



47th Woudschoten conference 2023

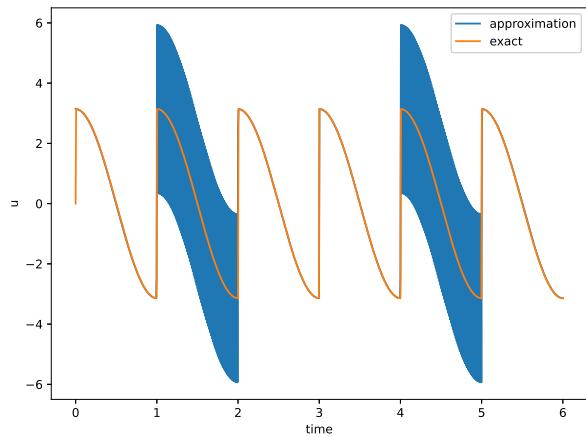
One-minute poster session

14:00-15:00 Line up from 01 till 24

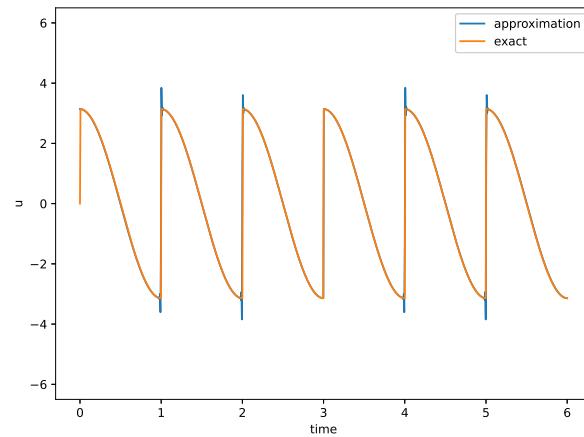
DUTCH-FLEMISH
SCIENTIFIC
COMPUTING SOCIETY

SCS

Stable adaptive least-squares space-time boundary element methods for the wave equation.



(a) Standard approach



(b) Least-squares approach

By:

D. M. Hoonhout, MSc.

DELFT UNIVERSITY OF TECHNOLOGY
FACULTY OF NUMERICAL ANALYSIS



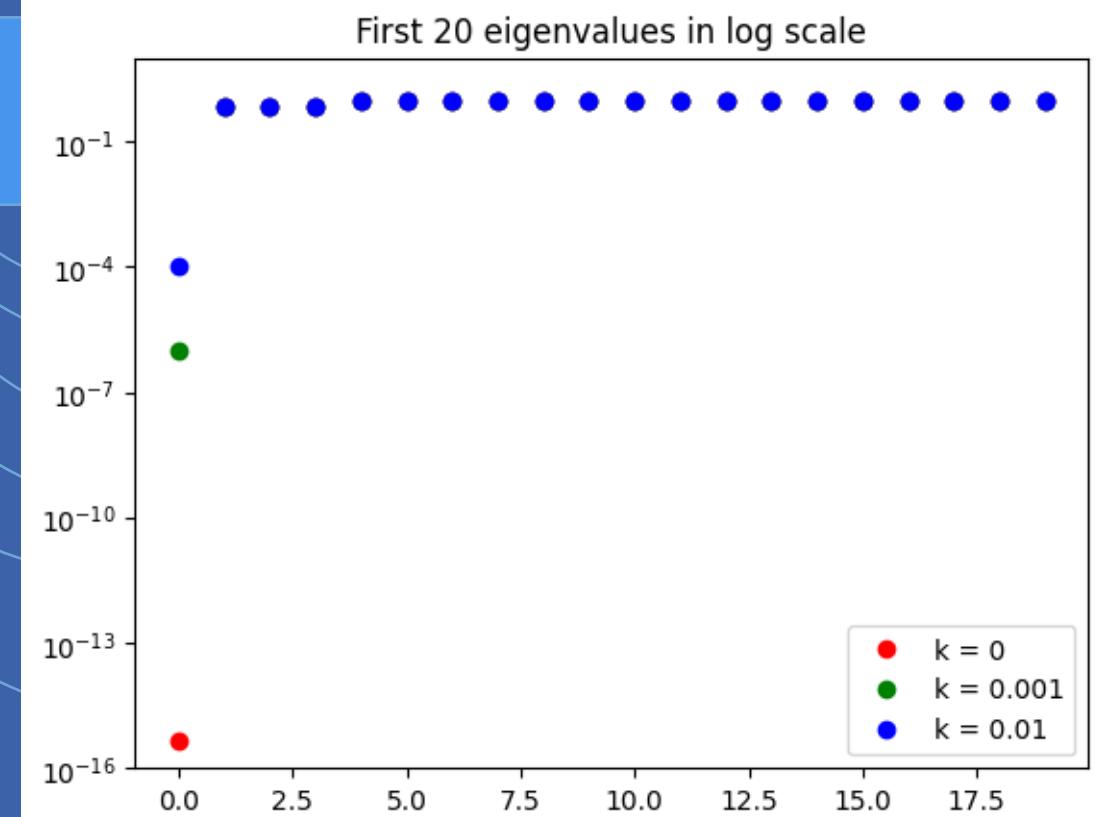
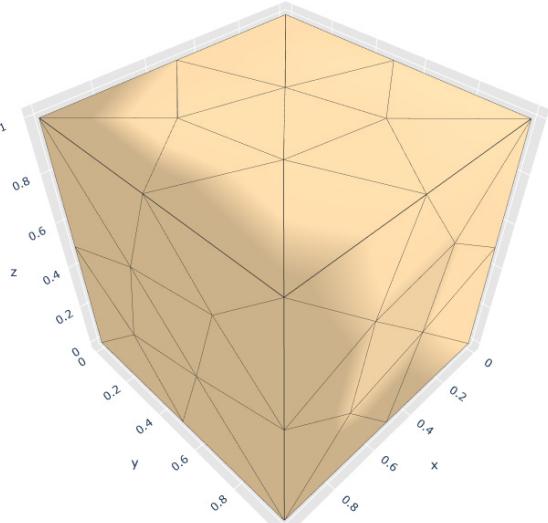
First-kind Galerkin BEM for the single layer operator of the Hodge-Helmholtz equation

Ralf Hiptmair^a, Carolina Urzúa-Torres^b, Anouk Wisse^b

^a Seminar for Applied Mathematics, ETH Zürich, Switzerland

^b Delft Institute of Applied Mathematics, Delft University of Technology, Netherlands

$$\operatorname{curl} \operatorname{curl} \mathbf{A} - \eta \nabla \operatorname{div} \mathbf{A} - \kappa^2 \mathbf{A} = 0$$



Novel Reduced Basis Sampling Method for problems with high-dimensional parameters

Evie Nielen, Oliver Tse, Karen Veroy

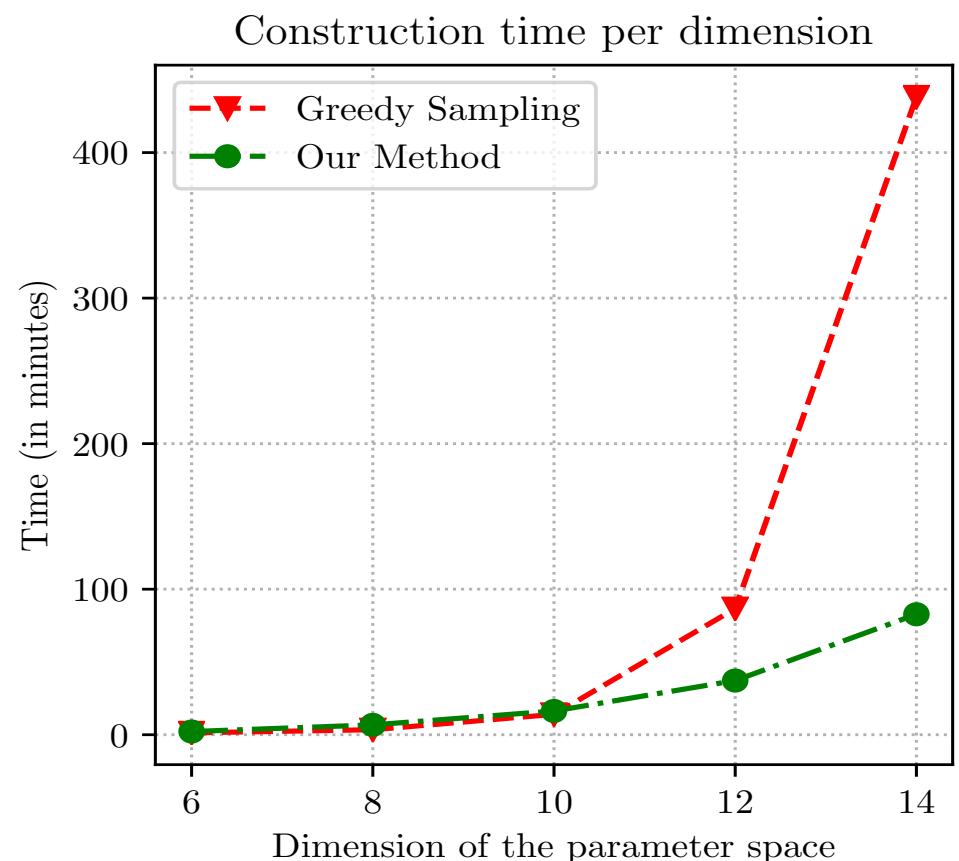
Set-up: Bilinear, coercive, linear form:

$$a(u, v; \mu) = f(v; \mu)$$

Goal: Construct a reduced basis

The catch: parameter μ is high-dimensional

Greedy Sampling asks for a lot of patience



Fast calculation of Potential Future Exposure and XVA sensitivities using Fourier series expansion

Gijs Mast Xiaoyu Shen Fang Fang

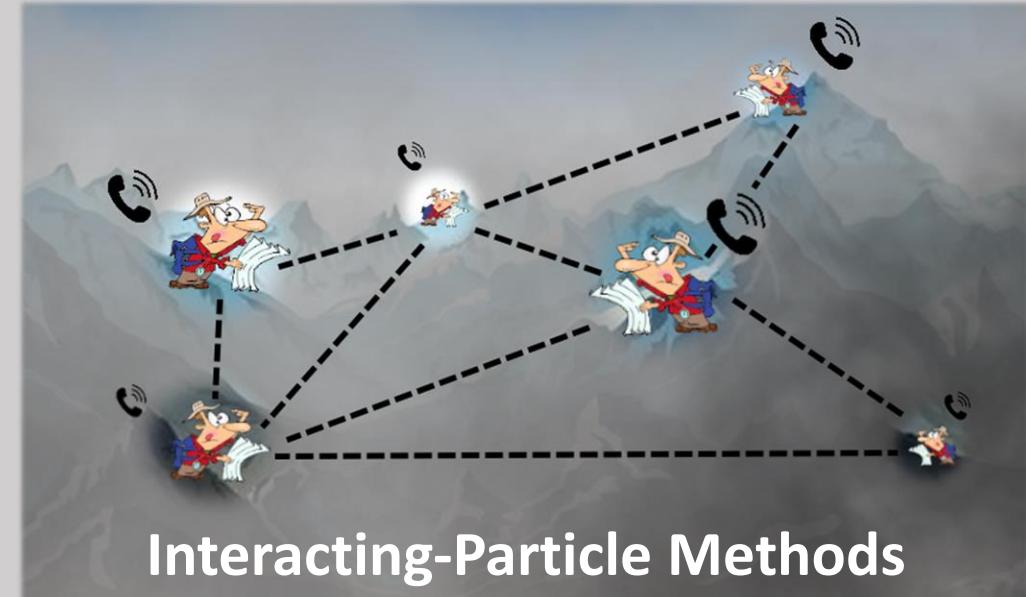
Delft University of Technology, The Netherlands
FF Quant Advisory B.V., The Netherlands

September 27, 2023

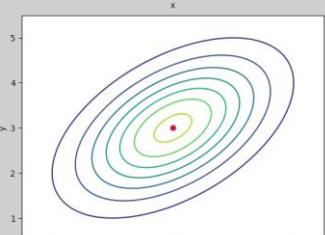
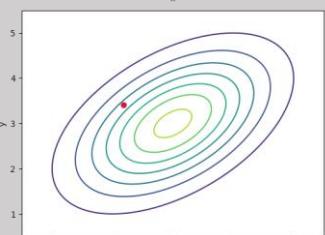
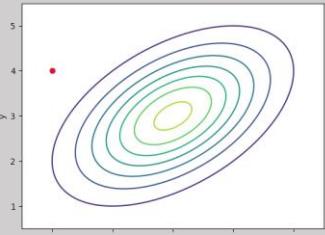
Single-Ensemble Multilevel Monte Carlo for Interacting-Particle Methods



Single-Particle Methods



Interacting-Particle Methods



Pros +

Greater exploration

Trivially parallelizable

Often gradient-free

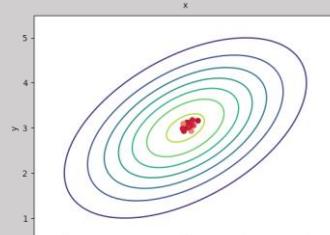
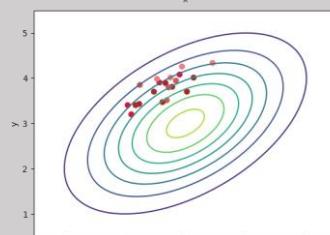
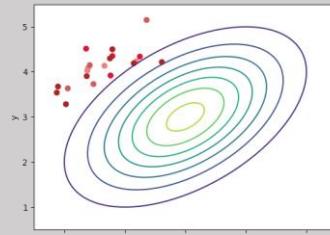
Cons -

Expensive evaluation
at every particle,
at every timestep

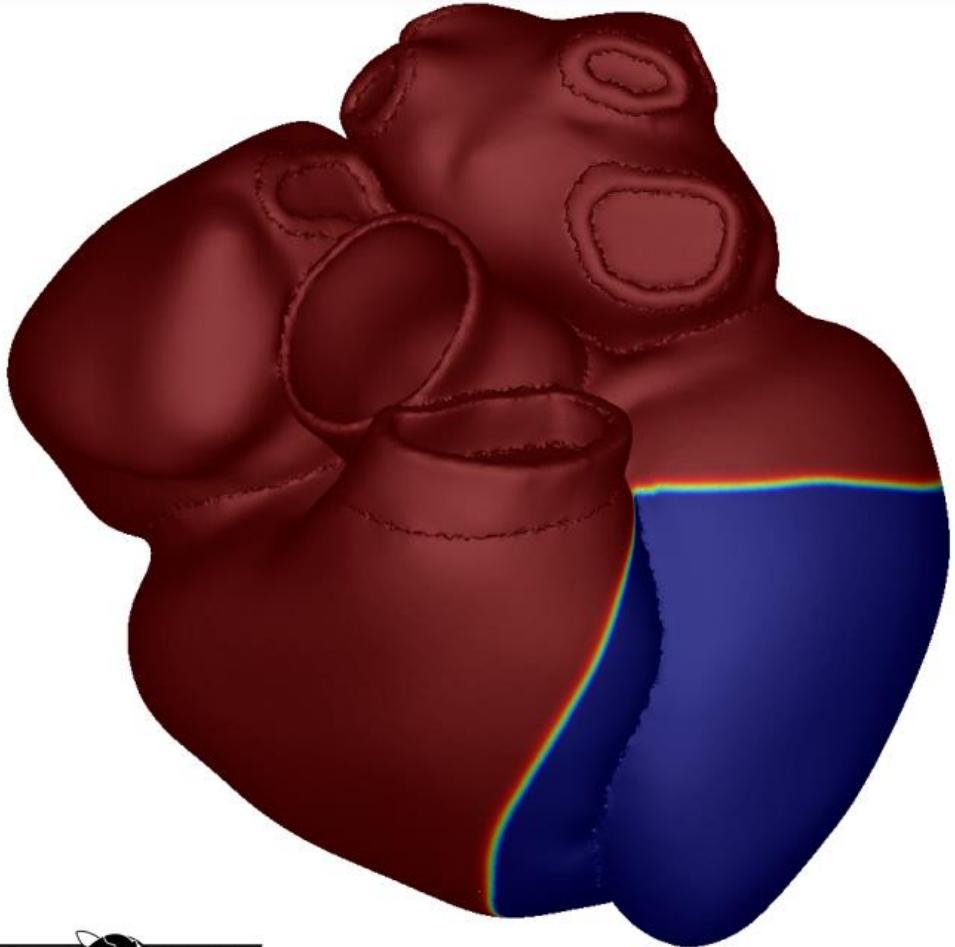


Solution

Leverage **cheap** approximations
with multilevel Monte Carlo



Markov Chain Monte Carlo methods for electrical conductivity estimation in the heart

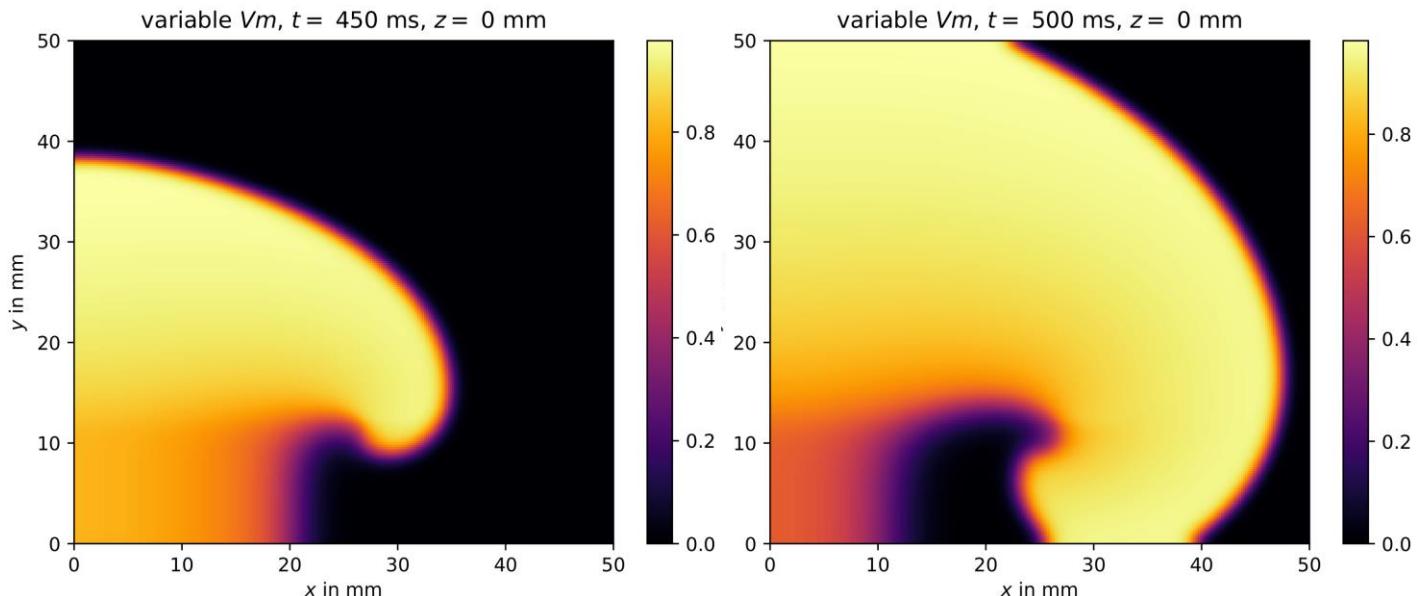


Maarten Volkaerts

KU Leuven

Department of Computer Science

$$\frac{\partial V_m}{\partial t} = \underbrace{\nabla \cdot D \nabla V_m}_{\text{wave propagation}} + \underbrace{R(V_m, u)}_{\text{ion currents}} \quad \frac{\partial u}{\partial t} = f(V_m, u)$$





Utrecht
University

Deltas

Adaptive moving meshes for space-fractional PDE models in 1D using the L2(NU)-method

Pu Yuan, Paul Zegeling, Ailbhe Mitchell

$$\text{MMPDE: } \frac{\partial x}{\partial t} = \frac{1}{\tau} \frac{\partial}{\partial \xi} \left(M \frac{\partial x}{\partial \xi} \right)$$

$${}_C D_{a,x}^\alpha u(x) = \frac{1}{\Gamma(2-\alpha)} \sum_{k=0}^{n-1} \int_{x_k}^{x_{k+1}} (x-s)^{1-\alpha} \frac{\partial^2 u}{\partial s^2} ds$$

Apply to

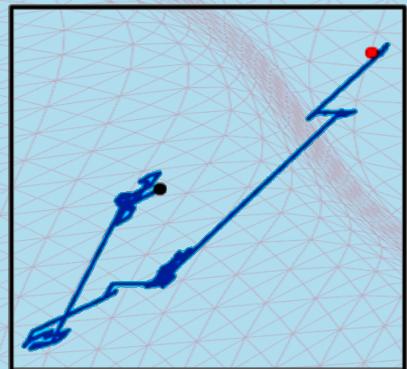
$$-(-\Delta)^{\frac{\alpha}{2}} u(x) = -\frac{1}{2 \cos(\alpha\pi/2)} ({}_C D_{x,R}^\alpha u(x) + {}_C D_{x,L}^\alpha u(x))$$

Solves

$$u_t = -(-\Delta)^{\frac{\alpha}{2}} u(x) + f(u)$$

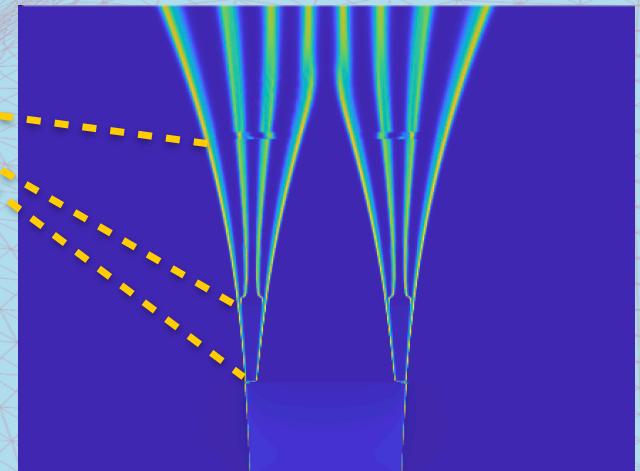


Brownian(random) walk
 $\alpha=2$



Levy flights
 $1 < \alpha < 2$

Detecting the bifurcations
in the space-fractional
Gray-Scott model



Mortgage prepayment: What is the “right price” of people’s behavior?

Leonardo Perotti

l.perotti@uu.nl



Mathematical Institute @ Utrecht University
Treasury Modelling @ Rabobank

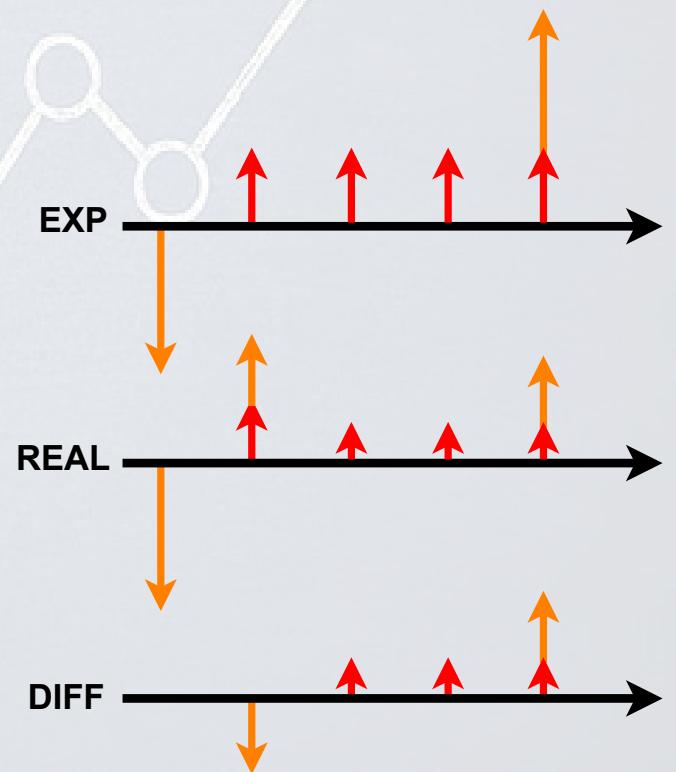


Buying a house and winning the lottery...

- Contractual **expected** repayments
- **Behavioral uncertainty** of prepayment
- What is the “**fair price**”?

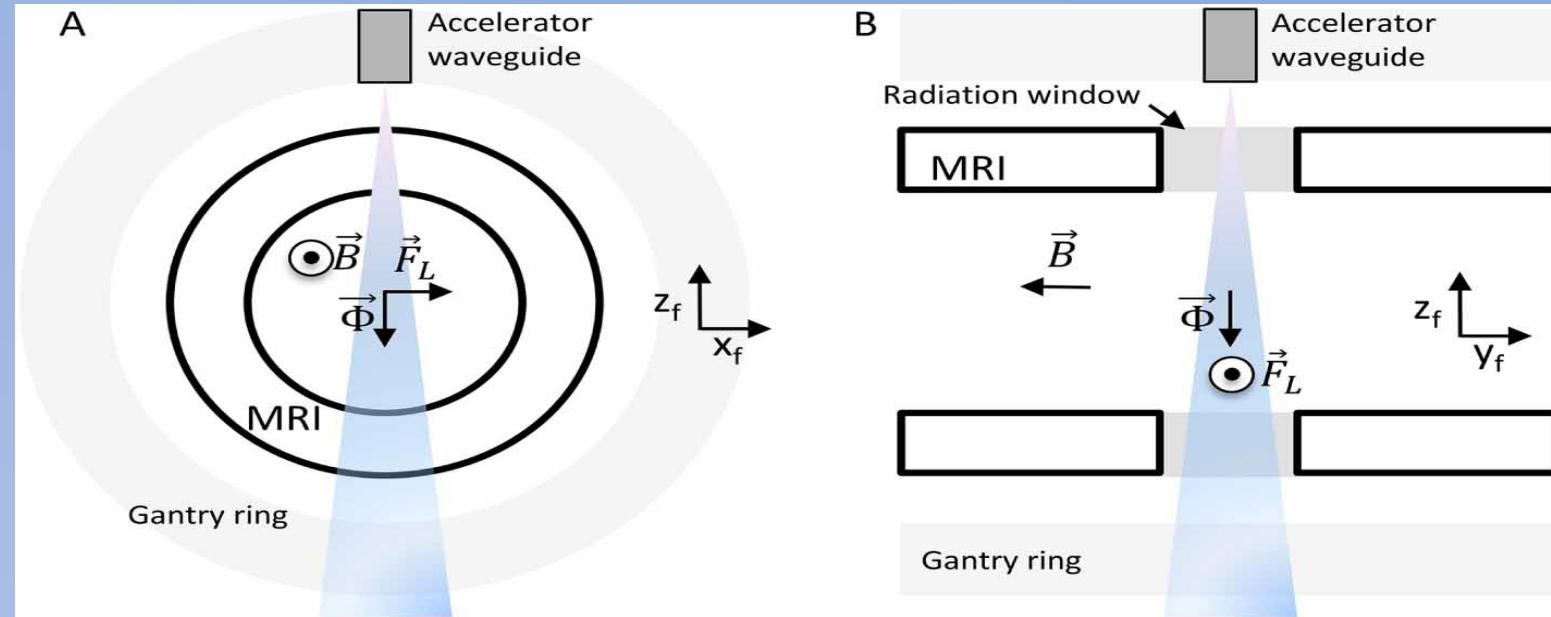
...with some math

- Stochastic optimal **control problem**
- **Measure change** (Girsanov’s Theorem)
- (**Deep**) machine **learning** application



Analysis and systematic discretization of a Fokker-Planck equation with Lorentz force

UNIVERSITY
OF TWENTE.

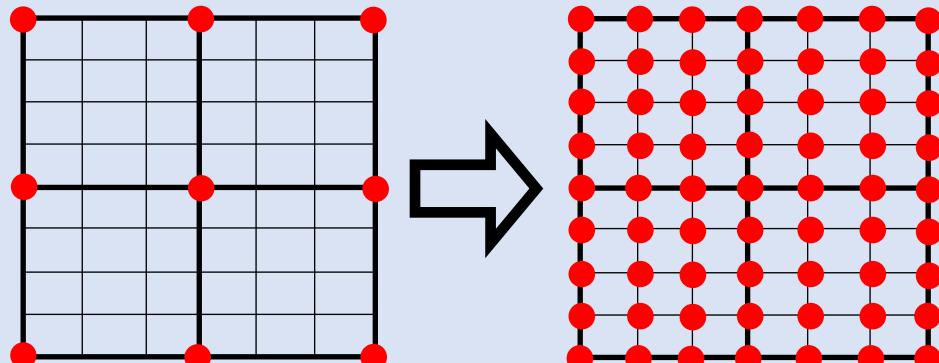


Multilevel MCMC with high-resolution observations

Pieter Vanmechelen, Geert Lombaert & Giovanni Samaey

ALGORITHMIC DEVELOPMENT

Extend MCMC sampling to use resolution-dependent data



APPLICATION ORIENTED

Focus on real-life applications in structural health monitoring



Structure-preserving Model Reduction on Manifolds

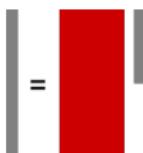
How well can classical model reduction methods, e.g., POD, perform?

Benchmark: Kolmogorov N -width

$$d_n((\mathcal{P})) := \inf_{V_n; \dim(V_n)=n} \sup_{\mu \in \mathcal{P}} \inf_{v_n \in V_n} \|x_N(\mu) - v_n\|$$

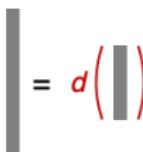
① Model Reduction on Manifolds

- Extend linear-subspace approximation, $\mathbf{V} \in \mathbb{R}^{2N \times 2n}$
- To nonlinear approximations, $d : \mathbb{R}^{2n} \rightarrow \mathbb{R}^{2N}$
- Focus on: polynomial embeddings, autoencoders



② Structure-preserving MOR

- Preserve given structure in reduced model, e.g.,
- Hamiltonian system: symplectic model reduction

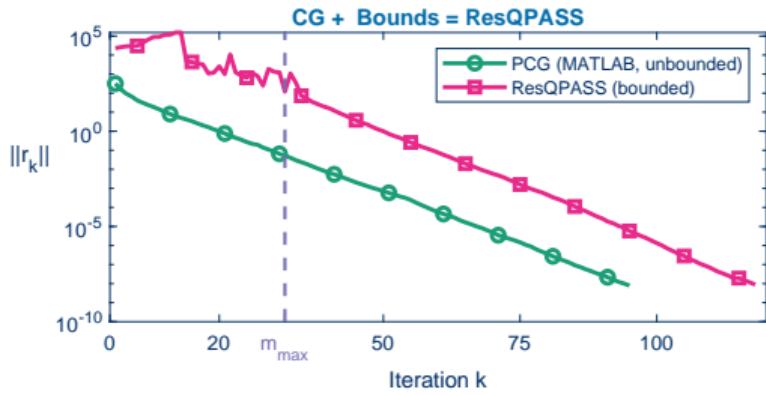
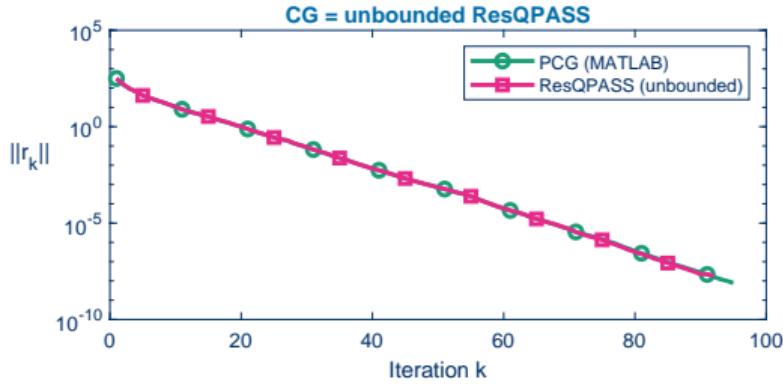


$$\frac{d}{dt} \mathbf{x}(t; \mu) = \mathbb{J}_{2N} \nabla_{\mathbf{x}} \mathcal{H}(\mathbf{x}(t; \mu); \mu)$$

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CG + bounded variables = ResQPASS

Bas Symoens



Uncertainty Quantification for Neural Field equations with random data

Francesca Cavallini

Vrije Universiteit Amsterdam

Amsterdam Center for Dynamics and Computation



Woudschoten conference , Sept 27 2023

Variational multiscale stabilization of the magnetohydro- dynamics equations

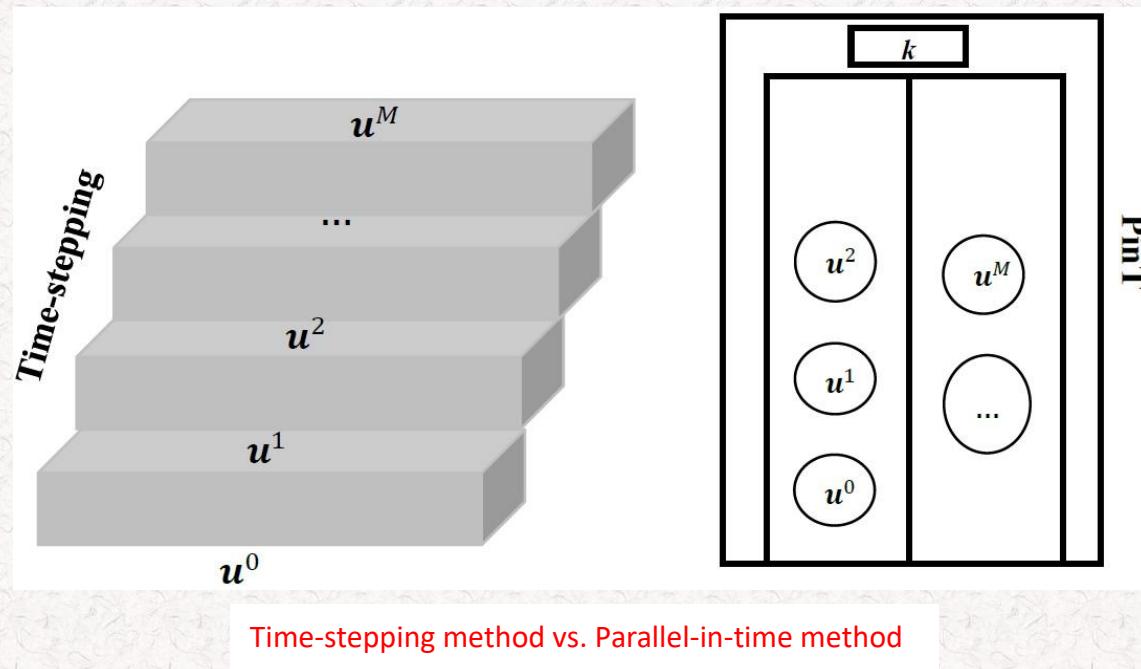
Kevin Dijkstra



Parallel-in-time iterative methods with Crank-Nicolson scheme for European option pricing PDEs

Xian-Ming Gu (SWUFE, China & Utrecht U., Netherlands), Y.-L. Zhao (SICNU, China), C. W. Oosterlee (Utrecht U., Netherlands)

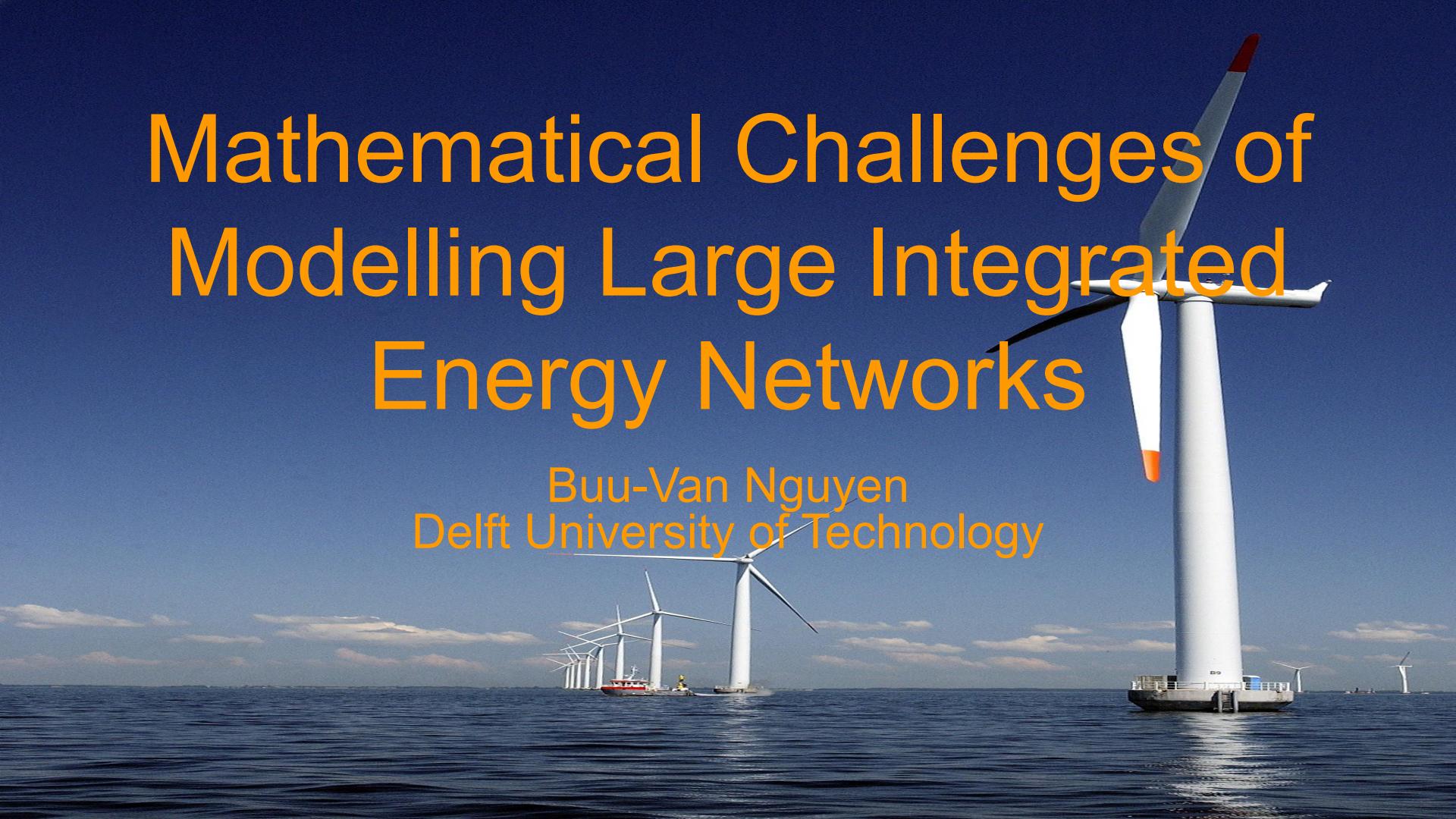
- ✓ Numerical methods of European option pricing PDEs find the solution in each time level one-by-one, namely the time-stepping scheme;
- ✓ Parallel-in-time methods solve the European option pricing PDEs for all the discrete time points simultaneously via matrix diagonalization.



Universiteit Utrecht

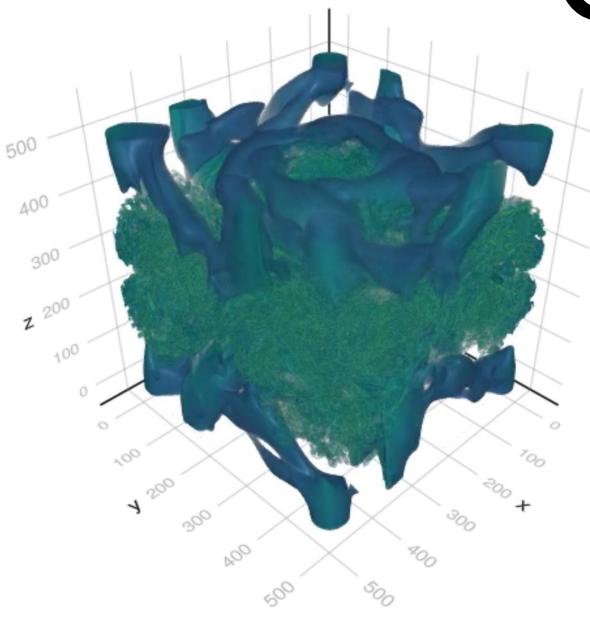
Mathematical Challenges of Modelling Large Integrated Energy Networks

Buu-Van Nguyen
Delft University of Technology



Closing Navier-Stokes

Once and for all



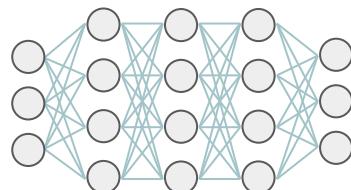
+

$$+ \frac{\partial}{\partial \theta}$$

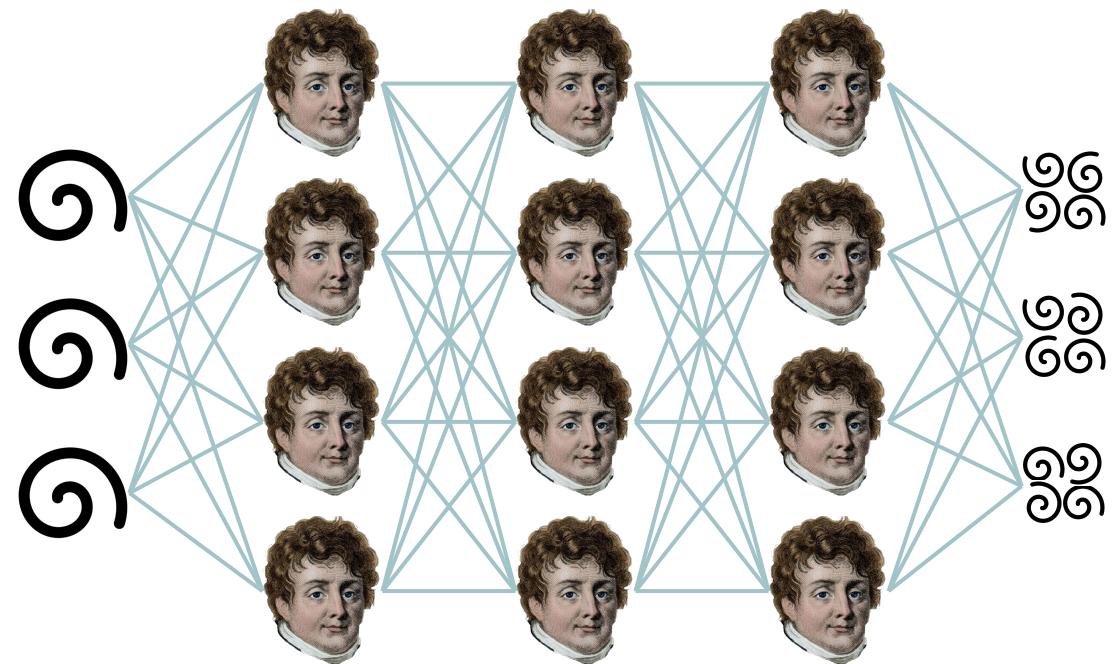
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Syver Døving Agdestein

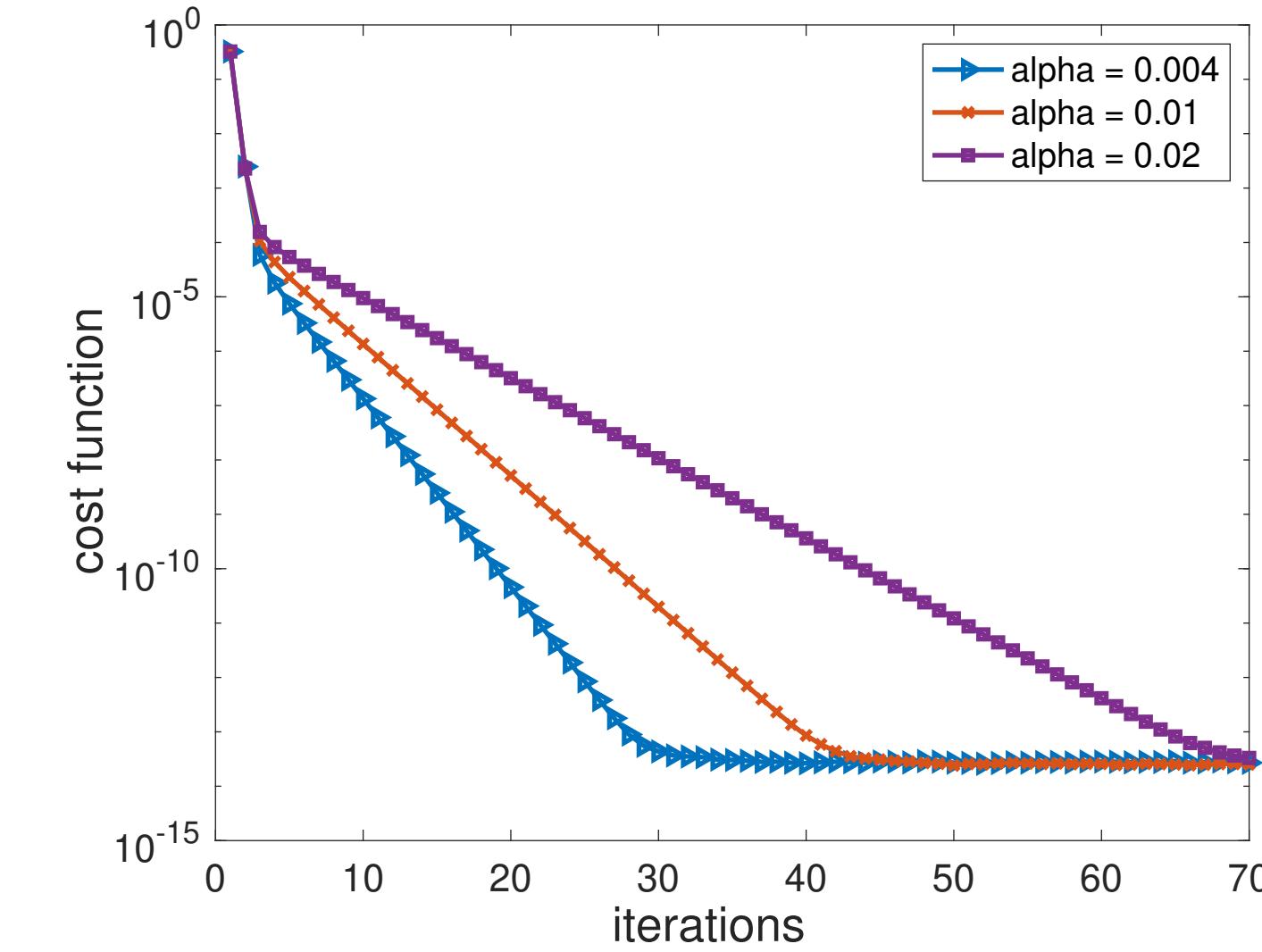
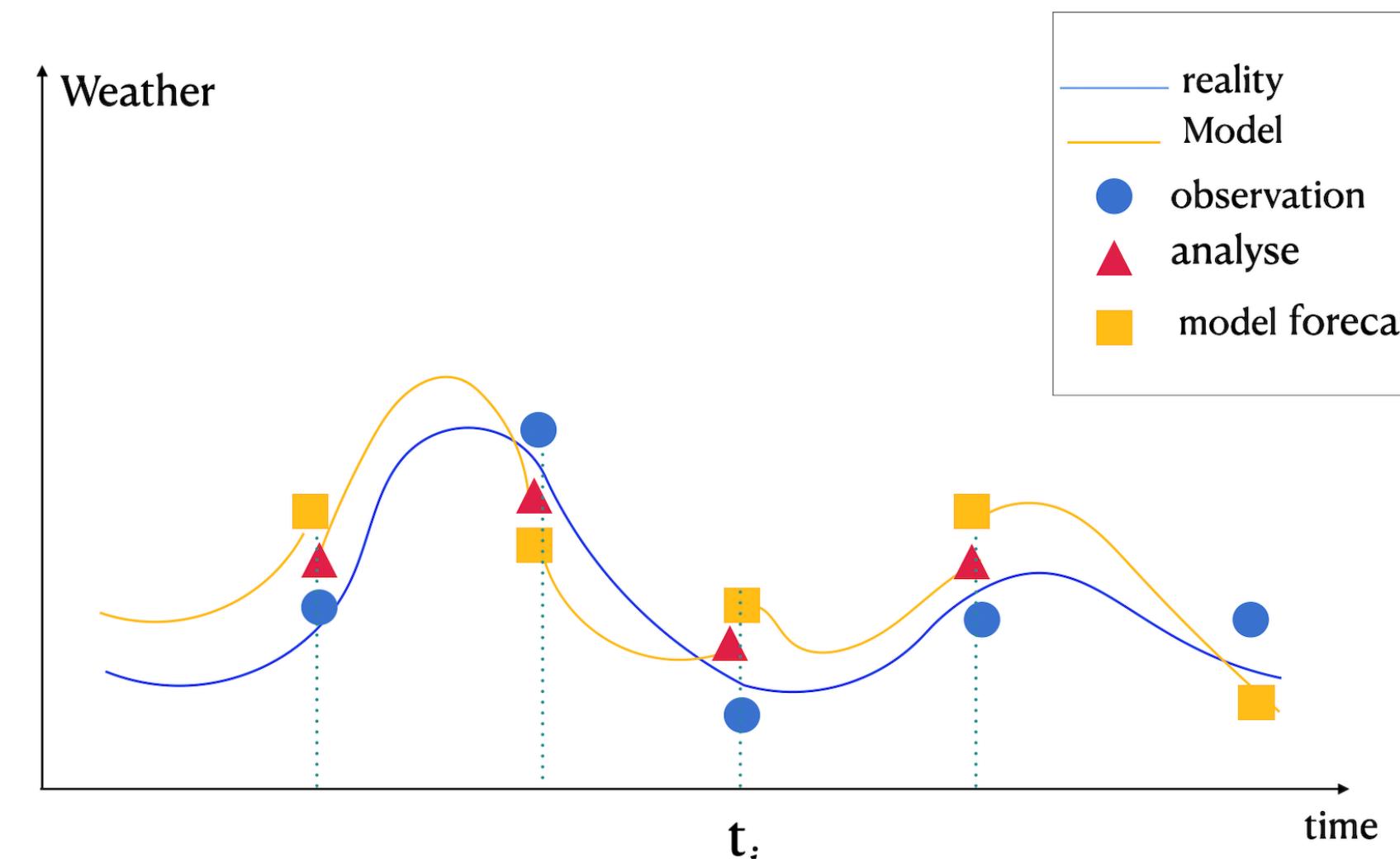
Neural closure models for the incompressible Navier-Stokes equations

CWI

Error analysis of a modified form of variational data assimilation

Nazanin Abedini

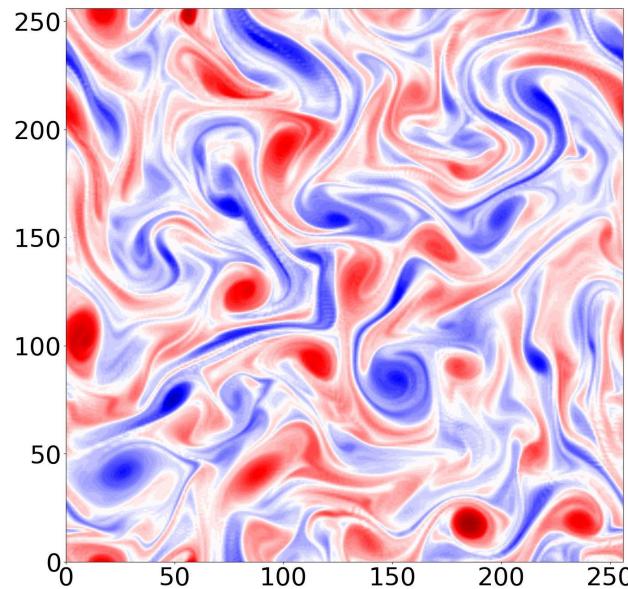
Vrije Universiteit Amsterdam



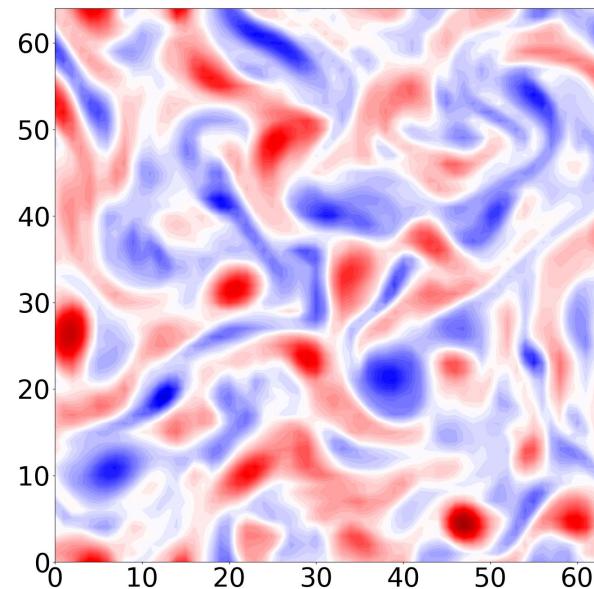
$$\min_{\mathbf{u} \in \mathbb{R}^{nN}} \frac{1}{2} \{ \|G(\mathbf{u})\|^2 + \alpha \|\mathbf{y} - H\mathbf{u}\|^2 \},$$

Low dimensional data-driven LES closures

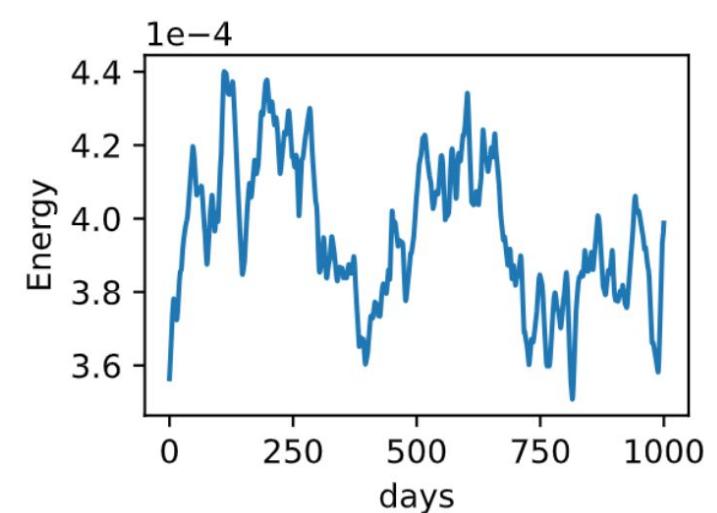
HF



LF



Qol

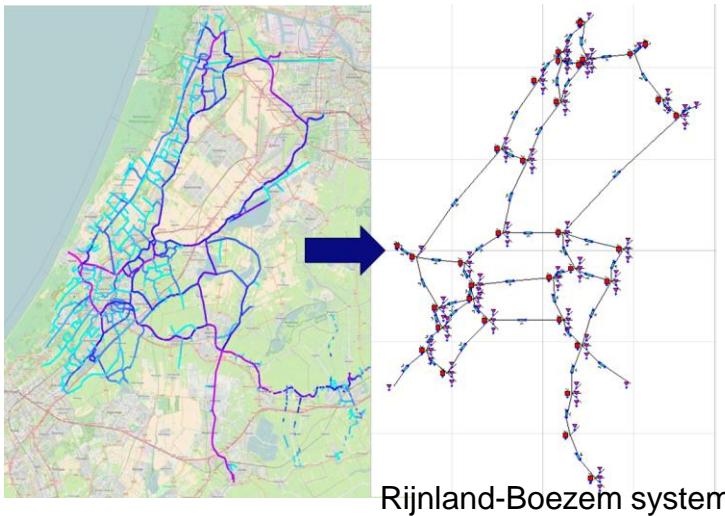


Towards prediction of low dimensional Qols with data-driven
LES closures in 2D turbulence.
Rik Hoekstra

CWI

Techniques applied to non-linear multi-objective optimization problems in water management

Ailbhe Mitchell on behalf of Deltares



Fluid flow:

$$F = \frac{\partial Q}{\partial t} + \frac{\partial}{\partial x} \left(\frac{Q^2}{A} \right) + gA \frac{\partial H}{\partial x} + g \frac{Q|Q|}{ARC^2} = 0,$$

Power equations:

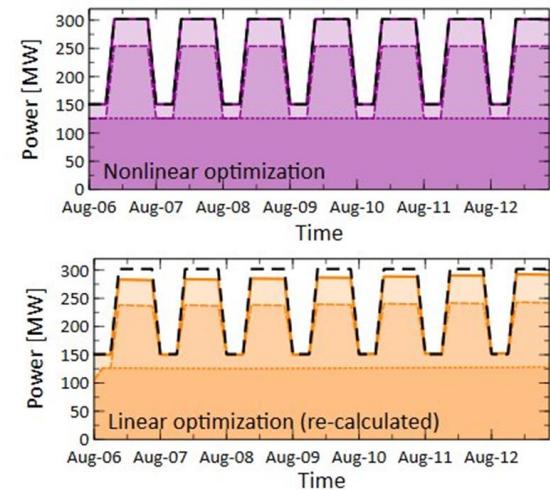
$$\begin{aligned} P &= \eta(Q, H_u, H_d) \cdot \rho \cdot g \cdot Q \cdot \Delta H, \\ \Delta H &= H_u - H_d, \end{aligned}$$

- Piecewise constant
- Piecewise linear
- Continuation method
- Discrete decisions?

Very large non-linear systems



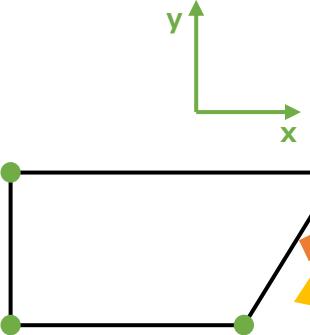
Approach



Physical space

All physical laws and equations are written/or expressed in this domain

Real geometries, may not be easy to model



Components of physical quantities defined in terms physical (cartesian) coordinates.

Vector equations written in cartesian coordinate directions

$$\begin{array}{ccccccc}
 0 & \xleftarrow{d} & e_i \otimes \Lambda'^{(2)} & \xleftarrow{d} & e_i \otimes \Lambda'^{(1)} & \xleftarrow{d} & e_i \otimes \Lambda'^{(0)} & \longleftarrow & \mathbb{R} \\
 & \uparrow^b & & \uparrow^b & & \uparrow^b & & & \text{Vector-valued forms} \\
 & \downarrow^b & & \downarrow^b & & \downarrow^b & & & \\
 \mathbb{R} & \longrightarrow & e^i \otimes \Lambda^{(0)} & \xrightarrow{d} & e^i \otimes \Lambda^{(1)} & \xrightarrow{d} & e^i \otimes \Lambda^{(2)} & \longrightarrow & 0 \\
 & & & & & & & & \text{Covector-valued forms}
 \end{array}$$

Partial transformation (Lagrangian)

Map given geometry onto a reference domain

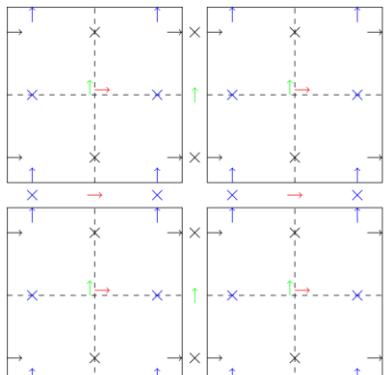
Can exploit favourable properties of reference domain

The map used to convert the form parts only

Vector equations written in cartesian (physical) coordinate directions

Equations converted from physical space

$$\begin{matrix}
 dx \otimes b d\eta \\
 \frac{\partial}{\partial x} \otimes a
 \end{matrix}$$

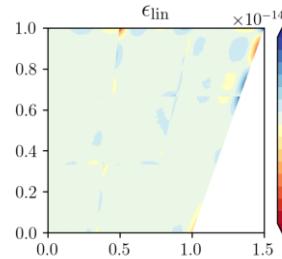


Full transformation

Map given geometry onto a reference domain

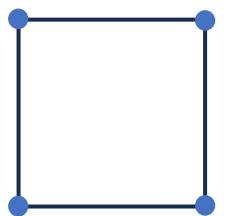
Can exploit favourable properties of reference domain

Vector equations written in reference coordinate directions

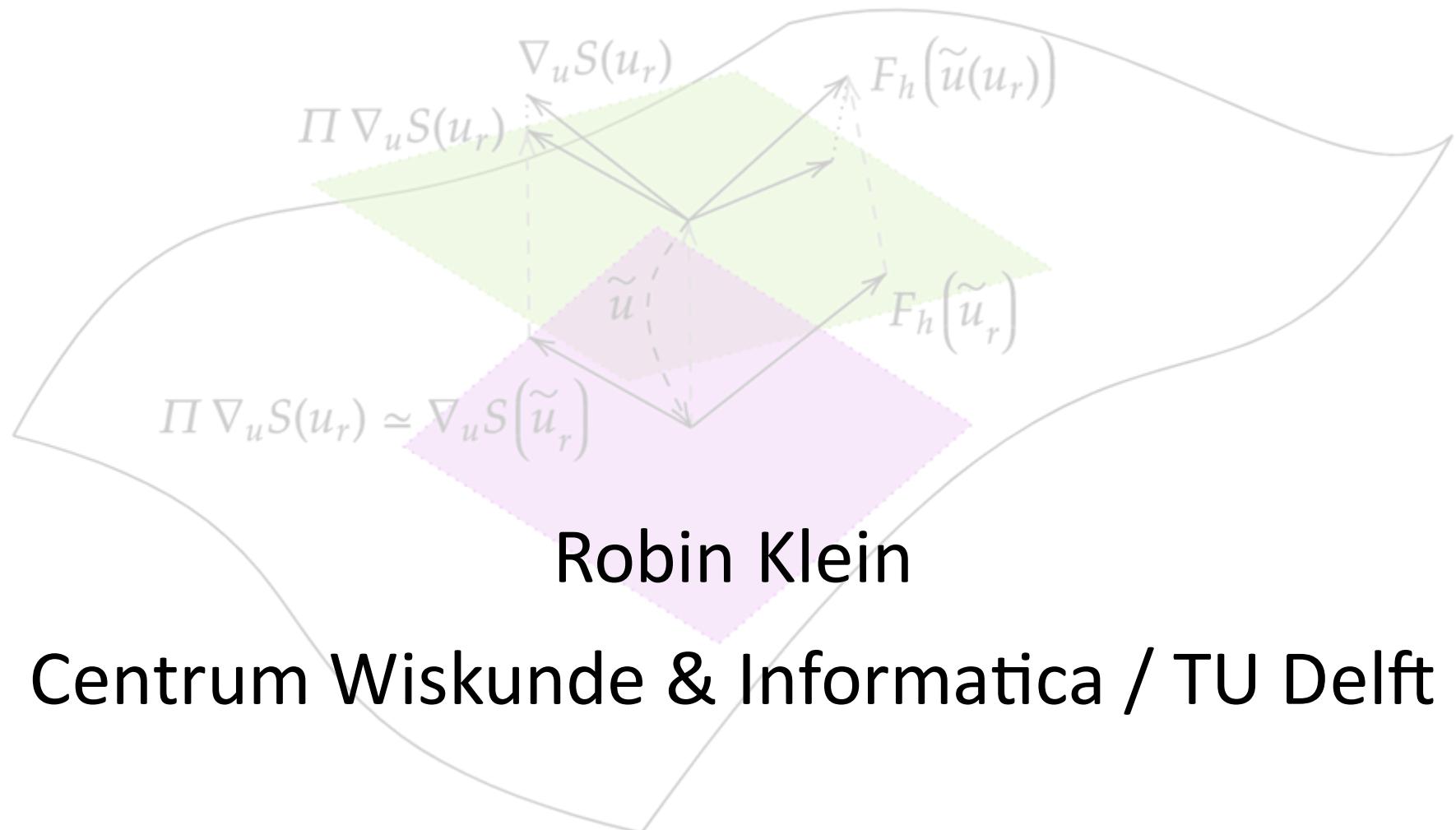


$$\begin{matrix}
 \frac{\partial}{\partial \xi} \otimes a \\
 d\xi \otimes b d\eta
 \end{matrix}$$

The map used to convert both the form and the value parts
Equations converted from physical space



Entropy Stable Model Reduction on Nonlinear Manifolds of Hyperbolic Systems





One Step Malliavin schemes: A BSDE approach for **Delta** **Gamma** hedging

Balint Negyesi*

model errors — BSDE

regression Monte Carlo

COS

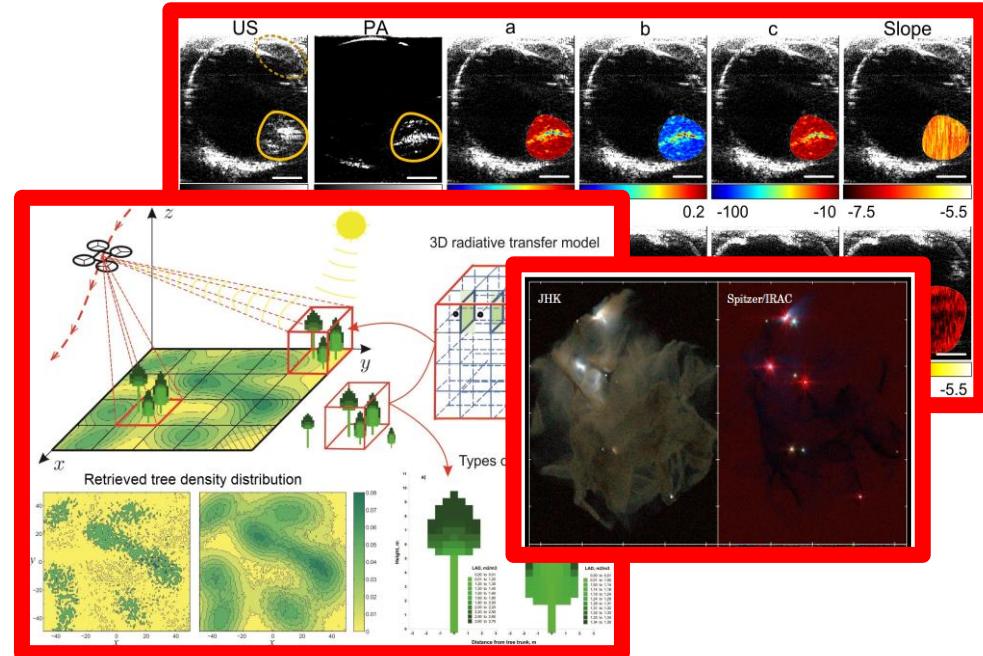
Δ & Γ approximations

European/Bermudan/American

deep learning (Deep BSDE)

high-dimensions

Profit and Loss



- New **low-rank tensor-product framework** for the numerical solution of the radiative transfer equation
- Full **compatibility** with iterative methods in Hilbert spaces
- Efficient implementation to save memory and time (**preconditioning** and combination with **rank truncation** methods)

A LOW-RANK TENSOR PRODUCT FRAMEWORK FOR RADIATIVE TRANSFER IN PLANE-PARALLEL GEOMETRY

RICCARDO BARDIN¹, MATTHIAS SCHLOTTBOM¹, MARKUS BACHMAYR²

¹ UNIVERSITY OF TWENTE

² RWTH AACHEN UNIVERSITY

UNIVERSITY OF TWENTE.

