}, D) \times L_2(D)$:

$$\begin{aligned} m(\mathbf{q}, \mathbf{v}) + b(p, \mathbf{v}) &= G(\mathbf{v}), \\ b(w, \mathbf{q}) &= 0 \quad \text{for all } (\mathbf{v}, w). \end{aligned}$$

Mixed FEM ($f = 0$ mixed BCs)

$$\begin{aligned} \mathbf{q} + k\nabla p &= 0, & \mathbf{q} \cdot \mathbf{n} &= 0 \quad \text{on } \partial D_1 \\ \nabla \cdot \mathbf{q} &= 0 & p &= g \quad \text{on } \partial D_2 \end{aligned}$$

Mixed approximation $(\mathbf{q}_h, p_h) \in RT_0 \times PC$ on a mesh \mathcal{T}_h :

$$\begin{aligned} m(\mathbf{q}_h, \mathbf{v}_h) + b(p_h, \mathbf{v}_h) &= G(\mathbf{v}_h), \\ b(w_h, \mathbf{q}_h) &= 0 \quad \text{for all } (\mathbf{v}_h, w_h) \end{aligned}$$

$$\begin{aligned} \mathbf{q} + k\nabla p &= 0, & \mathbf{q} \cdot \mathbf{n} &= 0 \quad \text{on } \partial D_1 \\ \nabla \cdot \mathbf{q} &= 0 & p &= g \quad \text{on } \partial D_2 \end{aligned}$$

Mixed approximation $(\mathbf{q}_h, p_h) \in RT_0 \times PC$ on a mesh \mathcal{T}_h :

$$\begin{aligned} m(\mathbf{q}_h, \mathbf{v}_h) + b(p_h, \mathbf{v}_h) &= G(v_h), \\ b(w_h, \mathbf{q}_h) &= 0 \quad \text{for all } (\mathbf{v}_h, w_h) \end{aligned}$$

h = finite element grid size.

PC = Piecewise constants

Space RT_0 :

$\mathbf{q}_h = a + b\mathbf{x}$ but divergence free $\implies b = 0$.

Mixed FEM ($f = 0$ mixed BCs)

$$\begin{aligned} \mathbf{q} + k\nabla p &= 0, & \mathbf{q}\cdot n &= 0 \quad \text{on } \partial D_1 \\ \nabla\cdot\mathbf{q} &= 0 & p &= g \quad \text{on } \partial D_2 \end{aligned}$$

Mixed approximation $(\mathbf{q}_h, p_h) \in RT_0 \times PC$ on a mesh \mathcal{T}_h :

$$\begin{aligned} m(\mathbf{q}_h, \mathbf{v}_h) + b(p_h, \mathbf{v}_h) &= G(v_h), \\ b(w_h, \mathbf{q}_h) &= 0 \quad \text{for all } (\mathbf{v}_h, w_h) \end{aligned}$$

h = finite element grid size.

PC = Piecewise constants

Space RT_0 :

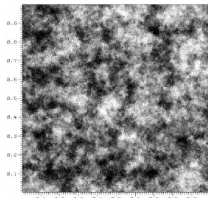
$\mathbf{q}_h = a + b\mathbf{x}$ but divergence free $\implies b = 0$.

Quadrature rule: sample $k(\mathbf{x}, \omega)$ **one point per element**

Enough for accuracy: IGG, Scheichl, Ullmann, 2014

Quantities of Interest - computational cell $D = (0, 1)^2$

$$\vec{q} \cdot \vec{n} = 0$$



$$p = 1$$

$$p = 0$$

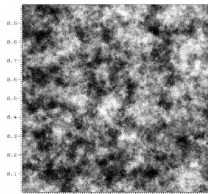
$$\vec{q} \cdot \vec{n} = 0$$

- **Pressure head** $p(\mathbf{x}, \omega)$, e.g. $\mathbf{x} = (1/2, 1/2)$.
- **Effective permeability**

$$k_{\text{eff}}(\omega) = \frac{\int_D q_1(\mathbf{x}, \omega) d\mathbf{x}}{-\int_D \partial p / \partial x_1(\mathbf{x}, \omega) d\mathbf{x}} = \int_{\Gamma_{\text{out}}} q_1(\mathbf{x}, \omega) d\mathbf{x}$$

Quantities of Interest - computational cell $D = (0, 1)^2$

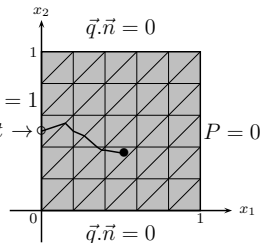
$$\vec{q} \cdot \vec{n} = 0$$



$$p = 1$$

$$p = 0$$

$$\vec{q} \cdot \vec{n} = 0$$



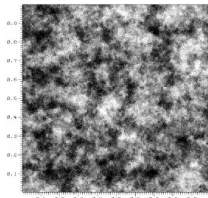
- **Pressure head** $p(\mathbf{x}, \omega)$, e.g. $\mathbf{x} = (1/2, 1/2)$.
- **Effective permeability**

$$k_{\text{eff}}(\omega) = \frac{\int_D q_1(\mathbf{x}, \omega) d\mathbf{x}}{-\int_D \partial p / \partial x_1(\mathbf{x}, \omega) d\mathbf{x}} = \int_{\Gamma_{\text{out}}} q_1(\mathbf{x}, \omega) d\mathbf{x}$$

- **Breakthrough time** $T_{\text{out}}(\omega)$ from q .
(Time to reach outflow boundary)

Quantities of Interest - computational cell $D = (0, 1)^2$

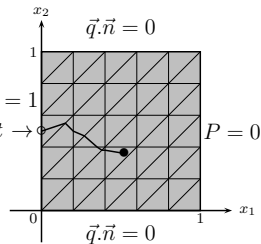
$$\vec{q} \cdot \vec{n} = 0$$



$$p = 1$$

$$p = 0$$

$$\vec{q} \cdot \vec{n} = 0$$



- **Pressure head** $p(\mathbf{x}, \omega)$, e.g. $\mathbf{x} = (1/2, 1/2)$.
- **Effective permeability**

$$k_{\text{eff}}(\omega) = \frac{\int_D q_1(\mathbf{x}, \omega) d\mathbf{x}}{-\int_D \partial p / \partial x_1(\mathbf{x}, \omega) d\mathbf{x}} = \int_{\Gamma_{\text{out}}} q_1(\mathbf{x}, \omega) d\mathbf{x}$$

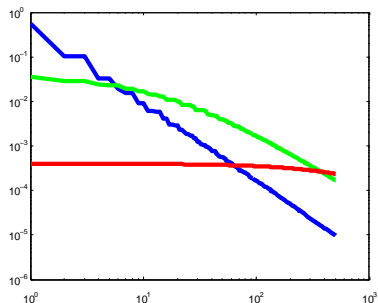
- **Breakthrough time** $T_{\text{out}}(\omega)$ from q .
(Time to reach outflow boundary)
- **General format:** find $\mathbb{E}[\mathcal{G}(p, \mathbf{q})]$ - some functional $\mathcal{G}(p, \mathbf{q})$.

Sampling by K-L truncation : the effect of lengthscale

$$Z(\mathbf{x}, \omega) = \sum_{j=1}^{\infty} \sqrt{\mu_j} \xi_j(\mathbf{x}) Y_j(\omega)$$

exponential covariance in 1D

log log plot of μ_j for $1 \leq j \leq 500$:



Plateau before decay starts

$\lambda = 1$

$\lambda = 0.1$

$\lambda = 0.01$

An extreme eigenvalue solver challenge!

Avoiding KL truncation: discretize first in space

Approximation of $\mathbb{E}[\mathcal{G}(p)]$ by $\mathbb{E}[\mathcal{G}(p_h)]$ (focus on pressure)

FEM + quadrature requires random vector

$\mathbf{Z} := \{Z(\mathbf{x}_i)\}$ at M quadrature points

Covariance Matrix: $R_{i,j} = \rho(\mathbf{x}_i - \mathbf{x}_j)$ $M \times M$

Seek matrix decomposition:

$$R = BB^\top \quad (*)$$

where B is $M \times s$, $s \geq M$.

Then (finite “discrete KL” expansion)

$$\mathbf{Z}(\omega) = B\mathbf{Y}(\omega), \quad \text{where } \mathbf{Y} \sim N(0, 1)^s \text{ i.i.d.}$$

Because

$$\mathbb{E}[\mathbf{Z}\mathbf{Z}^\top] = \mathbb{E}[B\mathbf{Y}\mathbf{Y}^\top B^\top] = BB^\top = R$$

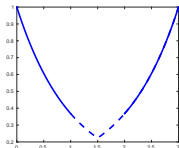
$M \sim h^{-d}$ and so s very large so (*) expensive(?), **but....**

Sampling via Circulant Embedding

not restrictive

For **uniform grids** and **stationary fields**: R is **block Toeplitz**

Embed R into C - **block circulant** $s \times s$ (Typically $s \sim (2^d)M$)



$$C = \begin{bmatrix} R & A \\ A^T & B \end{bmatrix}$$

(Cheap) Factorization: $C = F\Lambda F^H$ (by FFT)

implies Real Factorization: $C = BB^T$ (provided $\text{diag}(\Lambda) \geq \mathbf{0}$)

$$\begin{aligned} \mathbb{E}[\mathcal{G}(p)] &\approx \int_{\mathbb{R}^s} F(\mathbf{y}) \prod_{j=1}^s \phi(y_j) d\mathbf{y}, & F(\mathbf{y}) &= \mathcal{G}(p_h(\cdot, \mathbf{y})) \\ &= \int_{[0,1]^s} F(\Phi_s^{-1}(\mathbf{v})) d\mathbf{v} =: I_s(F). \end{aligned}$$

$\phi(y) = \exp(-y^2/2)/\sqrt{2\pi}$, $\Phi_s^{-1} = \text{inv. cum. normal}$

FEM (h) + high dimensional integration (?)

Integration over $[0, 1]^s$ (very large s): QMC methods

$$\int_{[0,1]^s} f(z) dz \approx \frac{1}{N} \sum_{k=1}^N f(z^{(k)})$$

Monte Carlo method

$z^{(k)}$ **random uniform**

$\mathcal{O}(N^{-1/2})$ convergence

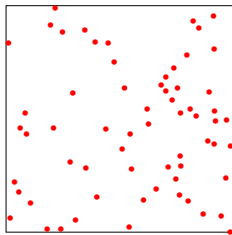
order of variables irrelevant

Quasi-Monte Carlo method

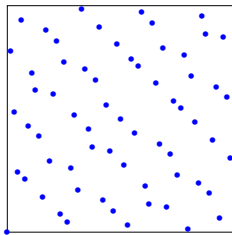
$z^{(k)}$ **deterministic**

close to $\mathcal{O}(N^{-1})$ convergence

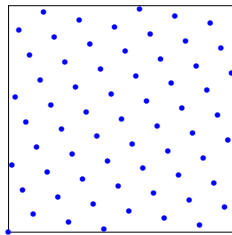
order of variables very important



64 random points



64 Sobol' points



64 lattice points

Covariance

$$r(\mathbf{x}, \mathbf{y}) = \sigma^2 \exp\left(-\|\mathbf{x} - \mathbf{y}\|_1/\lambda\right).$$

($\|\cdot\|_2$ similar).

Case 1	Case 2	Case 3	Case 4	Case 5
$\sigma^2 = 1$ $\lambda = 1$	$\sigma^2 = 1$ $\lambda = 0.3$	$\sigma^2 = 1$ $\lambda = 0.1$	$\sigma^2 = 3$ $\lambda = 1$	$\sigma^2 = 3$ $\lambda = 0.1$

FEM: Uniform grid $h = 1/m$ on $(0, 1)^2$, $M \sim m^2$.

Sampling: circulant embedding via FFT (dimension $s \geq 4M$)

High dimensional integration: QMC with N Sobol' points

Algorithm profile

Time (sec) for $N = 1000$, CASE 1:

percentages in red, orders in blue

m	s	Setup	InvN	FFT	AMG	TOT
33	4.1 (+3)	0.00	1.0 17	0.22 4	4.5 76	5.9
65	1.7 (+4)	0.01	3.9 17	1.2 5	16.5 75	22
129	6.6 (+4)	0.06	15 16	5.1 6	67 73	92
257	2.6 (+5)	0.15	62 16	31 8	290 73	400
513	1.0 (+6)	0.6	258 15	145 8	1280 73	1750
	m^2	m^2	m^2	$m^2 \log m$	$\sim m^2$	$\sim m^2$

InvN = Inversion of cumulative normal

AMG = Algebraic Multigrid = Fast system solver

Algorithm profile

Time (sec) for $N = 1000$, CASE 1:

percentages in red, orders in blue

m	s	Setup	InvN	FFT	AMG	TOT
33	4.1 (+3)	0.00	1.0 17	0.22 4	4.5 76	5.9
65	1.7 (+4)	0.01	3.9 17	1.2 5	16.5 75	22
129	6.6 (+4)	0.06	15 16	5.1 6	67 73	92
257	2.6 (+5)	0.15	62 16	31 8	290 73	400
513	1.0 (+6)	0.6	258 15	145 8	1280 73	1750
	m^2	m^2	m^2	$m^2 \log m$	$\sim m^2$	$\sim m^2$

InvN = Inversion of cumulative normal

AMG = Algebraic Multigrid = Fast system solver

One MFE solve with $513^2 = 2.6(+5)$ DOF takes ≈ 1.3 sec

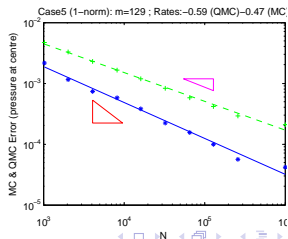
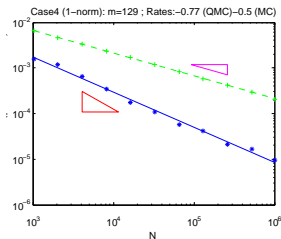
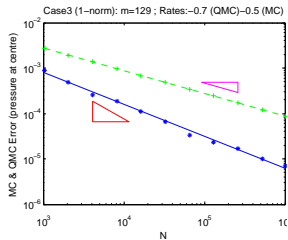
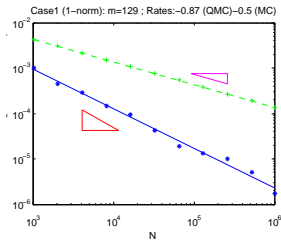
Standard deviation of mean pressure

16 random shifts used to estimate standard deviation.

Theorem: $\mathbb{E}[p_h(1/2, 1/2)] = \mathbb{E}[p(1/2, 1/2)]$ for all h .

No discretization error : good test for QMC

MC in green QMC in blue, Cases 1,3,4,5.

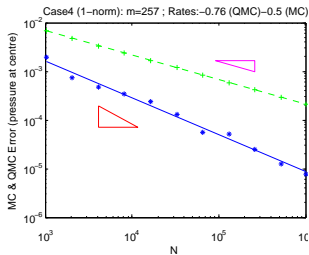
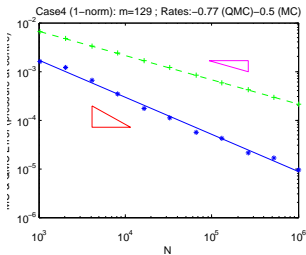
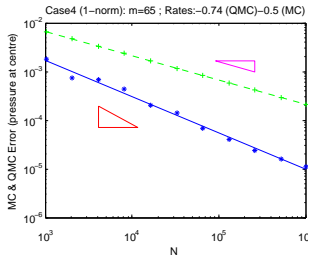
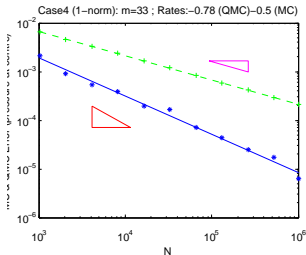


Dimension independence of QMC (and MC)

Standard deviation of mean pressure, Case 4:

as $m(= 1/h)$ (and hence s) increases

MC in green QMC in blue



Effective permeability k_{eff}

discretization error is present.

We estimated (by **linear regression**):

h needed to obtain a **discretization error** $< 10^{-3}$ ($< 2 \times 10^3$)

N needed to obtain (Q)MC error $< 0.5 \times 10^{-3}$ (10^{-3})
(95% confidence)

σ^2	λ	$1/h$	N (QMC)	N (MC)	CPU (QMC)	CPU (MC)
1	1	17	1.2(+5)	1.9(+7)	3 min	8 h
1	0.3	129	3.3(+4)	3.9(+6)	55 min	110 h
1	0.1	513	1.2(+4)	5.9(+5)	6.5 h	330 h
3	1	33	4.3(+6)	3.6(+8) *	9 h	750 h *
3	0.1	513	3.0(+4)	5.8(+5)	20 h	390 h

Smaller λ (lengthscale) needs smaller h but also smaller N .

Bigger σ^2 (variance) doesn't affect h but needs larger N

* extrapolated projections.

Strong superiority of QMC in all cases.

Here discretization error is more significant.

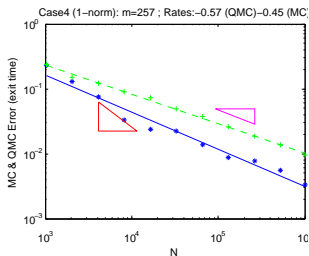
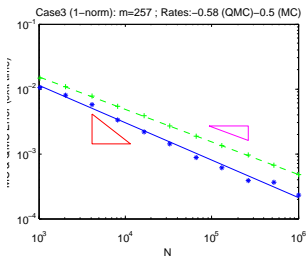
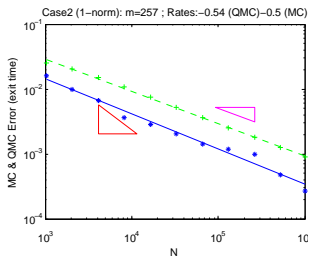
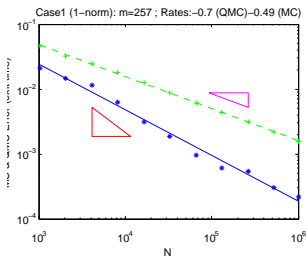
For **Cases 2 and 4** for discr. error $< 5 * (10^{-3})$ need $h = 1/65$

For statistical error $< 2.5 * 10^{-3}$ (95% confidence) need:

Case 2 $\sigma^2 = 1, \lambda = 0.3$ $N_{MC} = 5.2(+5)$ $N_{QMC} = 1.2(+5)$
speedup ≈ 4

Case 4 $\sigma^2 = 3, \lambda = 1$ $N_{MC} = 6.5(+7)$ $N_{QMC} = 4.3(+6)$
speedup ≈ 15

Breakthrough time, Cases 1-4



MC in green QMC in blue

QMC still superior but rate $1/N$ is now missing.

Recent progress on theory (brief)

Primal form (Dirichlet problem)

$$-\nabla \cdot k(\mathbf{x}, \omega) \nabla p = f \quad \text{on } D, \quad p = 0 \quad \text{on } \partial D .$$

- lognormal case: $k(\mathbf{x}, \omega) = \exp(Z(\mathbf{x}, \omega))$
 - piecewise linear FEM with quadrature: p_h
 - Linear functional $\mathcal{G}(p)$ $\mathcal{G}(p_h)$
 - Quantity of interest: $\mathbb{E}[\mathcal{G}(p)]$ $I_s(F)$
- where $F(\mathbf{y}) = \mathcal{G}(p_h(\cdot, \mathbf{y}))$
- Randomly shifted lattice rules $Q_{s,N}(\Delta, F)$
(with N points, defined next slide)

RMS Error $e_{h,N}^2 := \mathbb{E}^\Delta [|I_s(F) - Q_{s,N}(\Delta, F)|^2]$

Some QMC Theory (Lattice rules)

$$I_s(F) := \int_{\mathbb{R}^s} F(\mathbf{y}) \prod \phi(y_j) d\mathbf{y} = \int_{[0,1]^s} F(\Phi_s^{-1}(\mathbf{z})) d\mathbf{z}$$

$$Q_{s,N}(\Delta; F) := \frac{1}{N} \sum_{i=1}^N F \left(\Phi_s^{-1} \left(\text{frac} \left(\frac{i \mathbf{z}}{N} + \Delta \right) \right) \right)$$

generating vector: $\mathbf{z} \in \mathbb{N}^s$, $1 \leq z_j \leq N - 1$

random shift $\Delta \in [0, 1]^s$ **uniformly distributed.**

Weighted Sobolev norm: $\|F\|_{s,\gamma}^2 := \sum_{\mathbf{u} \subseteq \{1:s\}} \frac{1}{\gamma_{\mathbf{u}}} J_{\mathbf{u}}(F)^2$

where $J_{\mathbf{u}}(F)^2 =$

$$\int_{\mathbb{R}^{|\mathbf{u}|}} \left(\int_{\mathbb{R}^{s-|\mathbf{u}|}} \frac{\partial^{|\mathbf{u}|} F}{\partial \mathbf{y}_{\mathbf{u}}}(\mathbf{y}_{\mathbf{u}}; \mathbf{y}_{\{1:s\} \setminus \mathbf{u}}) \prod_{j \in \{1:s\} \setminus \mathbf{u}} \phi(y_j) d\mathbf{y}_{\{1:s\} \setminus \mathbf{u}} \right)^2 \prod_{j \in \mathbf{u}} \psi_j^2(y_j) d\mathbf{y}_{\mathbf{u}}$$

$\gamma_{\mathbf{u}}$ - **controls relative importance of the derivatives**

$\psi_j(y_j) = \exp(-\alpha_j |y_j|)$ - **controls behaviour as $|y_j| \rightarrow \infty$**

Theorem (Kuo and Nuyens FoCM 2015) Suppose $\|F\|_{s,\gamma} < \infty$. Then a generating vector $z \in \mathbb{N}^s$ can be constructed (efficiently) so that

$$\sqrt{\mathbb{E}^{\Delta} [|I_s(F) - Q_{s,N}(\Delta, F)|^2]} \leq 2 \left(\frac{1}{N}\right)^{1/2\lambda} C_s(\gamma, \alpha, \lambda) \|F\|_{s,\gamma} \quad (*)$$

for all $\lambda \in (1/2, 1]$. **So the next steps are ...**

- Estimate the derivatives $\partial^{|\mathbf{u}|} p_h / \partial \mathbf{y}_u$, **then derivatives of F**
- Then the norm $\|F\|_{s,\gamma}$.
- Choose γ_u and α_j to minimise the RHS of (*).
- RHS becomes $C(\lambda) \left(\frac{1}{N}\right)^{1/(2\lambda)}$, $C(\lambda)$ independent of s

provided.... eigenvalues of the circulant satisfy:

$$\sum_{j=1}^s \left(\frac{\lambda_j}{s}\right)^{\lambda/(1+\lambda)} \leq C \quad \text{for all } s.$$

Based on a heuristic for the Matérn family

Rates for the Matérn class

- Dimension independent rate $\mathcal{O}\left(\frac{1}{N^{-(1-\delta)}}\right)$ δ arbitrarily small, if $\nu > 2$.
- Dimension independent rate at least $\mathcal{O}\left(\frac{1}{N}\right)^{1/2}$ if $\nu > 1$

Heuristic assumes eigenvalues of the circulant approach eigenvalues of the corresponding periodic covariance integral operator.

Conclusion:

For Matérn parameter ν large enough, combined FE and QMC error:

$$\sqrt{\mathbb{E}^{\Delta} [|\mathbb{E}[\mathcal{G}(p)] - Q_{s,N}(\Delta, \mathcal{G}(p_h))|^2]} \leq C[h^2 + N^{-(1-\delta)}].$$

with δ arbitrarily close to 0 independent of dimension s .

Summary

- QMC improved on MC in all cases tested
- Speed up factors between 4 and 200.
- Can solve relatively hard problems of some interest in applications. Readily extends to 3D
- Rigorous analysis shows convergence up to $\mathcal{O}(h^2) + \mathcal{O}(1/N)$ independent of dimension.
- Theory contains some assumptions which have to be verified empirically.
- Constructing Sobol' sequences and lattice rules:
<http://web.maths.unsw.edu.au/~fkuo>
- Lots of recent work: **Multilevel and higher order methods** (Giles, Scheichl, Kuo, Schwab, Sloan, Dick,many others...)
- **The exponential covariance leaves open questions!**

Dimension independence of QMC (and MC)

Standard deviation of mean pressure, Case 4:

as $m(= 1/h)$ (and hence s) increases

MC in green QMC in blue

