

# Uncertainty Quantification Methods for Multiscale Modeling and Dimension Reduction

Nathan L. Gibson

Associate Professor  
Department of Mathematics



OSU Mathematics Colloquium  
November 9, 2020

## 1 Polynomial Chaos for Multiscale Modeling

- Dispersive Maxwell System
- Maxwell-Random Lorentz System
- Viscoelastic Materials
- Magnetohydrodynamics

## 2 Karhunen-Loève for Dimension Reduction

- Reservoir Operations
- Power Grid
- Tsunami Loading

# Outline

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# Maxwell's Equations

$$\frac{\partial \mathbf{B}}{\partial t} + \nabla \times \mathbf{E} = \mathbf{0}, \text{ in } (0, T) \times \mathcal{D} \quad (\text{Faraday})$$

$$\frac{\partial \mathbf{D}}{\partial t} + \mathbf{J} - \nabla \times \mathbf{H} = \mathbf{0}, \text{ in } (0, T) \times \mathcal{D} \quad (\text{Ampere})$$

$$\nabla \cdot \mathbf{D} = \nabla \cdot \mathbf{B} = 0, \text{ in } (0, T) \times \mathcal{D} \quad (\text{Poisson/Gauss})$$

$$\mathbf{E}(0, \mathbf{x}) = \mathbf{E}_0; \mathbf{H}(0, \mathbf{x}) = \mathbf{H}_0, \text{ in } \mathcal{D} \quad (\text{Initial})$$

$$\mathbf{E} \times \mathbf{n} = \mathbf{0}, \text{ on } (0, T) \times \partial \mathcal{D} \quad (\text{Boundary})$$

$\mathbf{E} =$  Electric field vector

$\mathbf{D} =$  Electric flux density

$\mathbf{H} =$  Magnetic field vector

$\mathbf{B} =$  Magnetic flux density

$\mathbf{J} =$  Current density

$\mathbf{n} =$  Unit outward normal to  $\partial \mathcal{D}$

# Constitutive Laws

$$\mathbf{D} = \epsilon \mathbf{E} + \mathbf{P}$$

$$\mathbf{B} = \mu \mathbf{H} + \mathbf{M}$$

$$\mathbf{J} = \sigma \mathbf{E} + \mathbf{J}_s$$

$\mathbf{P}$  = Polarization       $\epsilon$  = Electric permittivity

$\mathbf{M}$  = Magnetization       $\mu$  = Magnetic permeability

$\mathbf{J}_s$  = Source Current       $\sigma$  = Electric Conductivity

where  $\epsilon = \epsilon_0 \epsilon_\infty$  and  $\mu = \mu_0 \mu_r$ .

## Polarization

The **polarization** is defined as the average dipole moment in a material.

- For linear materials we can define  $\mathbf{P}$  in terms of a convolution with  $\mathbf{E}$

$$\mathbf{P}(t, \mathbf{x}) = g * \mathbf{E}(t, \mathbf{x}) = \int_0^t g(t-s, \mathbf{x}; \mathbf{q}) \mathbf{E}(s, \mathbf{x}) ds,$$

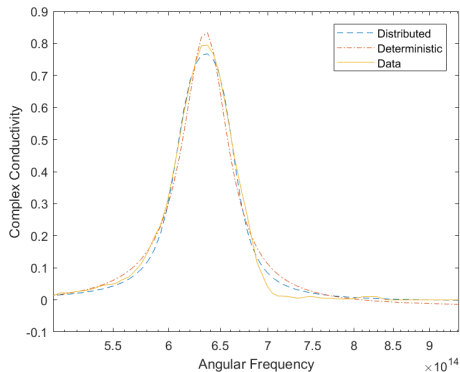
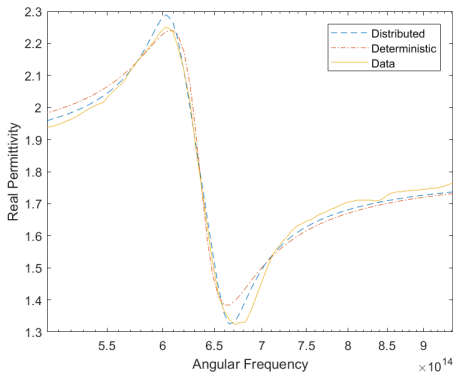
where  $g$  is the **dielectric response function** (DRF) and  $\mathbf{q}$  is a vector which contains all of the necessary dielectric parameters for a model.

- In the frequency domain

$$\hat{\mathbf{D}} = \epsilon \hat{\mathbf{E}} + \hat{\mathbf{g}} \hat{\mathbf{E}} = \epsilon_0 \epsilon(\omega) \hat{\mathbf{E}},$$

where  $\epsilon(\omega)$  is called the **complex permittivity**.

## Saltwater Data



**Figure:** Fits for single-pole, saltwater data [Query et al., 1972]<sup>1</sup>

<sup>1</sup>J. Alvarez, A. Fisher, **N. L. Gibson**, "Approximating Dispersive Materials With Parameter Distributions in the Lorentz Model", Applied Mathematics, Modeling and Computational Science 2019 Proceedings, 11 pages. *To appear*.



## Relaxation Polarization Models

$$\mathbf{P}(t, \mathbf{x}) = g * \mathbf{E}(t, \mathbf{x}) = \int_0^t g(t-s, \mathbf{x}; \mathbf{q}) \mathbf{E}(s, \mathbf{x}) ds,$$

- Debye model [1913]  $\mathbf{q} = [\epsilon_\infty, \epsilon_d, \tau]$

$$g(t, \mathbf{x}) = \epsilon_0 \epsilon_d / \tau e^{-t/\tau}$$

$$\text{or } \tau \dot{\mathbf{P}} + \mathbf{P} = \epsilon_0 \epsilon_d \mathbf{E}$$

$$\text{or } \epsilon(\omega) = \epsilon_\infty + \frac{\epsilon_d}{1 + i\omega\tau}$$

with  $\epsilon_d := \epsilon_s - \epsilon_\infty$  and  $\tau$  a relaxation time.

- Cole-Cole model [1941] (heuristic generalization)

$$\mathbf{q} = [\epsilon_\infty, \epsilon_d, \tau, \alpha]$$

$$\epsilon(\omega) = \epsilon_\infty + \frac{\epsilon_d}{1 + (i\omega\tau)^\alpha}$$

## Polynomial Chaos for Random Debye

- 1 The Cole-Cole model corresponds to a fractional order ODE in the time-domain and is difficult to simulate.
- 2 Debye is efficient to simulate, but does not represent permittivity well.
- 3 We showed<sup>2</sup> that applying Polynomial Chaos to the **Random Debye** model preserves the efficiency of Debye with the fidelity of Cole-Cole.
- 4 Stability estimates for the continuous and discrete system were shown, and dispersion analyses were performed.
- 5 The inverse problem for the distribution of parameters was also addressed. <sup>3</sup>

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<sup>2</sup>**N. L. Gibson**, “Polynomial Chaos for Dispersive Electromagnetics”, Communications in Computational Physics, 18 (5), 1234–1263, 2015.

<sup>3</sup>M. Armentrout and **N. L. Gibson**, “Electromagnetic Relaxation Time Distribution Inverse Problems in the Time-Domain”, Proceedings, WAVES 2011, 245–248, 2011.

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## Lorentz Polarization Model

**Lorentz model** in Auxiliary Differential Equation (ADE) form:

$$\ddot{\mathbf{P}} + 2\nu\dot{\mathbf{P}} + \omega_0^2\mathbf{P} = \epsilon_0\omega_p^2\mathbf{E}$$

where  $\omega_0$  is the resonant frequency,  $\nu$  is a damping coefficient, and  $\omega_p$  is referred to as a plasma frequency.

Taking a Fourier transform of  $\mathbf{D} = \epsilon\mathbf{E} + \mathbf{P}$ , we get

$$\epsilon(\omega) = \epsilon_\infty + \frac{\omega_p^2}{\omega_0^2 - \omega^2 - i2\nu\omega}$$

with  $\mathbf{q} = [\epsilon_\infty, \omega_0, \nu, \omega_p]$ .

## Distributions of Parameters

To account for the effect of distributions of parameters  $\mathbf{q}$  in a polarization model, consider the following *polydispersive* DRF

$$h(t, \mathbf{x}; F) = \int_{\mathcal{Q}} g(t, \mathbf{x}; \mathbf{q}) dF(\mathbf{q}),$$

where  $\mathcal{Q}$  is some admissible set and  $F \in \mathfrak{P}(\mathcal{Q})$ .

Then the polarization becomes:

$$\mathbf{P}(t, \mathbf{x}; F) = \int_0^t h(t-s, \mathbf{x}; F) \mathbf{E}(s, \mathbf{x}) ds.$$

Alternatively we can define the **random polarization**  $\mathcal{P}(t, \mathbf{x}; \mathbf{q})$  to satisfy

$$\mathcal{P} = g(t, \mathbf{x}; \mathbf{q}) * \mathbf{E}$$

but with  $\mathbf{q}$  random; the **macroscopic polarization** is then taken to be the expected value of the random polarization,

$$\mathbf{P}(t, \mathbf{x}; F) = \int_{\mathcal{Q}} \mathcal{P}(t, \mathbf{x}; \mathbf{q}) dF(\mathbf{q}).$$

## Random Lorentz Polarization

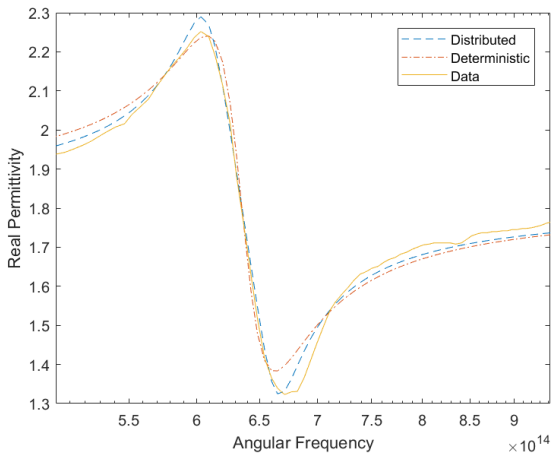
We allow the parameter  $\omega_0^2$  be a random variable with probability distribution  $F$  on the interval  $(a, b)$ . Then the **random Lorentz model** in ADE form is

$$\ddot{\mathcal{P}} + 2\nu\dot{\mathcal{P}} + \omega_0^2\mathcal{P} = \epsilon_0\omega_p^2 E$$

The **macroscopic polarization** is then taken to be the expected value of the random polarization,

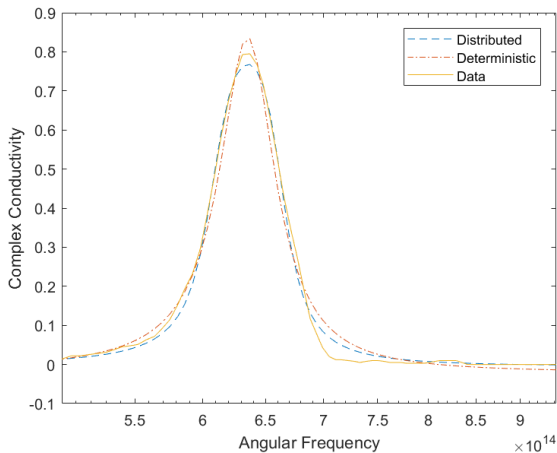
$$\mathbf{P}(t, \mathbf{x}) = \int_a^b \mathcal{P}(t, \mathbf{x}; \omega_0^2) dF(\omega_0^2).$$

## Saltwater Data



**Figure:** Real part of  $\epsilon(\omega)$  fits for single-pole, saltwater data [1].

# Saltwater Data



**Figure:** Imaginary part of  $\epsilon(\omega)/\omega$ , fits for single-pole, saltwater data [1].



## Maxwell-Random Lorentz system

Combining with Maxwell's equations, we have

$$\mu_0 \frac{\partial \mathbf{H}}{\partial t} = -\nabla \times \mathbf{E} \quad (1a)$$

$$\epsilon_0 \epsilon_\infty \frac{\partial \mathbf{E}}{\partial t} = \nabla \times \mathbf{H} - \frac{\partial \mathbf{P}}{\partial t} \quad (1b)$$

$$\ddot{\mathbf{P}} + 2\nu \dot{\mathbf{P}} + \omega_0^2 \mathbf{P} = \epsilon_0 \omega_p^2 \mathbf{E} \quad (1c)$$

with

$$\mathbf{P}(t, \mathbf{x}) = \int_a^b \mathcal{P}(t, \mathbf{x}; \omega_0^2) f(\omega_0^2) d\omega_0^2.$$

## 2D Maxwell-Random Lorentz Transverse Electric (TE) curl equations

$$\mu_0 \frac{\partial H}{\partial t} = -\text{curl } \mathbf{E}, \quad (2a)$$

$$\epsilon_0 \epsilon_\infty \frac{\partial \mathbf{E}}{\partial t} = \text{curl } H - \mathbf{J}, \quad (2b)$$

$$\frac{\partial \mathcal{P}}{\partial t} = \mathcal{J} \quad (2c)$$

$$\frac{\partial \mathcal{J}}{\partial t} = -2\nu \mathcal{J} - \omega_0^2 \mathcal{P} + \epsilon_0 \omega_p^2 \mathbf{E} \quad (2d)$$

where  $\mathbf{E} = (E_x, E_y)^T$ ,  $\mathbf{J} = (J_x, J_y)^T = \mathbb{E}[\mathcal{J}]$ ,  $\mathcal{J} = (\mathcal{J}_x, \mathcal{J}_y)^T$ ,  $\mathcal{P} = (\mathcal{P}_x, \mathcal{P}_y)^T$  and  $H = H_z$ .

Note  $\text{curl } \mathbf{U} = \frac{\partial U_y}{\partial x} - \frac{\partial U_x}{\partial y}$  and  $\text{curl } V = \left( \frac{\partial V}{\partial y}, -\frac{\partial V}{\partial x} \right)^T$ .

We introduce the random Hilbert space  $V_F = (L^2(\Omega) \otimes L^2(\mathcal{D}))^2$  equipped with an inner product and norm as follows

$$(\mathbf{u}, \mathbf{v})_F = \mathbb{E}[(\mathbf{u}, \mathbf{v})_2],$$

$$\|\mathbf{u}\|_F^2 = \mathbb{E}[\|\mathbf{u}\|_2^2].$$

The weak formulation of the **2D Maxwell-Random Lorentz TE** system is

$$\left( \mu_0 \frac{\partial H}{\partial t}, \mathbf{v} \right)_2 = (-\text{curl } \mathbf{E}, \mathbf{v})_2 \quad (3a)$$

$$\left( \epsilon_0 \epsilon_\infty \frac{\partial \mathbf{E}}{\partial t}, \mathbf{u} \right)_2 = (\text{curl } H, \mathbf{u})_2 - (\mathbf{J}, \mathbf{u})_2 \quad (3b)$$

$$\left( \frac{\partial \mathcal{P}}{\partial t}, \mathbf{q} \right)_F = (\mathcal{J}, \mathbf{q})_F \quad (3c)$$

$$\left( \frac{\partial \mathcal{J}}{\partial t}, \mathbf{w} \right)_F = (-2\nu \mathcal{J}, \mathbf{w})_F + (-\omega_0^2 \mathcal{P}, \mathbf{w})_F + (\epsilon_0 \omega_p^2 \mathbf{E}, \mathbf{w})_F. \quad (3d)$$

for  $v \in L^2(\mathcal{D})$ ,  $\mathbf{u} \in H_0(\text{curl}, \mathcal{D})^2$ , and  $\mathbf{q}, \mathbf{w} \in V_F$ .

We have the following result<sup>4</sup>

### Theorem (Stability of Maxwell-Random Lorentz)

Let  $\mathcal{D} \subset \mathbb{R}^2$  and suppose that  $\mathbf{E} \in C(0, T; H_0(\text{curl}, \mathcal{D})) \cap C^1(0, T; (L^2(\mathcal{D}))^2)$ ,  $\mathcal{P}, \mathcal{J} \in C^1(0, T; (L^2(\Omega) \otimes L^2(\mathcal{D}))^2)$ , and  $H(t) \in C^1(0, T; L^2(\mathcal{D}))$  are solutions of the weak formulation for the Maxwell-Random Lorentz system along with PEC boundary conditions. Then the system exhibits energy decay

$$\mathcal{E}(t) \leq \mathcal{E}(0) \quad \forall t \geq 0,$$

where the energy  $\mathcal{E}(t)$  is defined as

$$\mathcal{E}(t)^2 = \left\| \sqrt{\mu_0} H(t) \right\|_2^2 + \left\| \sqrt{\epsilon_0 \epsilon_\infty} \mathbf{E}(t) \right\|_2^2 + \left\| \sqrt{\frac{\omega_0^2}{\epsilon_0 \omega_p^2}} \mathcal{P}(t) \right\|_F^2 + \left\| \frac{1}{\sqrt{\epsilon_0 \omega_p^2}} \mathcal{J}(t) \right\|_F^2$$

where  $\|u\|_F^2 = \mathbb{E}[\|u\|_2^2]$  and  $\mathcal{J} := \frac{\partial \mathcal{P}}{\partial t}$ .

<sup>4</sup>A. Fisher, J. Alvarez, **N. L. Gibson**, "Analysis of Methods for the Maxwell-Random Lorentz Model", Results in Applied Mathematics, vol. 8, 1–17, 2020.

**Proof: (for 2D)**

By choosing  $\nu = H$ ,  $\mathbf{u} = \mathbf{E}$ ,  $\mathbf{q} = \mathcal{P}$  and  $\mathbf{w} = \mathcal{J}$  in the weak form, and adding all equations into the time derivative of the definition of  $\mathcal{E}^2$ , we obtain

$$\begin{aligned} \frac{1}{2} \frac{d\mathcal{E}^2(t)}{dt} &= - \left( \operatorname{curl} \mathbf{E}, H \right)_2 + \left( H, \operatorname{curl} \mathbf{E} \right)_2 - \left( \mathbf{J}, \mathbf{E} \right)_2 + \left( \frac{\omega_0^2}{\epsilon_0 \omega_p^2} \mathcal{J}, \mathcal{P} \right)_F \\ &\quad - \left( \frac{2\nu}{\epsilon_0 \omega_p^2} \mathcal{J}, \mathcal{J} \right)_F - \left( \frac{\omega_0^2}{\epsilon_0 \omega_p^2} \mathcal{P}, \mathcal{J} \right)_F + \left( \mathbf{E}, \mathcal{J} \right)_F \\ &= - \left\| \sqrt{\frac{2\nu}{\epsilon_0 \omega_p^2}} \mathcal{J} \right\|_F^2 \end{aligned}$$

$$\frac{d\mathcal{E}(t)}{dt} = \frac{-1}{\mathcal{E}(t)} \left\| \sqrt{\frac{2\nu}{\epsilon_0 \omega_p^2}} \mathcal{J} \right\|_F^2 \leq 0.$$



## Polynomial Chaos

Let  $\omega_0^2 = r\xi + m$  and  $\xi \in [-1, 1]$ . Suppressing the dimension of  $\mathcal{P}$  and the spatial dependence, we have

$$\mathcal{P}(\xi, t) = \sum_{i=0}^{\infty} \alpha_i(t) \phi_i(\xi) \rightarrow \ddot{\mathcal{P}} + 2\nu\dot{\mathcal{P}} + (r\xi + m)\mathcal{P} = \epsilon_0\omega_p^2 E.$$

Utilizing the Triple Recursion Relation for orthogonal polynomials:

$$\xi\phi_n(\xi) = a_n\phi_{n+1}(\xi) + b_n\phi_n(\xi) + c_n\phi_{n-1}(\xi),$$

the differential equation becomes

$$\sum_{i=0}^{\infty} [\ddot{\alpha}_i(t) + 2\nu\dot{\alpha}_i(t) + m\alpha_i(t)] \phi_i + r\alpha_i(t) [a_i\phi_{i+1} + b_i\phi_i + c_i\phi_{i-1}] = \epsilon_0\omega_p^2 E\phi_0.$$

## Galerkin Projection

We apply a Galerkin Projection onto the space of polynomials of degree at most  $p$  to get:

$$\ddot{\vec{\alpha}} + 2\nu\dot{\vec{\alpha}} + A\vec{\alpha} = \vec{f}$$

where  $\vec{f} = \hat{e}_1 \epsilon_0 \omega_p^2 E$  and

$$A = rM + ml, \quad M = \begin{pmatrix} b_0 & c_1 & 0 & \cdots & 0 \\ a_0 & b_1 & c_2 & & \vdots \\ 0 & \ddots & \ddots & \ddots & 0 \\ \vdots & & a_{p-2} & b_{b-1} & c_p \\ 0 & \cdots & 0 & a_{p-1} & b_p \end{pmatrix}.$$

Or we can write as a first order system:

$$\begin{aligned} \dot{\vec{\alpha}} &= \vec{\beta} \\ \dot{\vec{\beta}} &= -A\vec{\alpha} - 2\nu\vec{\beta} + \vec{f}. \end{aligned}$$

## Theorem (Energy Decay for Maxwell-PC Lorentz-FDTD)

If the *CFL condition* is satisfied, then the Yee scheme for the 2D TE mode Maxwell-Polynomial Chaos-Lorentz system satisfies the discrete identity

$$\delta_t \mathcal{E}_h^{n+\frac{1}{2}} = \frac{-1}{\mathcal{E}_h^{n+\frac{1}{2}}} \left\| \sqrt{\frac{2\nu}{\epsilon_0 \omega_p^2}} \vec{\beta}^{n+\frac{1}{2}} \right\|_\alpha^2$$

for all  $n$  where

$$\mathcal{E}_h^n = \left( \mu_0 (H^{n+\frac{1}{2}}, H^{n-\frac{1}{2}})_H + \|\sqrt{\epsilon_0 \epsilon_\infty} \mathbf{E}^n\|_E^2 + \left\| \frac{A^{1/2}}{\sqrt{\epsilon_0 \omega_p^2}} \vec{\alpha}^n \right\|_\alpha^2 + \left\| \sqrt{\frac{1}{\epsilon_0 \omega_p^2}} \vec{\beta}^n \right\|_\alpha^2 \right)^{1/2}$$

defines a discrete energy.

Note that  $\|\vec{\alpha}\|_\alpha^2 \approx \|\mathbb{E}[\mathcal{P}]\|_2^2 + \|\text{StdDev}(\mathcal{P})\|_2^2 = \mathbb{E}[\|\mathcal{P}\|_2^2] = \|\mathcal{P}\|_F^2$  so that this is a natural extension of the Maxwell-Random Lorentz energy.<sup>4</sup>

<sup>4</sup>A. Fisher, J. Alvarez, **N. L. Gibson**, "Analysis of Methods for the Maxwell-Random Lorentz Model", Results in Applied Mathematics, vol. 8, 1–17, 2020.



## Theorem

The *discrete dispersion relation* for the Maxwell-PC FDTD Lorentz scheme is given by

$$\frac{\omega_{\Delta}^2}{c^2} \epsilon_{\Delta}(\omega) = K_{\Delta}^2$$

where the *discrete expected complex permittivity* is given by

$$\epsilon_{\Delta}(\omega) := \epsilon_{\infty} + \omega_{p,\Delta}^2 \hat{e}_1^T (A_{\Delta} - \omega_{\Delta}^2 I - i2\nu_{\Delta} \omega_{\Delta} I)^{-1} \hat{e}_1$$

and the *discrete wavenumber* and quantity  $K_{\Delta}$  are given by

$$k_{\Delta} := \sqrt{k_{x,\Delta}^2 + k_{y,\Delta}^2}, \quad K_{\Delta} := \sqrt{K_{x,\Delta}^2 + K_{y,\Delta}^2},$$

with

$$K_{x,\Delta} := \frac{2}{\Delta x} \sin\left(\frac{k_{x,\Delta} \Delta x}{2}\right), \quad K_{y,\Delta} := \frac{2}{\Delta y} \sin\left(\frac{k_{y,\Delta} \Delta y}{2}\right) \dots$$

## Theorem (Continued)

and the *discrete PC matrix* and *discrete damping* are given by

$$A_{\Delta} := \cos^2(\omega\Delta t/2)A, \quad \nu_{\Delta} := \cos\left(\frac{\omega\Delta t}{2}\right)\nu.$$

Similarly,

$$\omega_{\Delta} := \frac{2}{\Delta t} \sin\left(\frac{\omega\Delta t}{2}\right), \quad \omega_{p,\Delta} := \cos\left(\frac{\omega\Delta t}{2}\right)\omega_p.$$

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## PC for Viscoelastic Volterra Kernels

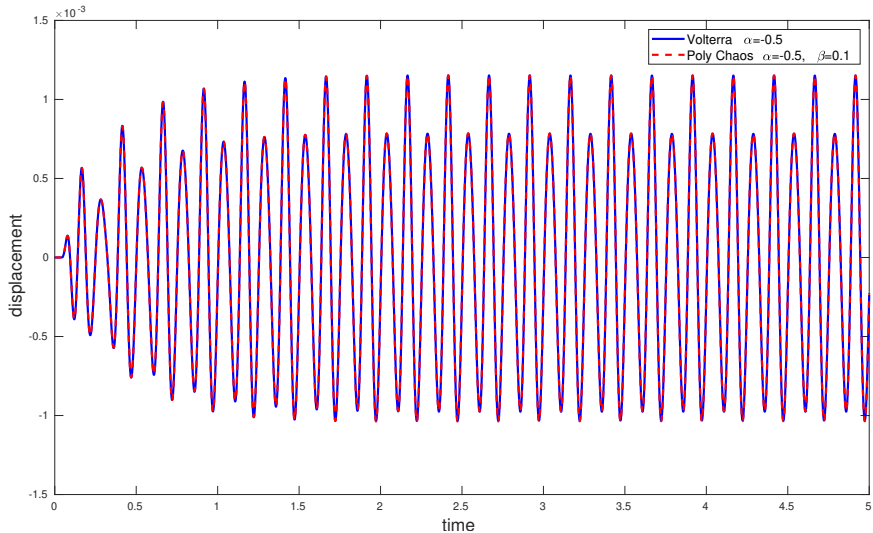
The shear stress,  $\sigma$ , in a linear viscoelastic body is given as the following functional of shear strain,  $\varepsilon$ :

$$\sigma(t) = \mu(t)\varepsilon(0) + \int_0^t \mu(t-s)\dot{\varepsilon}(s) ds \quad (5)$$

where  $\mu$  is a stress relaxation function, often of exponential form. However, many real materials can be observed to relax slower than exponentially. For this reason a *power law* dependence is often preferred wherein  $\mu(t) = \mu_0 t^{-\alpha}$  for  $\mu_0 > 0$  and  $\alpha \in (0, 1)$ . The disadvantage with this is that there is no local form of an ADE, the entire past history must be preserved when simulating. <sup>5</sup>

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<sup>5</sup>**N. L. Gibson** and S. Shaw, “Polynomial Chaos for Viscoelastic Volterra Kernels”, in *preparation*.



**Figure:** Comparison of simulations of power law Volterra kernel vs continuous spectrum with Polynomial Chaos.

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# Magnetohydrodynamics (MHD)

MHD = Maxwell + Navier-Stokes

## Collaborators

- Rigel Woodside, NETL Albany
- Duncan McGregor, ORISE Fellow, 9/2014–6/2016
- Evan Rajbhandari, ORISE Fellow, 7/2020–6/2022
- Vrushali Bokil (PI), NSF-DMS Computational Mathematics, 8/1/2020–7/31/2022

## PC for Hall MHD

Ohm's Law becomes

$$\mathbf{J} = \sigma(\mathbf{E} + \mathbf{u} \times \mathbf{B}) + \beta_e(\mathbf{J} \times \mathbf{B})$$

where  $\mathbf{u}$  is the velocity, and  $\beta_e = \omega_e \tau_e$  is the Hall parameter.

$$\mathbf{J} = \bar{\sigma}(\mathbf{E} + \mathbf{u} \times \mathbf{B}),$$

where

$$\bar{\sigma} = \sigma \begin{bmatrix} \frac{1}{1+\omega_e^2 \tau_e^2} & \frac{-\omega_e \tau_e}{1+\omega_e^2 \tau_e^2} & 0 \\ \frac{\omega_e \tau_e}{1+\omega_e^2 \tau_e^2} & \frac{1}{1+\omega_e^2 \tau_e^2} & 0 \\ 0 & 0 & 1 \end{bmatrix}$$

Compare to

$$\epsilon(\omega) = \epsilon_\infty + \epsilon_d \frac{1}{1 + \omega^2 \tau^2} + \epsilon_d \frac{\omega \tau}{1 + \omega^2 \tau^2} \mathbf{i}.$$



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## Acknowledgments

- Co-PI, Bonneville Power Administration (BPA) Technology Innovation Program, “Towards reduction of uncertainty in the operation of reservoir systems”, with Arturo Leon (PI, Civil Engineering) and Christopher Hoyle (Co-PI, Mechanical Engineering), 10/2012–9/2015, \$665,593.
- Co-PI, BPA Technology Innovation Program, “Framework for Quantification of Risk and Valuation of Flexibility in the FCRPS”, with Arturo Leon (PI, Civil Engineering), Christopher Hoyle (Co-PI, Mechanical Engineering), Claudio Fuentes (Co-PI, Statistics), Yong Chen (Co-PI, Applied Economics), 10/2015–5/2018, \$1.2M.

# Reservoir Operations

The broad context of the problem of interest is a PDE-constrained optimal control problem with uncertainty. In particular, one must

- maximize revenue (minimize cost to the consumer)
- minimize ecological violations
- meet electrical demand with hydro-power production
- at least 9 other constraints

## Simulation of Unsteady Flows

- Most free surface flows are unsteady and nonuniform.
- Unsteady flows in river systems are most efficiently simulated using 1D models.

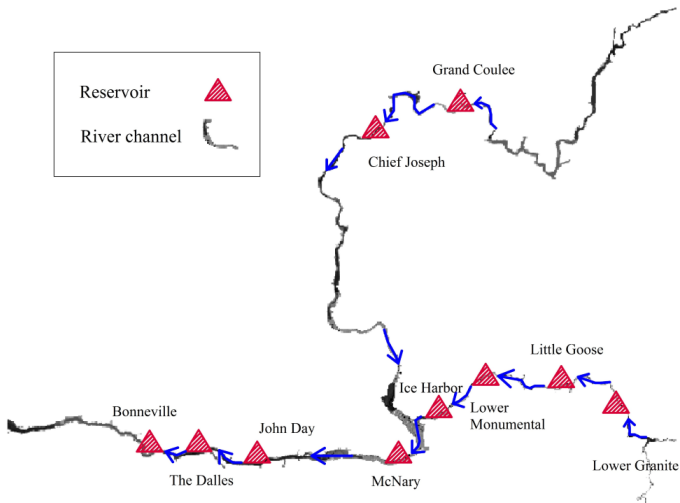
**Saint-Venant equations:** PDEs representing conservation of mass and momentum for a control volume:

$$B \frac{\partial y}{\partial t} + \frac{\partial Q}{\partial x} = 0, \quad (6)$$

$$\frac{\partial Q}{\partial t} + \frac{\partial}{\partial x} \left( \frac{Q^2}{A} \right) + gA \left( \frac{\partial y}{\partial x} + S_f - S_0 \right) = 0, \quad (7)$$

where  $x$  is a distance along the channel in the longitudinal direction,  $t$  is time,  $y$  is a water depth,  $Q$  is a flow discharge,  $B$  is a width of the channel,  $g$  is an acceleration due to gravity,  $A$  is a cross-sectional area of the flow,  $S_f$  is a friction slope,  $S_0$  is a river bed slope. Initial, boundary and interface conditions are required to close the system.

# Big 10 Columbia River System



**Unknowns:** flow discharges  $Q_i$  for  $i = 1, \dots, 10$ .

## Dimension Reduction

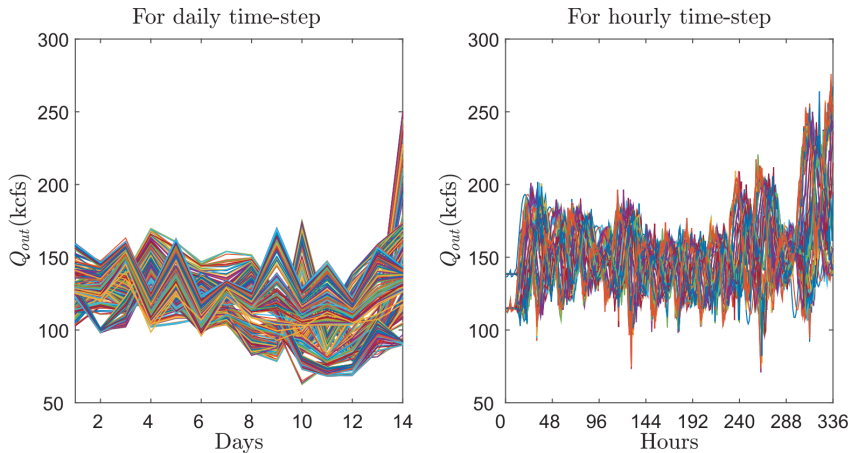
- Simulations are required to be two weeks in duration.
- Solving for decision variables on each time step (daily or hourly) is computationally impractical.
- We wish to construct a reduced dimensional basis for the decisions.
- Fortunately there exist years worth of data.
- We solve only for the optimal coefficients of an expansion in this basis (Spectral Optimization Method<sup>6</sup>).
- Specifically, we construct a truncated Karhunen-Loeve (KL) expansion (or PCA) using the historical solutions

$$Q(t_j, \vec{\xi}) = \bar{Q}(t_j) + \sum_{k=1}^M \sqrt{\lambda_k} \psi_k(t_j) \xi_k$$

and optimize over  $\xi_k, k = 1 \dots M$ .

<sup>6</sup>D. Chen, A. S. Leon, **N. L. Gibson**, P. Hosseini, "Dimension reduction of decision variables for multi-reservoir operation: A spectral optimization model", Water Resources Research, 52 (1), 36–51, 2016.

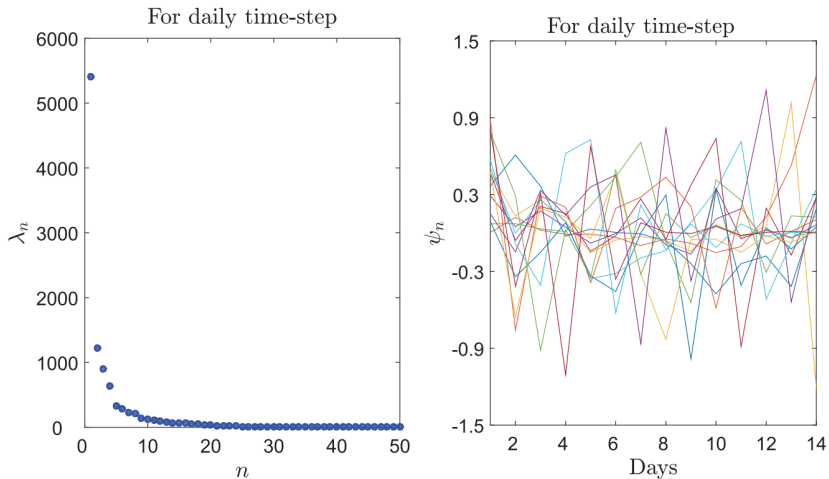
# Grand Coulee outflows



**Figure:** Synthetic data for outflows at Grand Coulee.

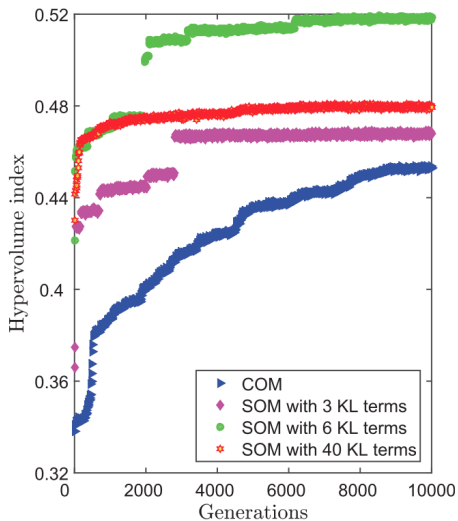


# Grand Coulee KL Expansion



**Figure:** Eigenvalues and eigenvectors of the covariance matrix for Grand Coulee.

# Optimization Results



**Figure:** Goodness of multi-objective optimization results with various reduced dimension decision spaces.

# Outline

## 1 Polynomial Chaos for Multiscale Modeling

- Dispersive Maxwell System
- Maxwell-Random Lorentz System
- Viscoelastic Materials
- Magnetohydrodynamics

## 2 Karhunen-Loève for Dimension Reduction

- Reservoir Operations
- Power Grid
- Tsunami Loading

## Probabilistic Load Flow (PLF) problem

- A load flow analysis tests the reliability of the power grid under various supply and demand scenarios.
- Probabilistic Load Flow allows for each supply source and/or demand location to be a random variable.
- These are typically solved via Monte-Carlo methods or so-called convolution methods.

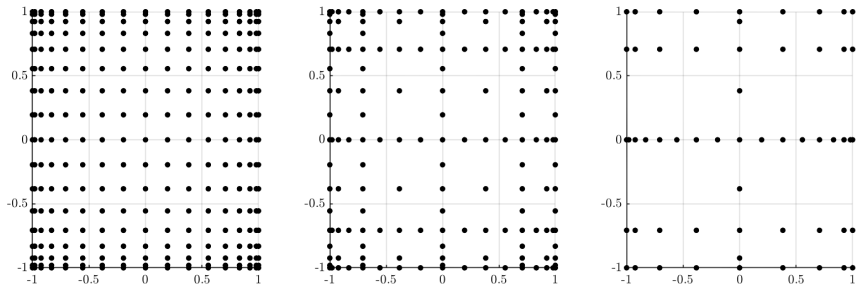
## Probabilistic Load Flow (PLF) problem (continued)

- Our approach<sup>7</sup>: treat all of the solar power sources as spatial points within one underlying stochastic process.
- KL expansion results in 194 dependent random variables reduced to 12 uncorrelated random variables.
- Enables Anisotropic Sparse Grid Interpolation (Stochastic Collocation)

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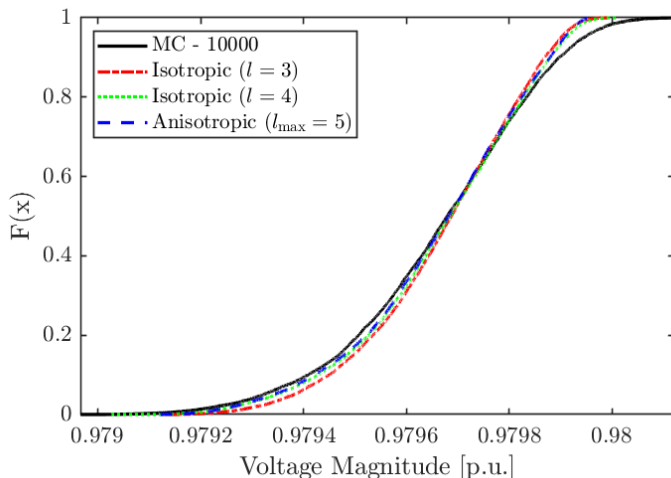
<sup>7</sup>B. Johnson, **N. L. Gibson** and E. Cotilla-Sanchez, "A Coupled Karhunen-Loève and Anisotropic Sparse Grid Interpolation Method for the Probabilistic Load Flow Problem", Electric Power Systems Research, 24 pages. *Accepted, to appear.*

# Anisotropic Sparse Grid



**Figure:** Demonstration of full tensor grid, sparse grid, and anisotropic sparse grid.

## PLF Results



**Figure:** Voltage magnitude CDF at Bus 93 in the IEEE 118-Bus system.

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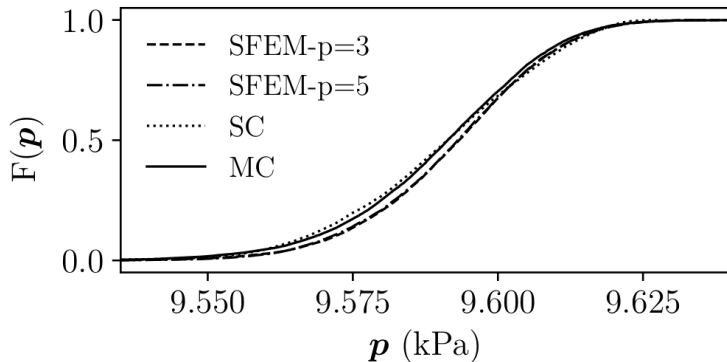
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## Tsunami Loading

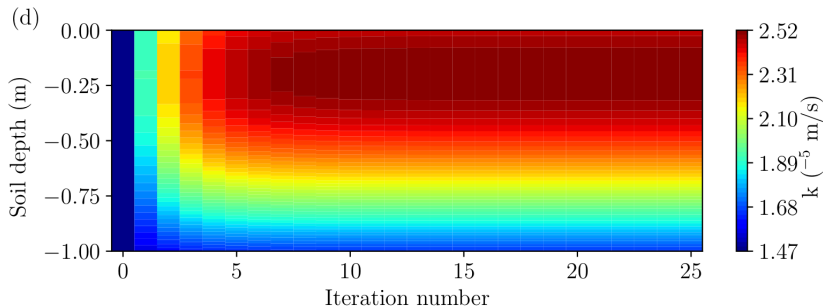
In collaboration with Ben Mason and Yingqing Qiu (Civil Engineering)

- We have applied KL expansions to an uncertain hydraulic conductivity for a numerical soil model under wave loading.
- We compared Stochastic Finite Element Method to Stochastic Collocation and Monte Carlo.



## Tsunami Loading Inverse Problem

- Determine the coefficients of a KL expansion for an unknown hydraulic conductivity given measurements of pressure.
- Data obtained from Hinsdale wave lab experiment.
- 20 dimensions reduced to 6; 50 Newton iterations reduced to 15.



# Summary

- KL expansions used for dimension reduction
  - Forward problems in power flow and wave loading
  - Optimal control for reservoir modeling
  - Parameter estimation for wave loading
- PC expansions used for multiscale modeling
  - Random Lorentz polarization
    - Well-posedness (Continuous and Discrete)
    - Dispersion analysis
  - Viscoelastic relaxation
  - Toward Hall MHD