

## Uncertainty Quantification of Low-Dimensional Models

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# Outline

## 1 Introduction

## 2 Methodology

## 3 Example: Cylinder Flow

# Topic

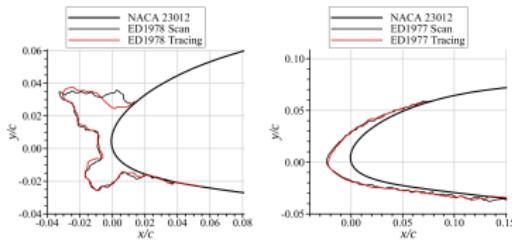
## 1 Introduction

## 2 Methodology

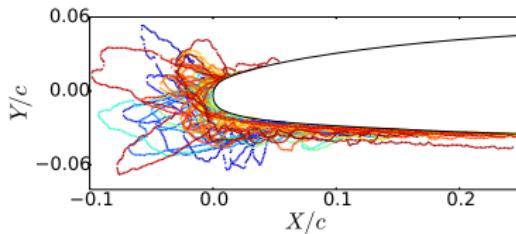
## 3 Example: Cylinder Flow

## Motivation

- Many fluid systems have uncertainties associated with them
  - Governing parameters
  - Boundary conditions
- Wing icing <sup>1, 2</sup>



Broeren, 2013



Addy, 2000

<sup>1</sup>Broeren et. al. *Swept-Wing Ice Accretion Characterization and Aerodynamics*. AIAA 2013-2824.

<sup>2</sup>Addy, H. E. *Ice Accretions and Icing Effects for Modern Airfoils*. NASA TP 2000-210031.

# Motivation

- Many fluid systems have uncertainties associated with them
  - Governing parameters
  - Boundary conditions
- Airplane cargo hold fires <sup>3</sup>

Colder Source

Hotter Source

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<sup>3</sup>DeGennaro, Lohry et. al. *Uncertainty Quantification for Cargo Hold Fires*. To appear at AIAA Scitech 2016.

# Motivation

**Goal: apply uncertainty quantification tools to low-dimensional models**

- Understand statistical variations in flow with parameters

## Potential applications

- Investigate statistical variations in spatial structures and dynamics
  - POD modes, DMD modes
  - DMD eigenvalues
- POD Galerkin models
  - Sensitive to parametric variation/uncertainty

# Topic

## 1 Introduction

## 2 Methodology

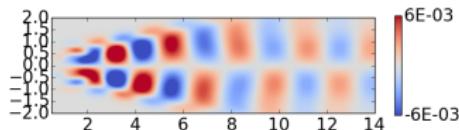
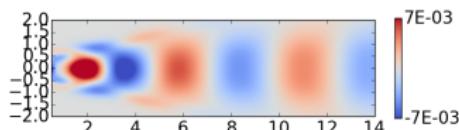
## 3 Example: Cylinder Flow

## Background: Low-Dimensional Modeling

- Proper Orthogonal Decomposition (POD)
  - Data compression, dominant spatial features
  - Modes are eigenvectors of the dataset covariance matrix
  - Modes describe dataset better than any other linear basis
- Dynamic Mode Decomposition (DMD)
  - Describe dataset as linear dynamical system
  - Spatial modes + (frequencies, growth/decay rates)

### POD/DMD Modes

Cylinder, Re = 100



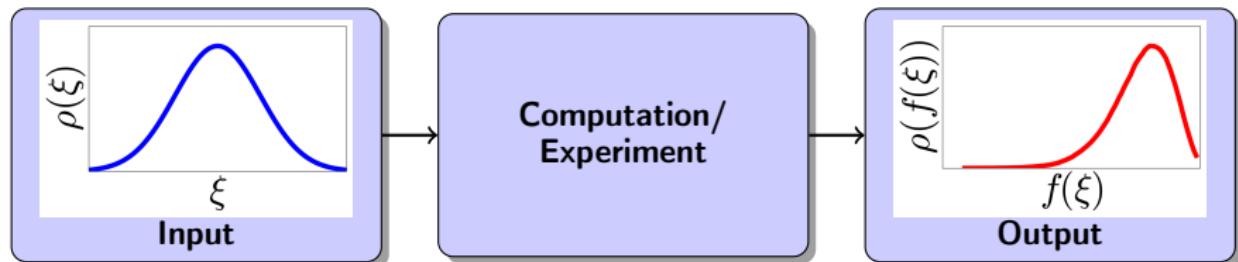
# Background: Polynomial Chaos Expansions (PCE)

- Polynomial Chaos Expansions (PCE)

- Method for quantifying parametric uncertainty efficiently
- Spectral method in probability space
- Expand output in terms of basis polynomial functions of random variables

$$f(\xi) \approx \sum_i^N a_i \phi_i(\xi)$$

$$\langle f, g \rangle = \int_{\Gamma} f(\xi)g(\xi)\rho(\xi)d\xi \quad , \quad \langle \phi_i, \phi_j \rangle = \delta_{ij}$$



# Methodology

## Quantify Uncertain Input

- Identify source of uncertainty
  - Physical parameters (eg. Reynolds number)
  - Boundary conditions
- Write a probabilistic description of uncertainty (ie. PDF)

## Explore Uncertain Parameter Space

- Utilize efficient sampling of probability space
  - Quadrature nodes corresponding to a spectral basis
- Collect simulation data using discrete points in probability space
  - Immersed boundary projection method (IBPM) code

## Quantify Uncertain Output

- Quantify uncertainty in outputs
  - POD modes
  - DMD modes
  - DMD eigenvalues

# Topic

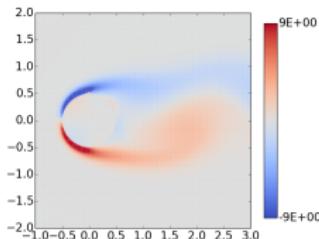
## 1 Introduction

## 2 Methodology

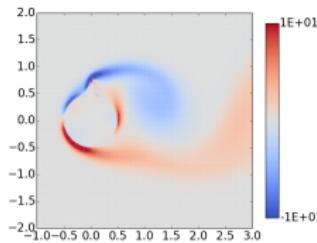
## 3 Example: Cylinder Flow

## Setup

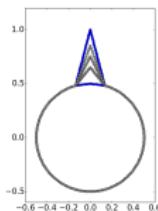
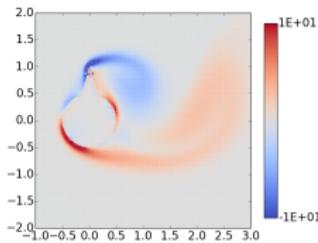
Small Spike



Medium Spike



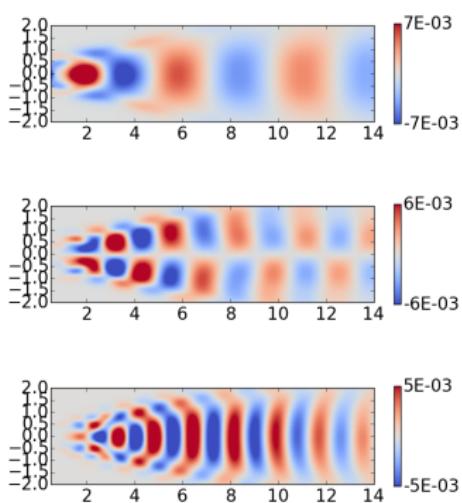
Large Spike



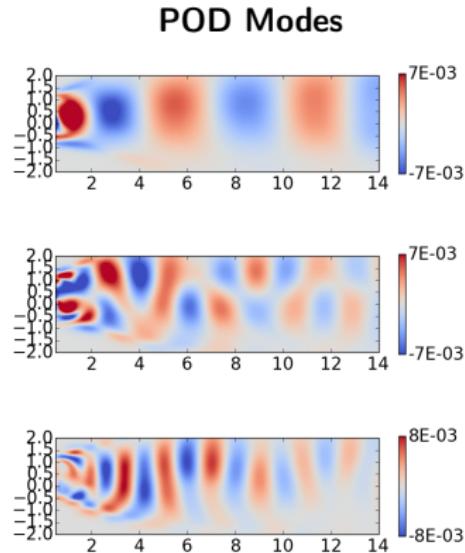
- Assume spike height is uniformly distributed between limits shown
- $Re = 100$
- Output = wake POD modes, DMD eigenvalues

## Range of Flow Behavior

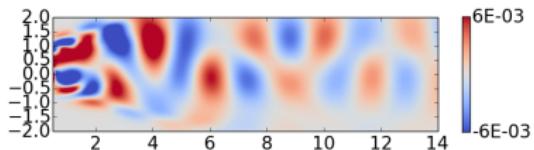
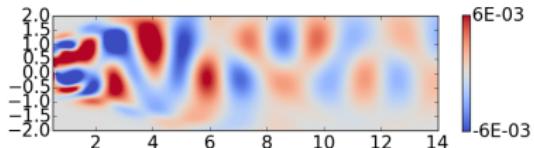
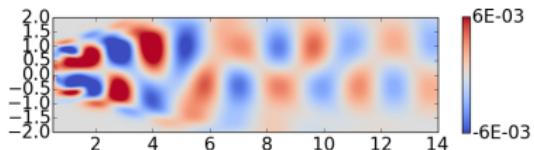
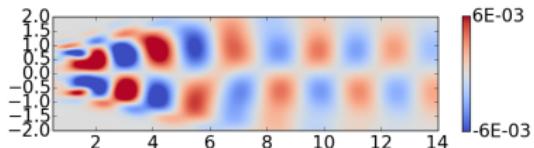
Cylinder,  $Re = 100$



Perturbed Cylinder,  $Re = 100$

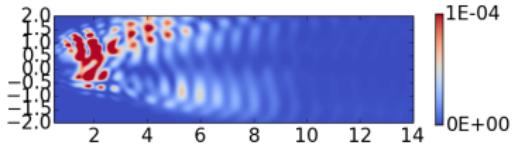
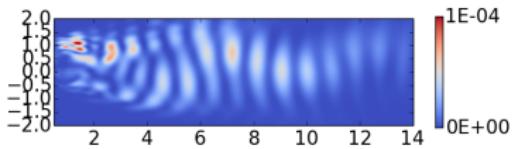
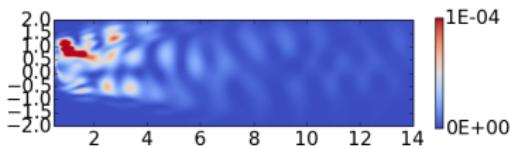
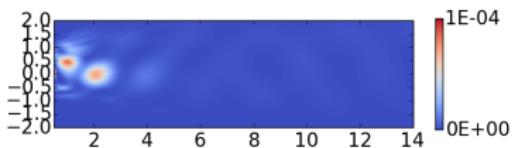


## Query the Surrogate



- Can query the surrogate PCE model at different spike heights
  - Height = 0.14
  - Height = 0.36
  - Height = 0.63
  - Height = 0.86
- Behavior consistent with simulations

## Statistical Variance in Modes



## Projection Error

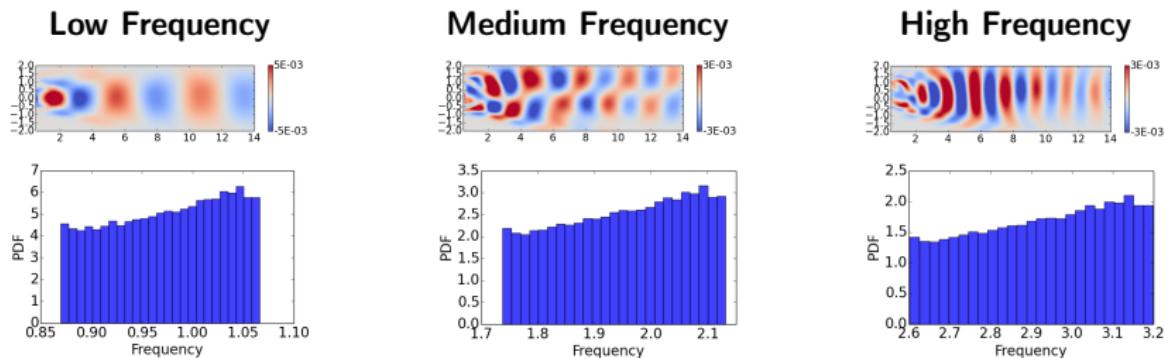
- Choose the  $Q - 1$  points halfway between  $Q$  quadrature nodes
- Calculate true modes and interpolated modes at  $Q - 1$  points
- Compare error between true modes and interpolated modes vs. true modes and mean modes

$$N(Y) \equiv \max(||Y(\xi_k) - \Phi(\xi_k)||_2) \quad , \quad k = 1 \dots Q - 1$$

MODE	$N(y_P)$	$N(\bar{y})$	$N(\bar{y})/N(y_P)$
1	4e-3	3e-1	75
2	3e-2	9e-1	30
3	2e-1	1.2	6
4	7e-1	1.5	2
5	2e-1	1.8	9

- PCE model captures range of symmetrical to asymmetrical modes

## DMD Eigenvalues



- Output is the imaginary part of DMD eigenvalues
- Histograms are based on 10,000 Monte Carlo samples of the PCE surrogate
- Modest deformation of uniform distribution for all frequencies

# Conclusions

- Uncertainty quantification techniques provide a fast, efficient, and accurate methodology for quantifying how low-dimensional models change with parametric uncertainty
  - POD modes
  - DMD modes/eigenvalues
- Further research
  - Multiple parameters
  - Apply to POD Galerkin models