

# Coupling network models with porous media equations

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in collaboration with

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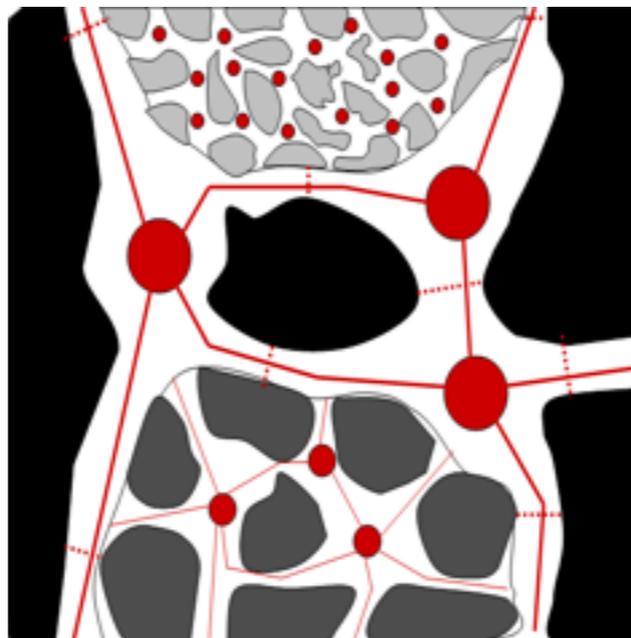
London Mathematical Society Durham Symposium  
Numerical Analysis of Multiscale Problems, July 5 - July 15, 2010

# Objectives

- Effective solution of a conservation law

$$\begin{aligned} \nabla \cdot F(P, \nabla P, x) &= h(x), \quad x_L < x < x_R & \frac{\partial S}{\partial t} + \mathbf{v} \cdot \nabla g(S) &= h_w \\ F(x_L) &= P_L, F(x_R) = P_R \end{aligned}$$

- Upscaling very large (nonlinear) network models



# Conservation law at continuum

$$\nabla \cdot F(P, \nabla P, x) = h(x)$$

$$F(P, 0, x) \equiv 0$$

E.g. linear flux:  $F = -k(x)\nabla P$

$$k(x, \frac{x}{\epsilon}; \omega)$$

$$k_{\text{hom}}(x)$$

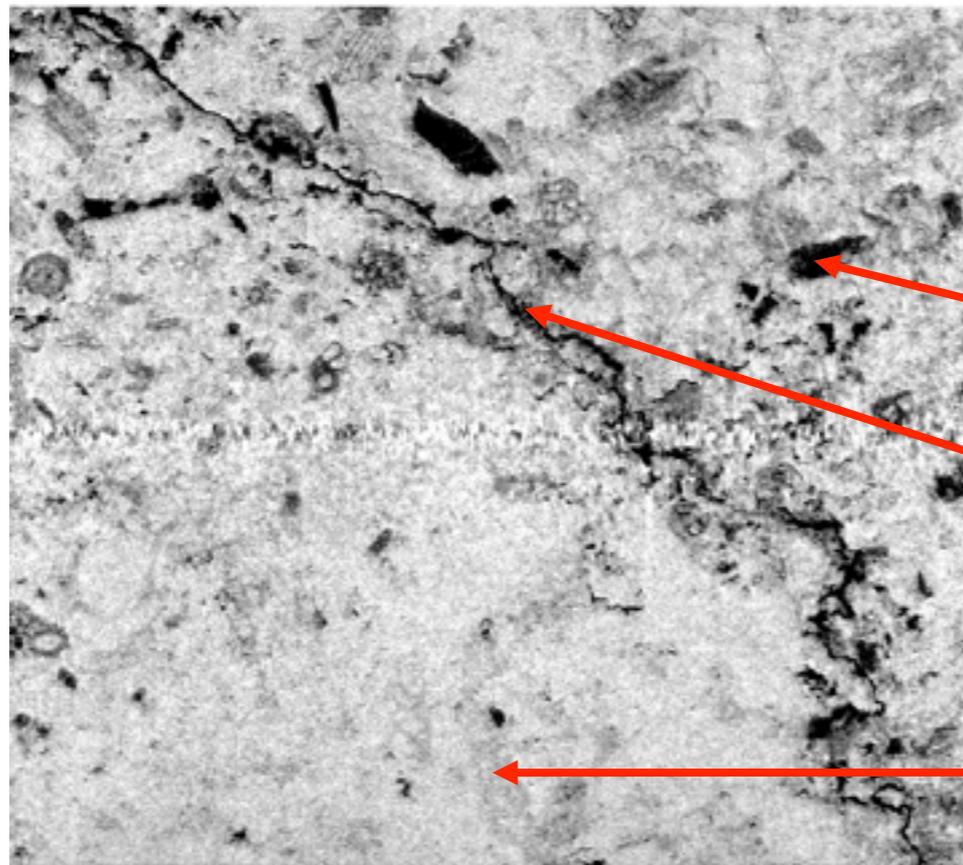
effective flux

numerical homogenization:

multiscale finite element methods, dual-porosity method

Effective flux of a pore scale network model.

# Challenges from heterogeneous media



Many such media are of economic interest (oil and gas), but heterogeneity makes predictions difficult.

(macro-)pores

fracture

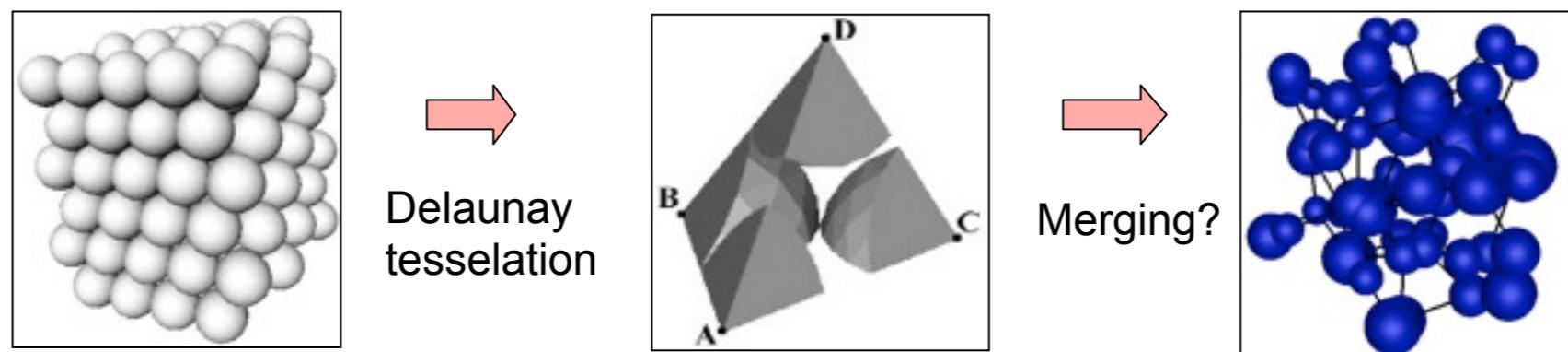
Micro-porous regions  
(everywhere else)

Naturally fractured carbonate,  $dx = 3.1\mu m$

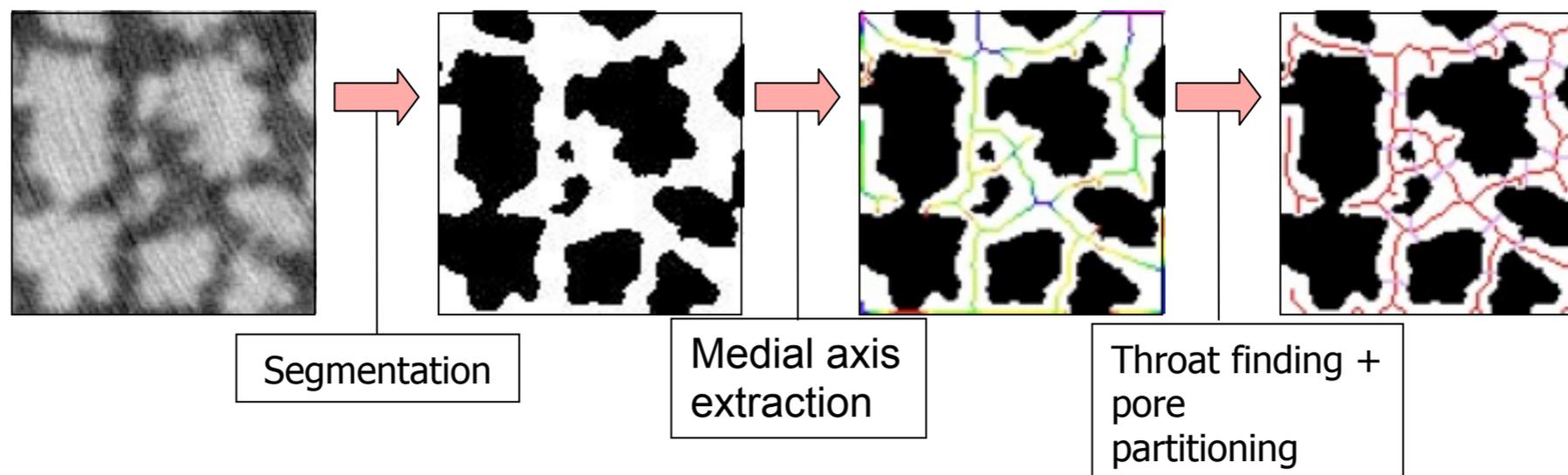
Image courtesy of M. Knackstedt & R. Sok, Australian Nat'l Univ.

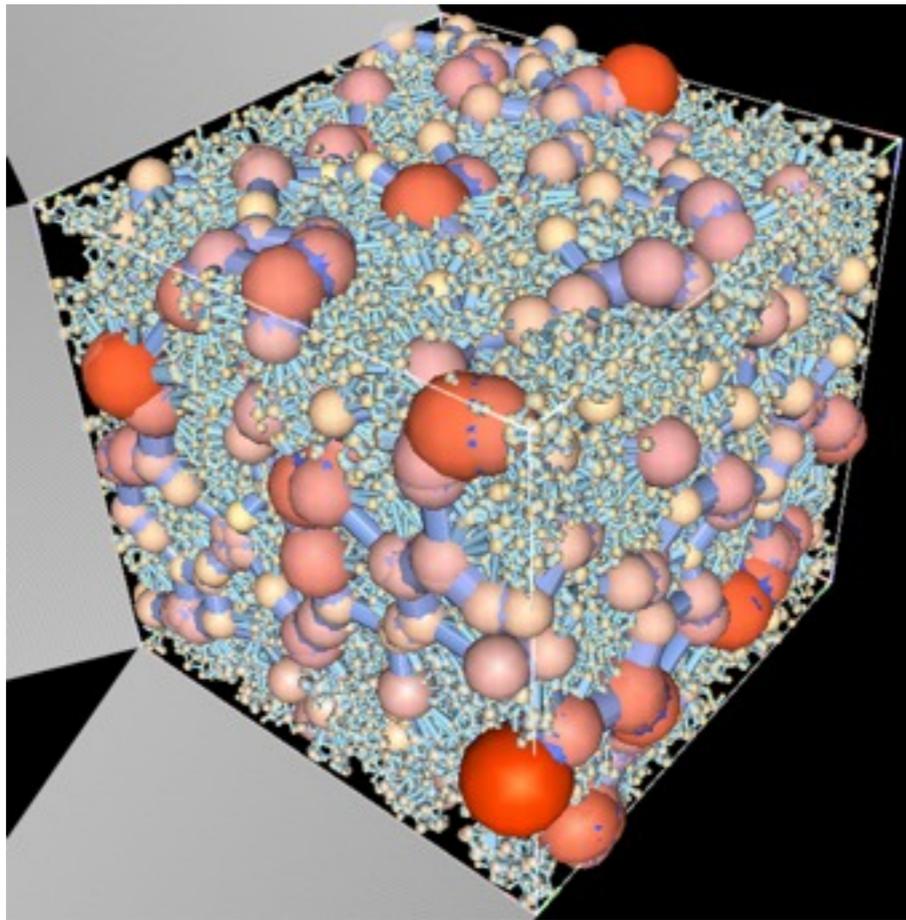
# Obtaining network models

## Model/granular media

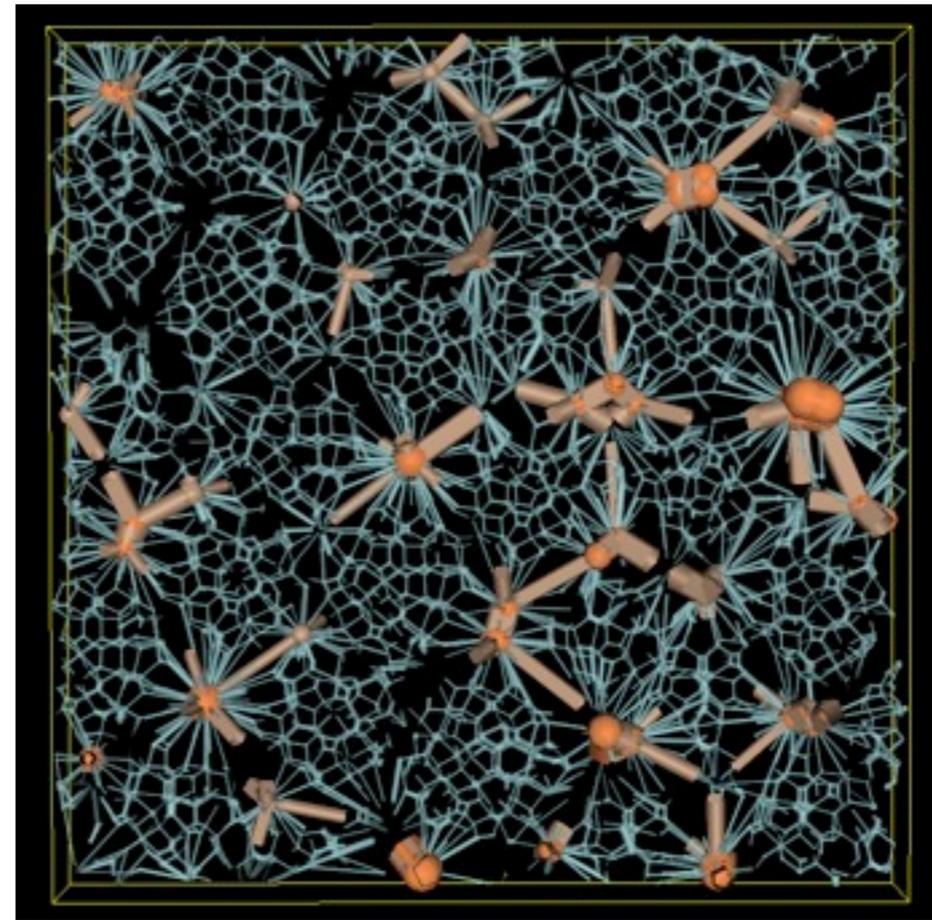


## Imaged / real media





76673 pores and 166853 throats

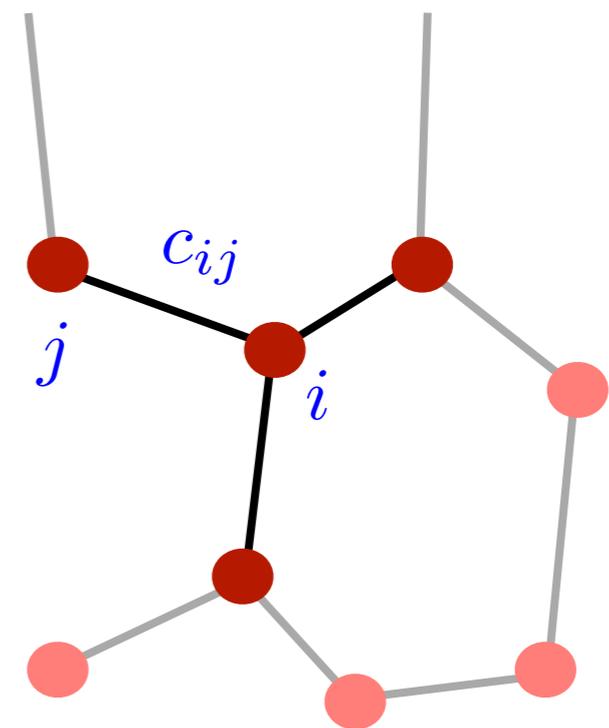
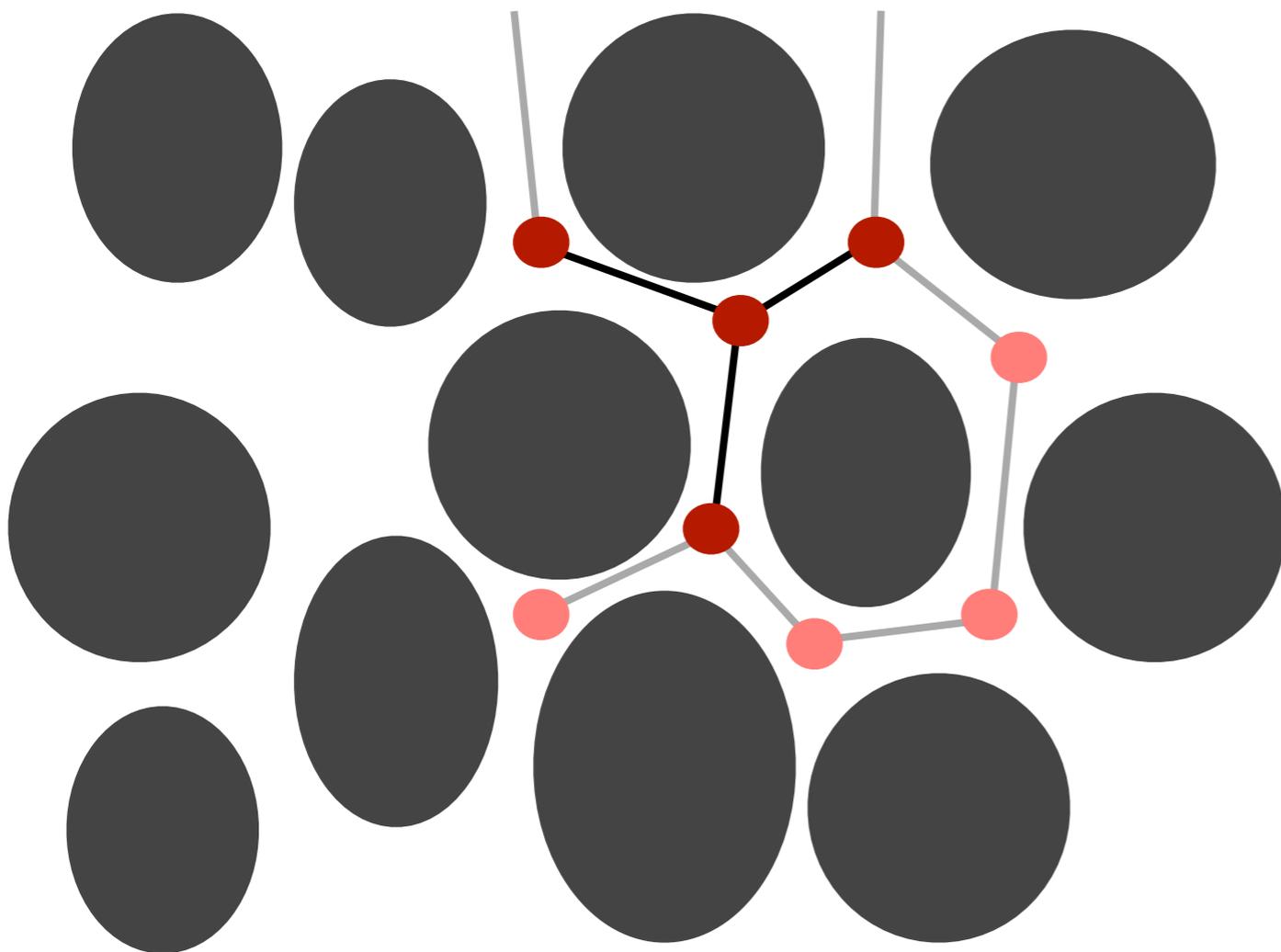


Top view of a slice through 3D network

# Pore scale network model

conductance:

$$c_{ij} = c(x_i, p_i, p_j)$$



conservation of mass:

$$\sum_{j \in \text{Nbr}(i)} c_{ij} (p_j - p_i) = 0$$

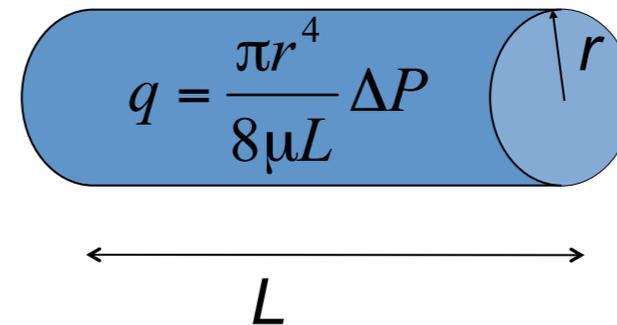
# Conductance

- Conductance contains the physics and geometry
- Newtonian fluid of viscosity  $\mu$  in a tube

$$C_p = b$$

Properties of linear networks:

- positive conductance
- invertibility
- maximum principle



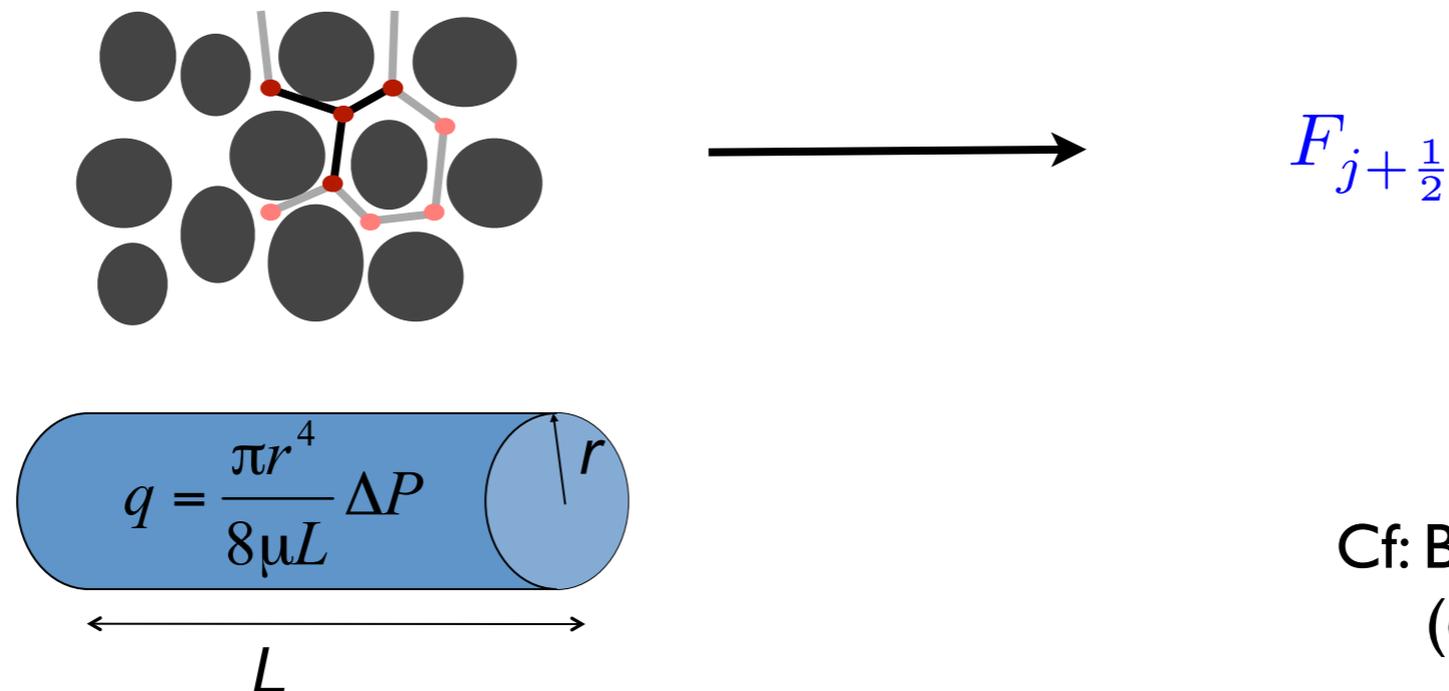
$q$ : discharge of fluid

# Coupling under HMM

- Finite volume discretization for the PDE

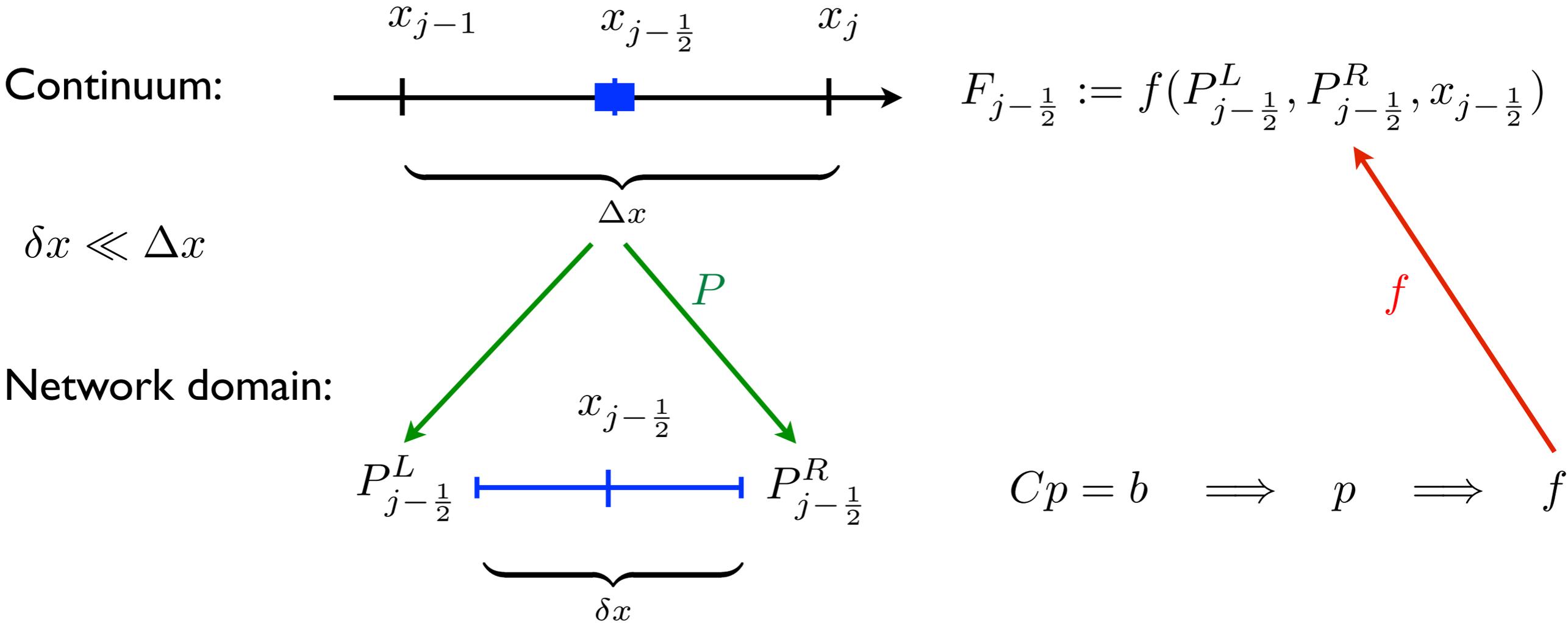
$$\nabla \cdot F(P, \nabla P, x) = h(x), \quad x_L < x < x_R \quad F_{j+\frac{1}{2}} - F_{j-\frac{1}{2}} = \Delta x h(x_j)$$
$$F(x_L) = P_L, F(x_R) = P_R$$

- Flux evaluated by small-size network simulations



Cf: Balhoff et al. 2007  
(domain decomp.)

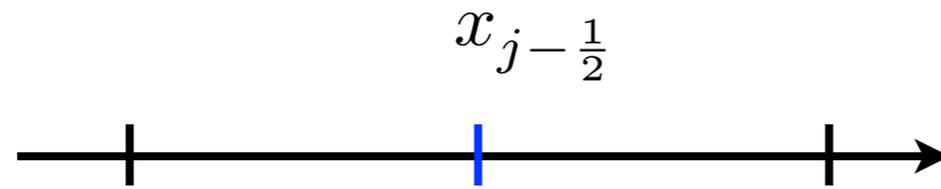
# Coupling



Need to recover the effective pressure field  $P$ .

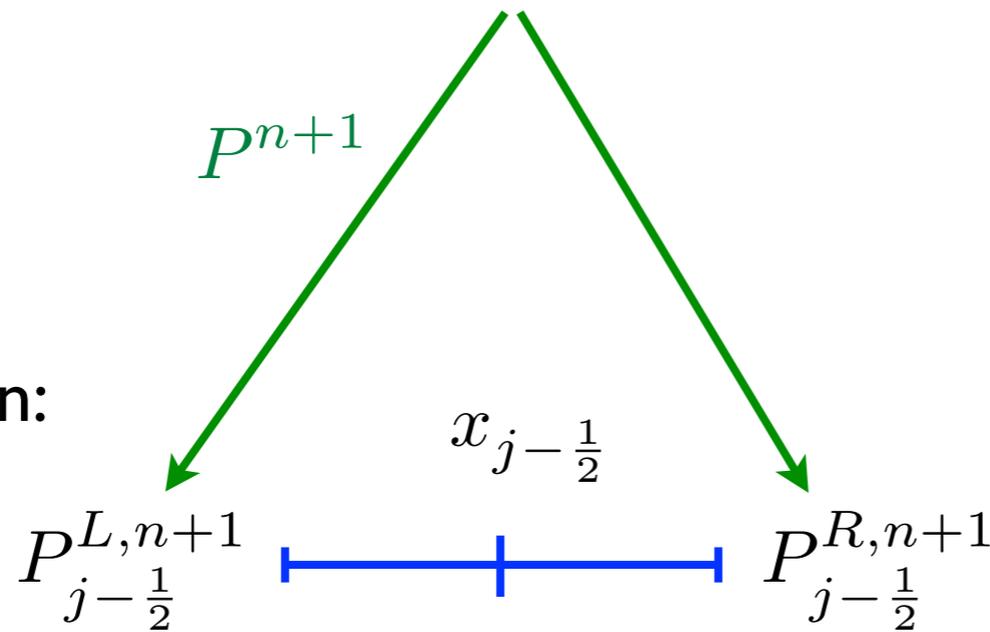
# Macro-micro iterations

Continuum:



$$F_{j-\frac{1}{2}}^{n+1} := f^{n+1} \approx K^n \frac{P_j^{n+1} - P_{j-1}^{n+1}}{\Delta x}$$

Network domain:



$$K^n := \frac{F^n}{\Delta P^n} \Delta x$$

$$f = \sum \sum f_{ij}$$

$$C^{n+1} p^{n+1} = b^{n+1}$$

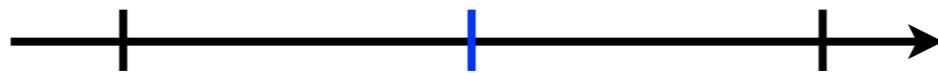
$$f_{ij} = -c_{ij} (p_i + p_j) (p_i - p_j)$$

# Macro-micro iterations

$$\mathbf{P}^{n+1} := \mathbf{P}^n - \Delta x^2 (\mathbf{K}^n)^{-1} G(\mathbf{P}^n)$$

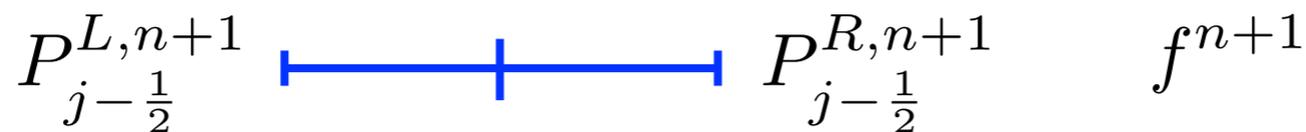
$$G(\mathbf{P}) := (D_0 F_j - h_j)^T$$

Continuum:



$$f = F_{j-\frac{1}{2}}^{n+1} \simeq K^n \frac{P_j^{n+1} - P_{j-1}^{n+1}}{\Delta x} \quad K^n := \frac{F^n}{\Delta P^n} \Delta x$$

Network domain:



# Properties of the scheme

$$\mathbf{P}^{n+1} := \mathbf{P}^n - \Delta x^2 (\mathbf{K}^n)^{-1} G(\mathbf{P}^n)$$

- Iterations converge under suitable conditions

$$\frac{\partial G}{\partial \mathbf{P}} = \frac{1}{\Delta x^2} (\mathbf{K} + \mathbf{A})$$

- **Linear network:**  $\mathbf{A} := 0$

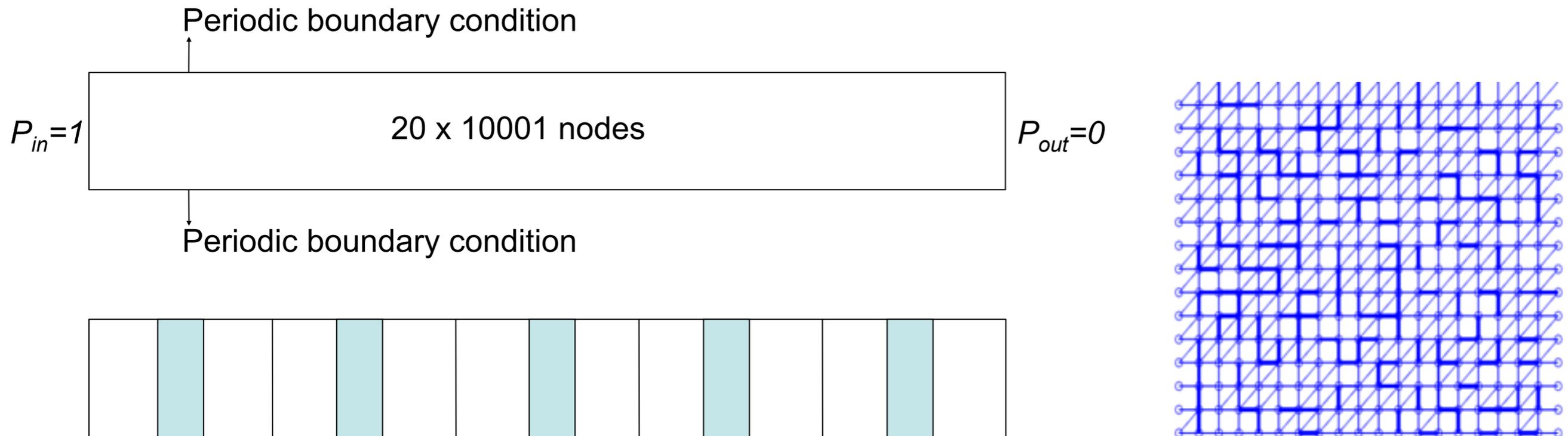
Newton's method and converges in 1 step.

- **Nonlinear network:**  $\mathbf{A} := \left( (D^- P_{j-1}) \frac{\partial K_{j-1/2}}{\partial P_k} - (D^- P_j) \frac{\partial K_{j+1/2}}{\partial P_k} \right)$

Quasi-Newton style iterations.

Convergence under some conditions.

# Simulation setup



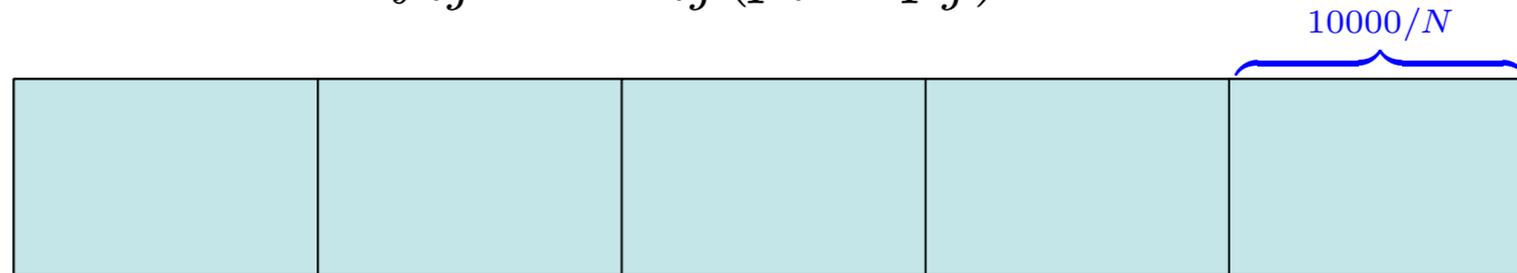
- The conductance  $c_{ij}$  is randomly distributed from (0, 1000) with uniform distribution.
- Compare the pressure and the flux from [full sampling](#) and [partial sampling](#) with results from the [direct numerical simulation](#) using the full system.

Error averaged over 100 different random conductance.

# Linear network model

$$f_{ij} = -c_{ij}(p_i - p_j)$$

Full sampling



	$N = 5$	$N = 10$	$N = 20$	$N = 50$
Error in pressure	0.0008	0.0014	0.0022	0.0041
Error in flux	0.0048	0.0111	0.0235	0.0620

Partial sampling



Error in pressure

	$M = 40$	$M = 100$	$M = 200$	$M = 400$
$N = 3$	0.0567	0.0273	0.0188	0.0117
$N = 5$	0.0688	0.0370	0.0218	0.0122
$N = 10$	0.1454	0.0442	0.0257	0.0158

Error in flux

	$M = 40$	$M = 100$	$M = 200$	$M = 400$
$N = 1$	0.0760	0.0514	0.0299	0.0170
$N = 3$	0.1226	0.0513	0.0334	0.0192
$N = 5$	0.2111	0.0685	0.0374	0.0214
$N = 10$	0.6638	0.1347	0.0571	0.0277

# Nonlinear network model I

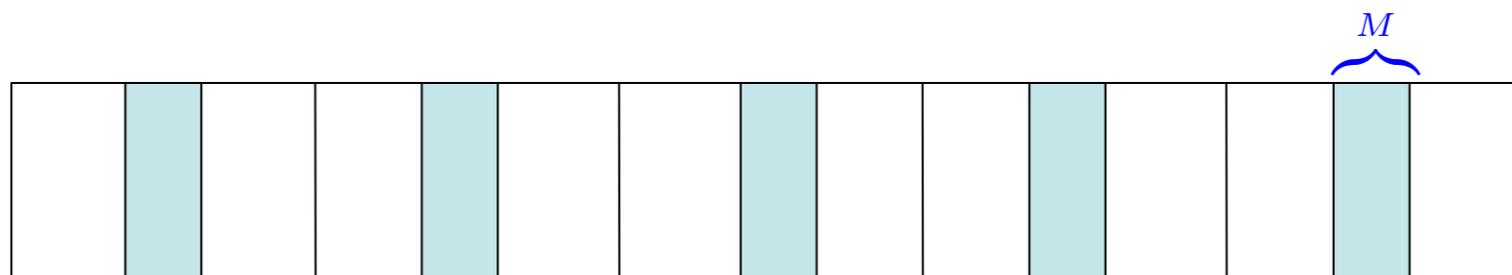
$$f_{ij} = -c_{ij}(p_i + p_j)(p_i - p_j)$$

Full sampling



	$N = 5$	$N = 10$	$N = 20$	$N = 50$
Error in pressure	0.0005	0.0009	0.0016	0.0032
Error in flux	0.0036	0.0082	0.0177	0.0473

Partial sampling



Error in pressure

	$M = 40$	$M = 100$	$M = 200$	$M = 400$
$N = 3$	0.0373	0.0184	0.0116	0.0072
$N = 5$	0.0532	0.0253	0.0176	0.0093
$N = 10$	0.1076	0.0365	0.0207	0.0118

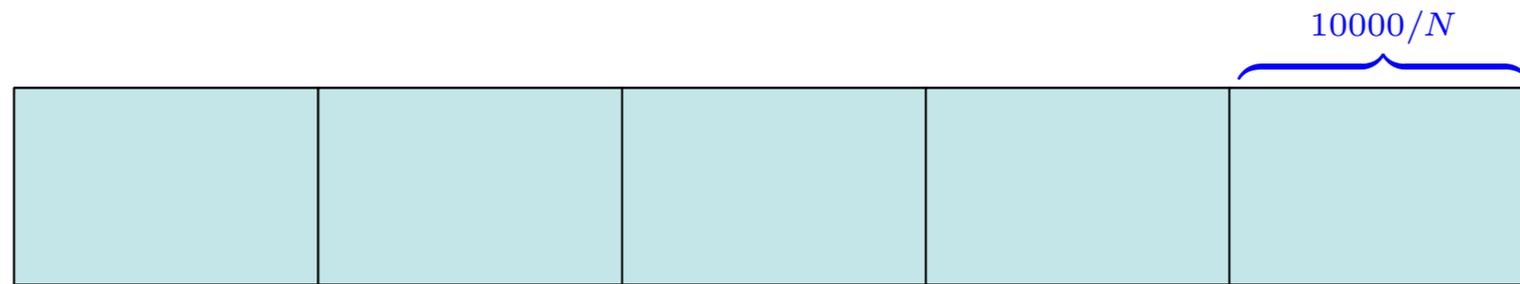
Error in flux

	$M = 40$	$M = 100$	$M = 200$	$M = 400$
$N = 1$	0.0661	0.0370	0.0244	0.0173
$N = 3$	0.0987	0.0382	0.0258	0.0140
$N = 5$	0.1358	0.0560	0.0308	0.0168
$N = 10$	0.4330	0.1048	0.0470	0.0242

# Nonlinear network model II

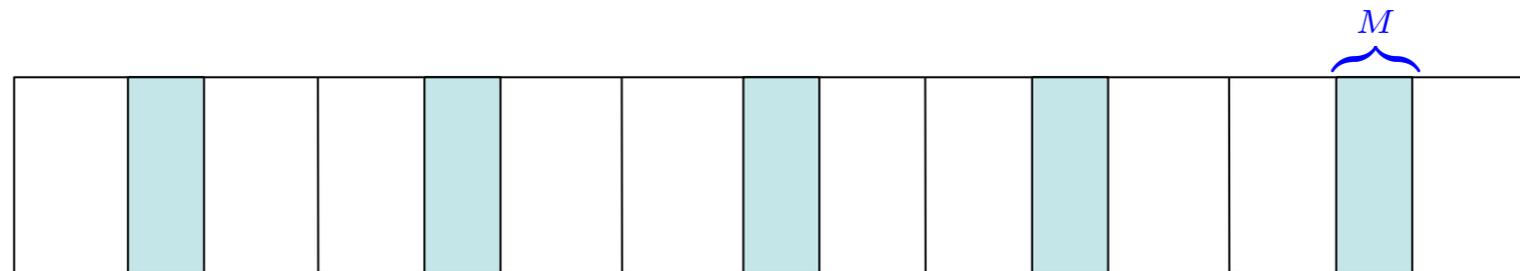
$$f_{ij} = -(c_{ij} + \beta c_{ij}^2 |p_i - p_j|)(p_i - p_j) \quad (\text{The Forchheimer equation})$$

Full sampling



	$N = 5$	$N = 10$	$N = 20$	$N = 50$
Error in pressure	0.0007	0.0012	0.0021	0.0039
Error in flux	0.0047	0.0108	0.0235	0.0626

Partial sampling



Error in pressure

	$M = 40$	$M = 100$	$M = 200$	$M = 400$
$N = 3$	0.0481	0.0274	0.0176	0.0101
$N = 5$	0.0695	0.0332	0.0213	0.0118
$N = 10$	0.1474	0.0442	0.0259	0.0150

Error in flux

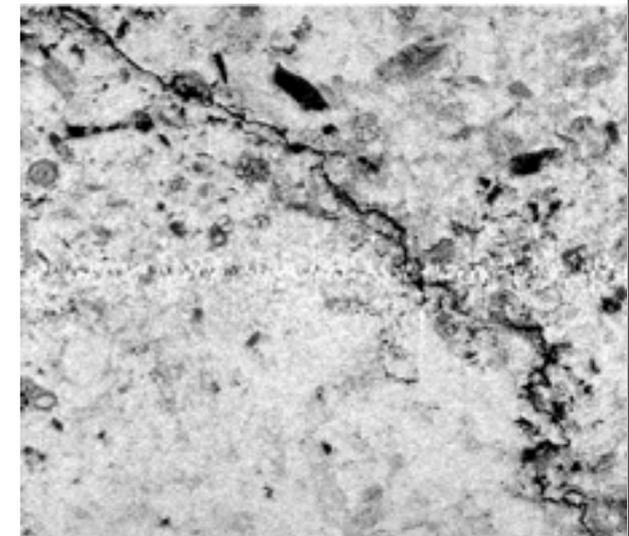
	$M = 40$	$M = 100$	$M = 200$	$M = 400$
$N = 1$	0.0749	0.0474	0.0298	0.0184
$N = 3$	0.1424	0.0602	0.0373	0.0209
$N = 5$	0.2133	0.0795	0.0403	0.0203
$N = 10$	0.7410	0.1524	0.0657	0.0296

# Further macro-micro interaction

- Fluid pressure causes the **formation of new crack/fracture**.
- Formation of new fracture allows the **fluid to enter and extend the crack further**.
- Fracture is represented as throats with very high conductance.
- Iterations:

**micro:** given network conductance and boundary pressure)  
solve network pressure --> **update network conductance** -->  
solve network pressure

**Macro:** (update continuum model) & update pressure

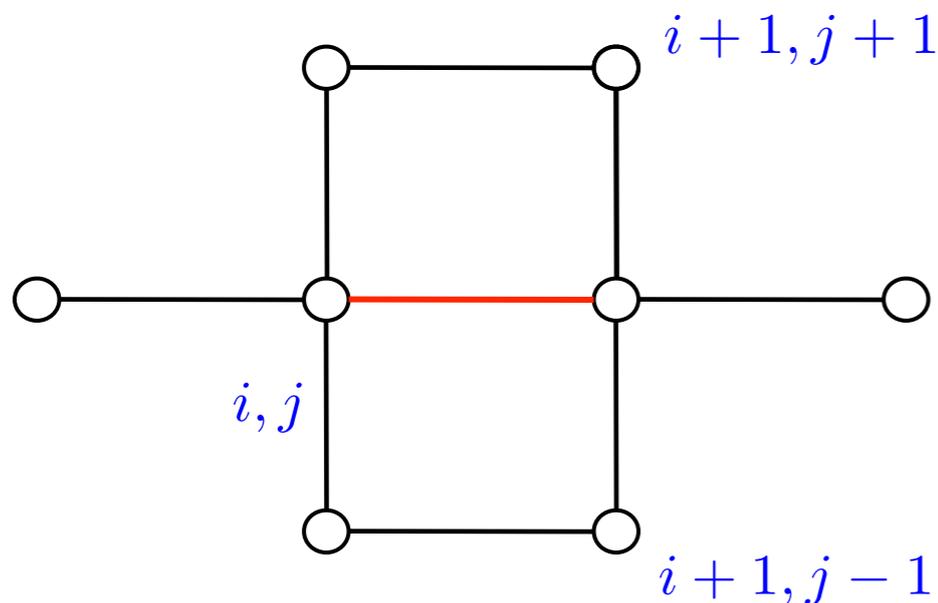


# Conductance and stress

Conductance increases (i.e. crack propagates) if  $G = K_I^2 + K_{II}^2 \geq G_C$ .

$$K_I = C_I \sigma_N \quad K_{II} = C_{II} (|\sigma_T| - \mu |\sigma_N|)$$

Estimate the normal and tangential stresses ( $\sigma_N$  and  $\sigma_T$ ) by local pressure.



$$\sigma_N \approx p_{i+\frac{1}{2}, j+1} - 2 p_{i+\frac{1}{2}, j} + p_{i+\frac{1}{2}, j-1}$$

$$\sigma_T \approx |(p_{i+1, j+1} - p_{i, j+1}) - (p_{i+1, j-1} - p_{i, j-1})|$$

Compute stresses in similar fashion by suitable projections in non-cartesian network models.

Reference: T. Reuschle (1998), Yuan and Harrison (2006)

# Simulation result

Memory effect:  $c_{ij}^{n,m+1} = \max(c_{ij}^{n,m}, c_{frac})$

Simulation domain : 21 x 100 nodes.

Initial conductance is 1 or 1000 (red dot).

$G_C$  (critical crack extension force) is randomly distributed: i.e. some throats open more easily

# Summary

- New collaborative work in progress. A lot more work to be done.
- The proposed scheme (**multiscale, domain decomposition, subsampling**) produces reasonable approximations for linear and nonlinear fluxes defined by uniformly distributed random conductance.
- Local stress computation may be used to capture hydraulic fracturing behavior.

Thank you for your attention.

# 1D periodic case

The network is 1 x 1001 linear model and the conductance  $c_i$  is given by

$$c_i = \frac{1.1 + \cos(x/\epsilon)}{1.1 + \sin(x/\epsilon)},$$

where  $x = 2\pi i/1000$ . Partially sampling is used: 1, 3, 5, 8 blocks with 10, 20, ..., 90, 100 nodes in each sampling domain.

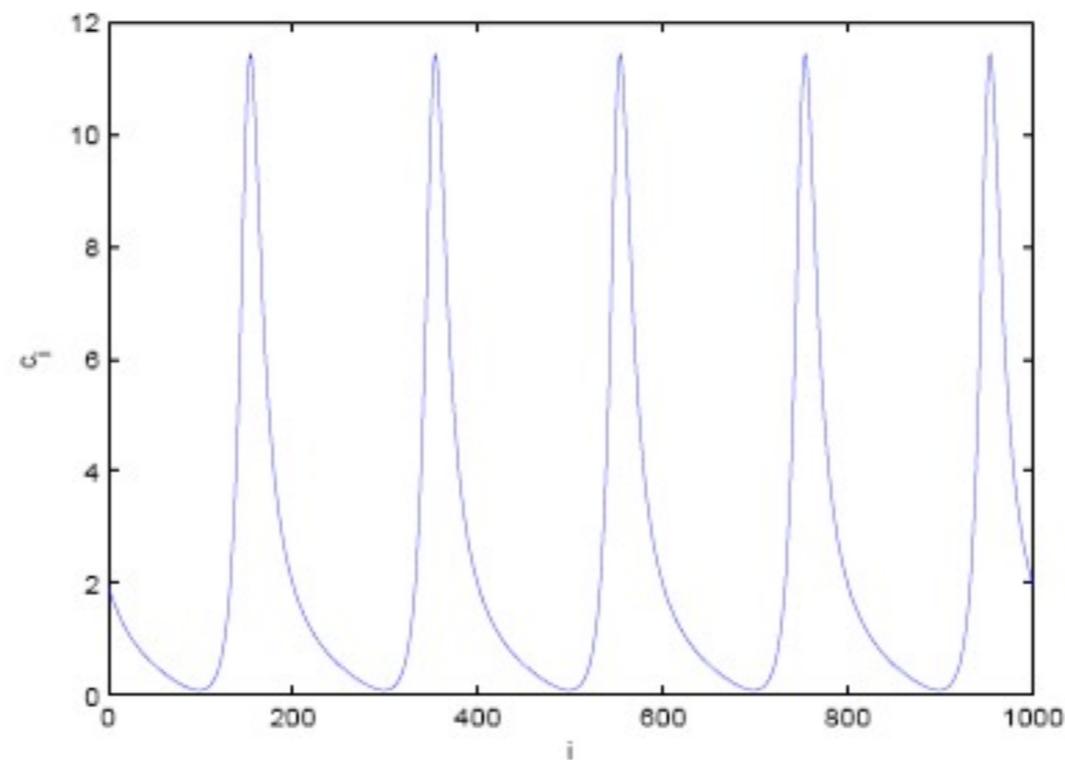
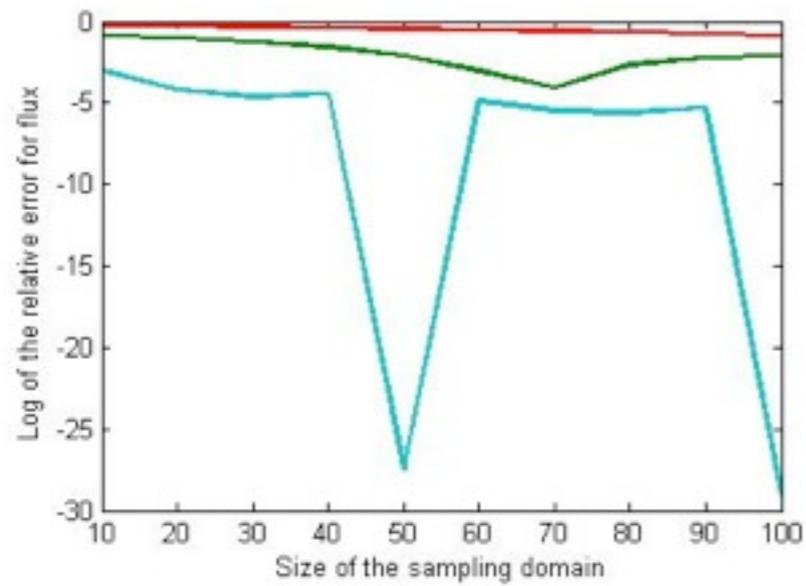
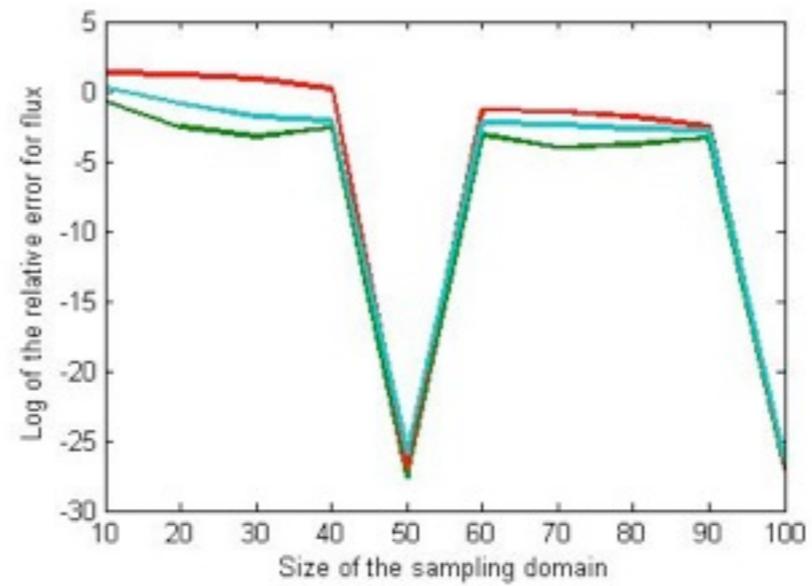


Figure 1: Illustration of  $c_i$  with  $\epsilon = 1/5$ .

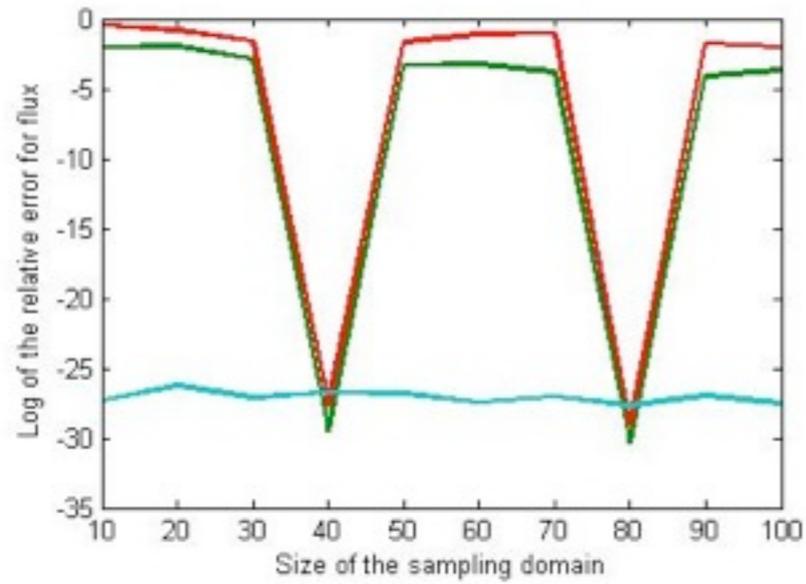
$\epsilon = 0.2$



$\epsilon = 0.05$



$\epsilon = 0.04$



$\epsilon = 0.025$

