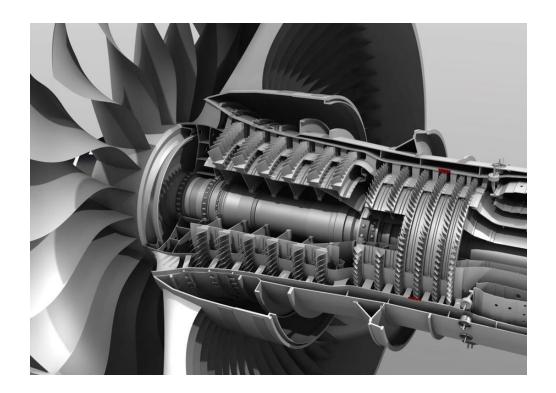
Dr.
Alessandra
Vizzaccaro

Model Order Reduction for Engineering Applications



### Bio

- ☐ PhD @ Imperial College London:
  - ➤ ROM of Large Scale Simulation



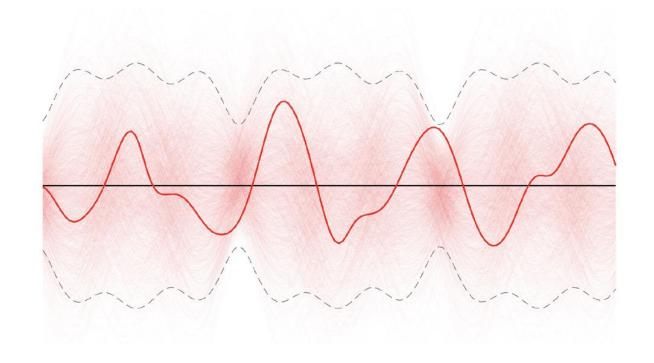
### Bio

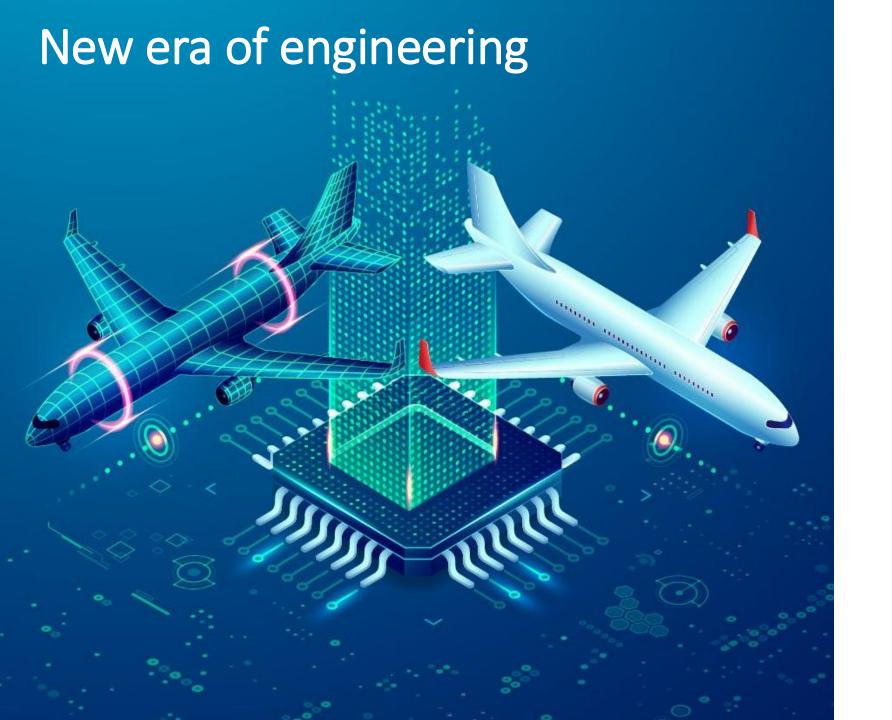
- ☐ PhD @ Imperial College London:
  - ➤ ROM of Large Scale Simulation
- ☐ PostDoc @ University of Bristol:
  - Real Time Hybrid testing



### Bio

- ☐ PhD @ Imperial College London:
  - ➤ ROM of Large Scale Simulation
- ☐ PostDoc @ University of Bristol:
  - Real Time Hybrid testing
- ☐ Senior Lecturer @ University of Exeter:
  - > UQ & ROM from data







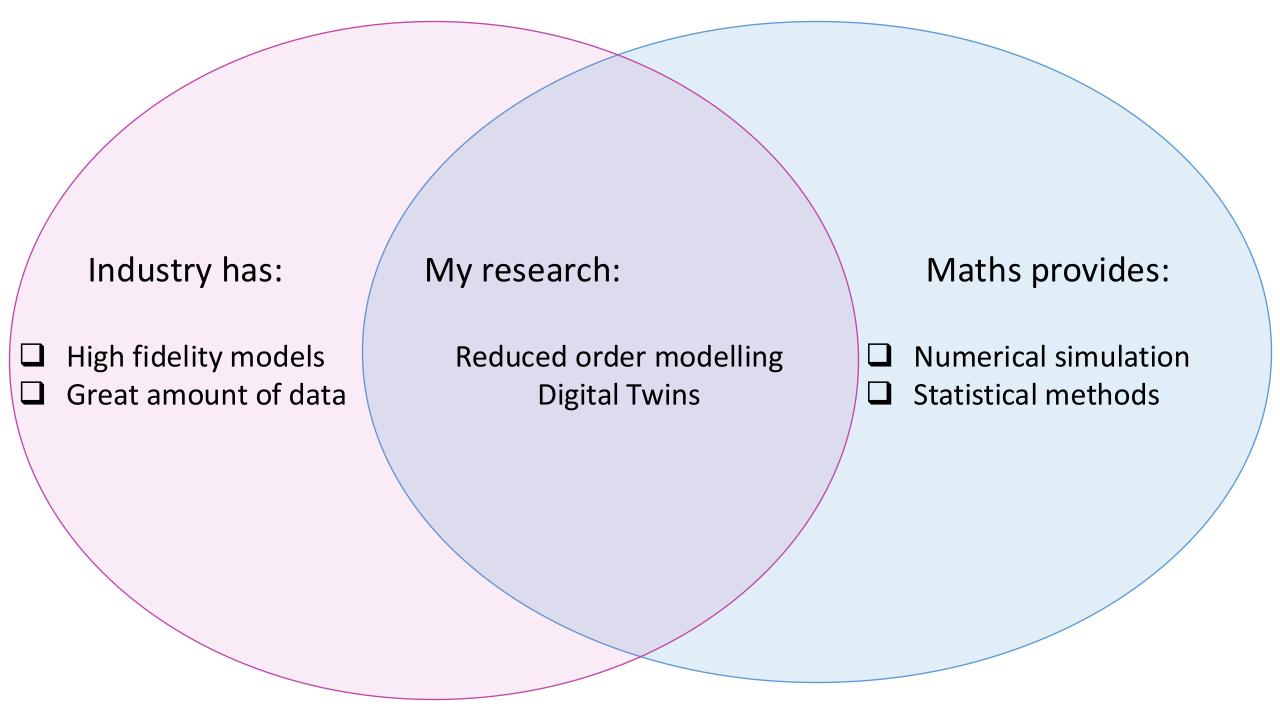
Unprecedented Computational Power



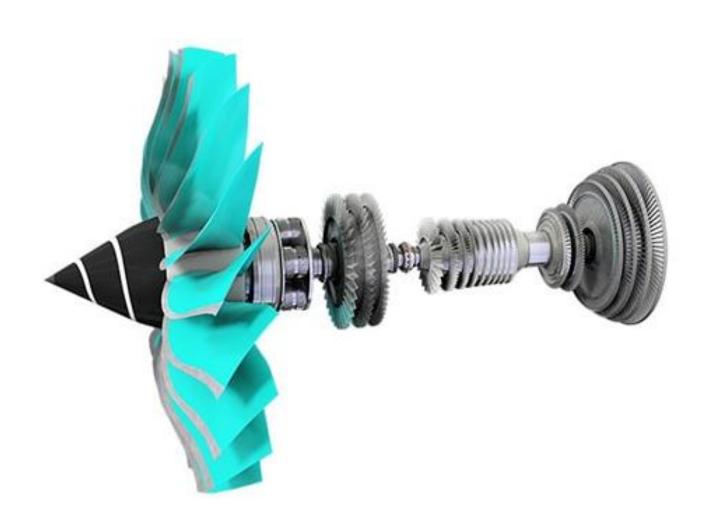
Better Sensing and monitoring



Artificial intelligence and decision making



### Simulation-free ROMs



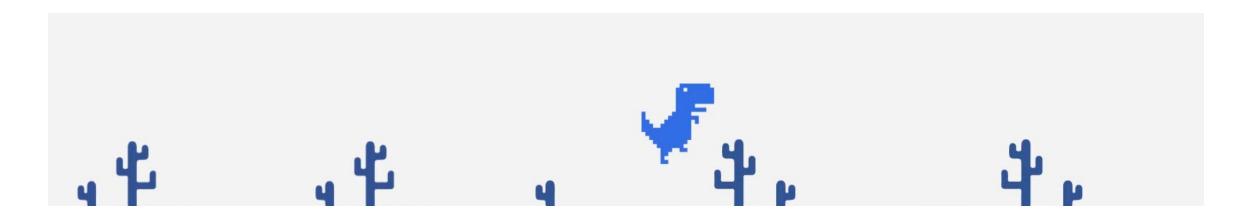
- Design stage
- ☐ Virtual testing
- ☐ Design Sensors
- Monitoring

Physics based models won't disappear, but we need better!

#### Equation based ROMs:

- ✓ Manageable
- ✓ Interpretable
- ✓ Coupled with data

### When should we use ROMs?



High fidelity Models: Large number of DOFs

Run full dynamic simulations: Hours-days

Hard to accelerate computationally

The dynamics live in a much lower dimensional space

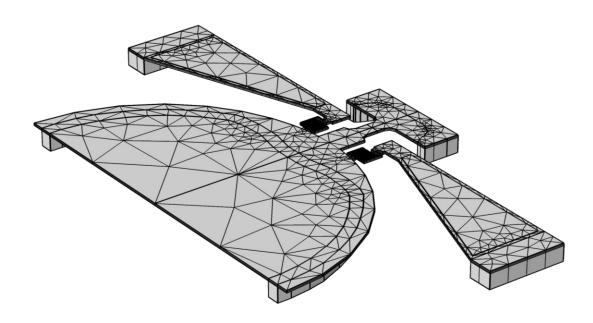
With **ROM**:

**Seconds-minutes** 

Accurate & fast surrogate

### Main Idea

Large scale 3D finite elements model



Nonlinear Dynamical system with up to **Millions** of degrees of freedom

$$\dot{y} = F(y), \qquad y \in \mathbb{R}^N$$

Capture the **characteristic** dynamics with **low dimensional** models

$$\dot{z} = f(z)$$
  $z \in \mathbb{C}^n$ ,  $n \ll N$ 



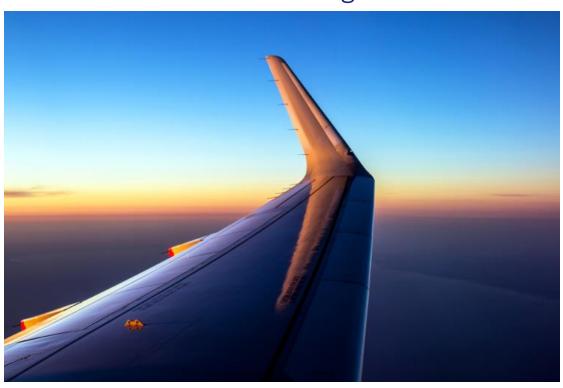


#### Characteristics of ROMs:

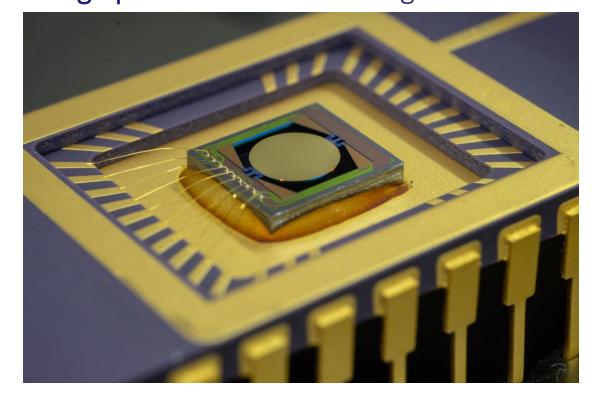
- Small number of parameters
- Physically interpretable
- Manageable
- Fast yet accurate

### Example of Application: geometric nonlinearities

Slender structures in large vibrations



High precision devices in large rotation



### Outline

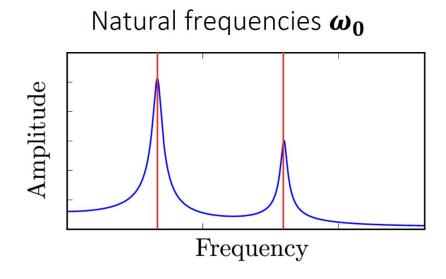
#### Nonlinear ROM

- Introduction
- Parametrisation Method
- Applications

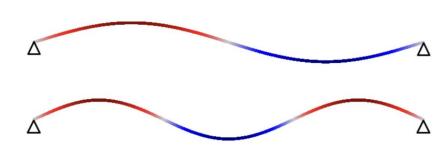
## The simplest ROM

**Large** scale **3D** finite elements model with up to **millions** of degrees of freedom:

$$M\ddot{U} + KU = 0$$



Mode shapes  $\phi_0$ 



Change of Coordinates
Reduced Dynamics

$$U = \phi_0 u$$

$$\ddot{\mathbf{u}} + \boldsymbol{\omega_0}^2 \, \mathbf{u} = 0$$

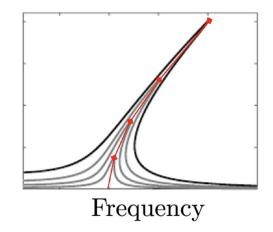
Linear Modal Analysis is the most trivial of ROMs

#### Nonlinear case

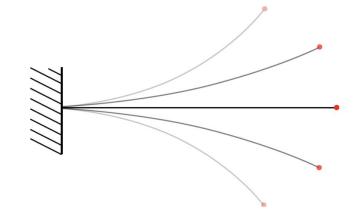
**Large** scale **3D** finite elements model with up to **millions** of degrees of freedom:

$$M\ddot{U} + KU + G(U, U) + H(U, U, U) = 0$$

Natural frequencies  $\omega_{\rm nl} = \omega_{\rm nl}(a)$ 



Mode shapes  $\phi_{nl} = \phi_{nl}(a)$ 



Change of Coordinates

Reduced Dynamics

$$U = \Psi(u, \dot{u})$$

$$\ddot{\mathbf{u}} + \omega_{\mathrm{n}}^{2} \mathbf{u} + \mathbf{f}(\mathbf{u}, \dot{\mathbf{u}}) = 0$$

The two main ingredients of every Nonlinear ROM

### Outline

#### Nonlinear ROM

- Introduction
- Parametrisation Method
- Applications

### Linear case

Nonlinear Dynamical system with up to **Millions** of degrees of freedom

$$\dot{y} = F(y), \qquad y \in \mathbb{R}^N$$

$$y \in \mathbb{R}^N$$

Equilibrium

$$F(0)=0$$

Linearisation at equilibrium

$$\nabla F(0) = A$$

Dissipative system:

$$\operatorname{Re}[\lambda_N] \le \operatorname{Re}[\lambda_{N-1}] \le \dots \le \operatorname{Re}[\lambda_1] < 0$$

Linear case

$$\dot{y} = A y$$

Slow eigenvector

$$A V_1 = \lambda_1 V_1$$

Coordinates on subspace

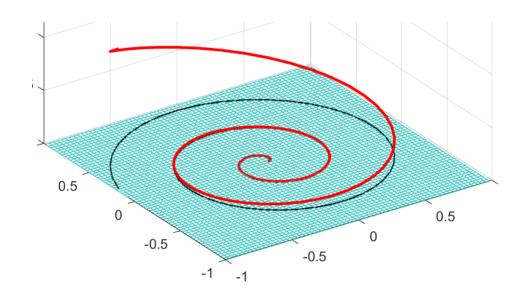
$$y = V_1 x$$

Projection on subspace

$$V_{L1}^T V_1 \dot{x} = V_{L1}^T A V_1 x$$

Reduced dynamics

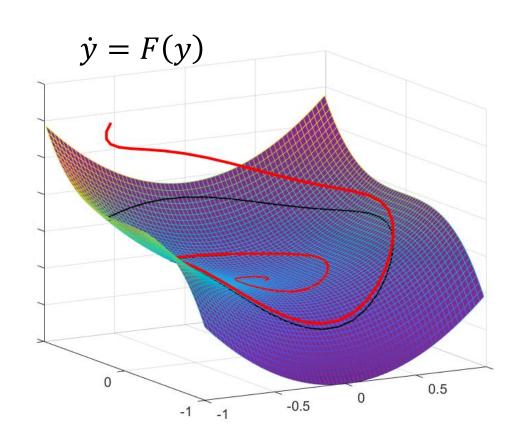
$$\dot{x} = \lambda_1 x$$



## Parametrisation method for Slow Invariant manifold

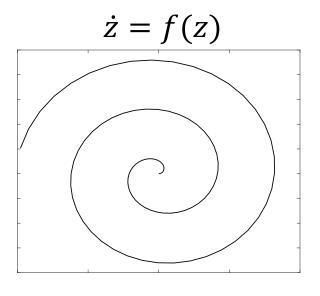
Invariant manifold tangent to linear slow subspace

☐ Sound ROM



$$y = \Psi(z)$$

$$\nabla \Psi(z) f(z) = F(\Psi(z))$$



#### Parametrisation Method

$$\dot{x} = \check{F}(x) 
\nabla \check{F}(0) = \operatorname{diag}[\lambda_1, \lambda_2, ..., \lambda_N] 
\dot{z} = f(z)$$

$$\dot{y} = V x$$

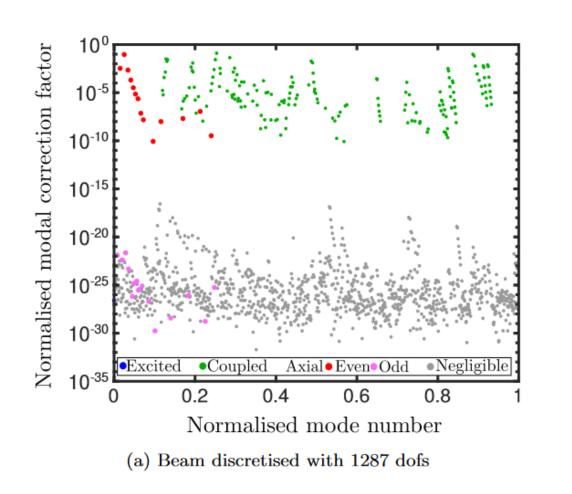
$$\dot{y} = F(y) 
\nabla F(0) = A$$

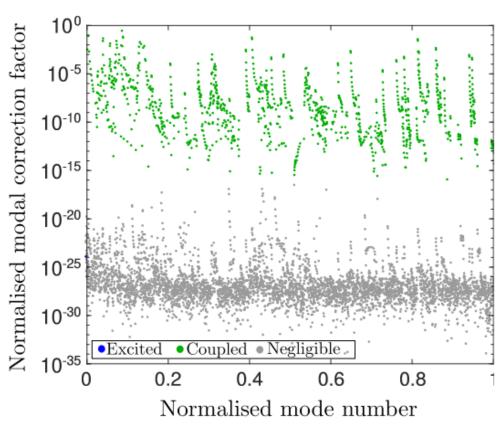
$$y = Vw(z) 
\dot{z} = f(z)$$

Limitations of Parametrisation Method for Large Scale FE models

- 1. Full eigenvector matrix computation
- 2. Sparsity of nonlinear tensor in physical coordinates

### 1. Limitation of Parametrisation Method

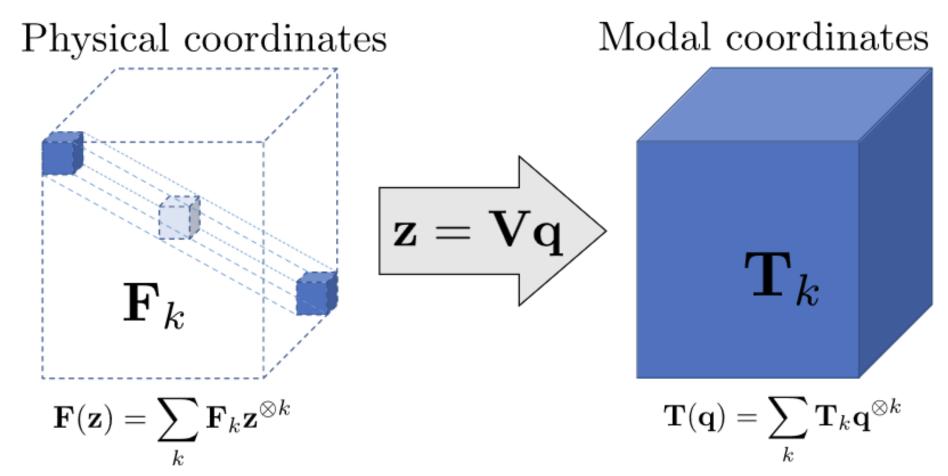




(b) Beam discretised with 5733 dofs

Non-intrusive reduced order modelling for the dynamics of geometrically nonlinear flat structures using three-dimensional finite elements. AV et al. **Comput Mech, 2020** 

#### 2. Limitation of Parametrisation Method



How to compute invariant manifolds and their reduced dynamics in high-dimensional finite element models. Jain and Haller. **Nonlin Dyn, 2022** 

#### **Direct** Parametrisation Method

$$\dot{x} = \check{F}(x)$$

$$\nabla \check{F}(0) = \operatorname{diag}[\lambda_1, \lambda_2, \dots, \lambda_N]$$

$$y = V x$$

$$\dot{y} = F(y)$$

$$\nabla F(0) = A$$

$$\dot{z} = f(z)$$

$$\dot{z} = f(z)$$

- ☐ Full eigenvector matrix computation
- ☐ Sparsity of nonlinear tensor in physical coordinates

## Direct Parametrisation of Invariant Manifolds (DPIM)

$$\dot{y} = F(y)$$

> Parametrisation of manifold as an embedding

Reduced dynamics on it (at the same time)

Both as polynomials

we have the same time 
$$y = \Psi(z)$$

ced dynamics on it (at the same time)
$$\dot{z} = f(z)$$
as polynomials
$$xx(1) = xx(2) = xx(n)$$

$$\Psi(\mathbf{z}) = \Psi_{i_1}^{(1)} z_{i_1} + \Psi_{i_1 i_2}^{(2)} z_{i_1} z_{i_2} + \dots + \Psi_{i_1 i_2 i_3 \dots i_p}^{(p)} z_{i_1} z_{i_2} z_{i_3} \dots z_{i_p}$$

$$\mathbf{f}(\mathbf{z}) = \mathbf{f}_{i_1}^{(1)} z_{i_1} + \mathbf{f}_{i_1 i_2}^{(2)} z_{i_1} z_{i_2} + \dots + \mathbf{f}_{i_1 i_2 i_3 \dots i_p}^{(p)} z_{i_1} z_{i_2} z_{i_3} \dots z_{i_p}$$

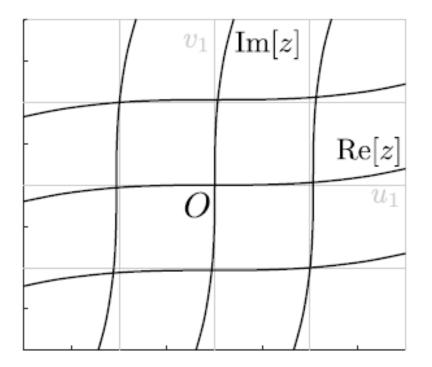
#### Linear monomials

$$\Psi(\mathbf{z}) = \Psi_{i_1}^{(1)} z_{i_1}$$
 $\dot{\mathbf{z}} = \mathbf{f}_{i_1}^{(1)} z_{i_1}$ 

$$I = \{i_1\}$$

$$(A - \lambda_{i_1} \mathrm{Id}) \Phi_{i_1} = \mathbf{0}$$

- > Linear homological = eigenproblem
- > Tangency to master subspace



### Higher order monomials

$$\Psi(\mathbf{z}) = \Phi_{i_1} z_{i_1} + \Psi_{i_1 i_2}^{(2)} z_{i_1} z_{i_2} + \dots + \Psi_{i_1 i_2 i_3 \dots i_p}^{(p)} z_{i_1} z_{i_2} z_{i_3} \dots z_{i_p}$$

$$\dot{\mathbf{z}} = \lambda_{i_1} z_{i_1} + \mathbf{f}_{i_1 i_2}^{(2)} z_{i_1} z_{i_2} + \dots + \mathbf{f}_{i_1 i_2 i_3 \dots i_p}^{(p)} z_{i_1} z_{i_2} z_{i_3} \dots z_{i_p}$$

$$I = \{i_1 i_2 i_3 \dots i_p\}$$

$$\sigma_I = \lambda_{i_1} + \lambda_{i_2} + \lambda_{i_2} + \dots + \lambda_{i_p}$$

Invariance Equation:

$$\nabla \Psi(z) f(z) = F(\Psi(z))$$

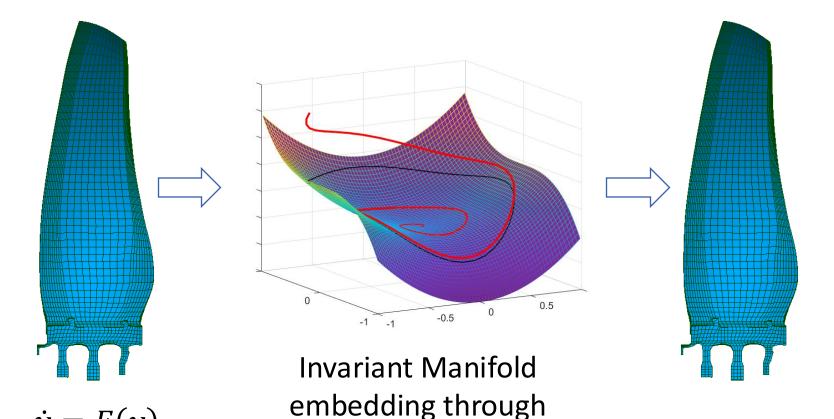
Homological Equation:

$$\Psi_{I}^{(p)} \sigma_{I} = A \Psi_{I}^{(p)} + \Xi_{I}^{(p)}$$
Singular if:  $\sigma_{I} = \lambda_{I}$ 

#### Parametrisation method

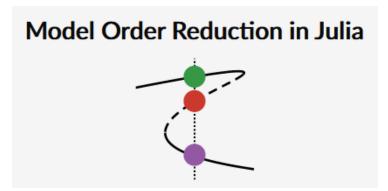
A priori method for ROM of large-scale FE models

 $\dot{y} = F(y)$ 



parametrisation

 $y = \Psi(z)$   $\dot{z} = f(z)$ 











AV et al., CMAME (2021)
Opreni et al., Nonlin Dyn (2021)
AV et al., Nonlin Dyn (2022)
Opreni et al., Nonlin Dyn (2022)
AV et al., Nonlin Dyn (2023)

### Outline

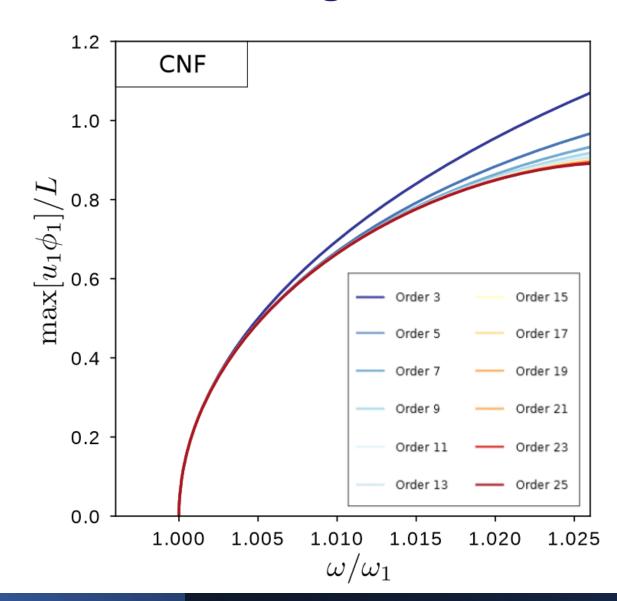
#### Nonlinear ROM

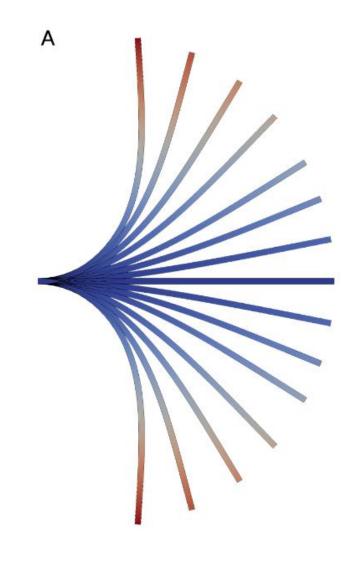
- Introduction
- Parametrisation Method
- Applications

### Automated Higher Order Expansion

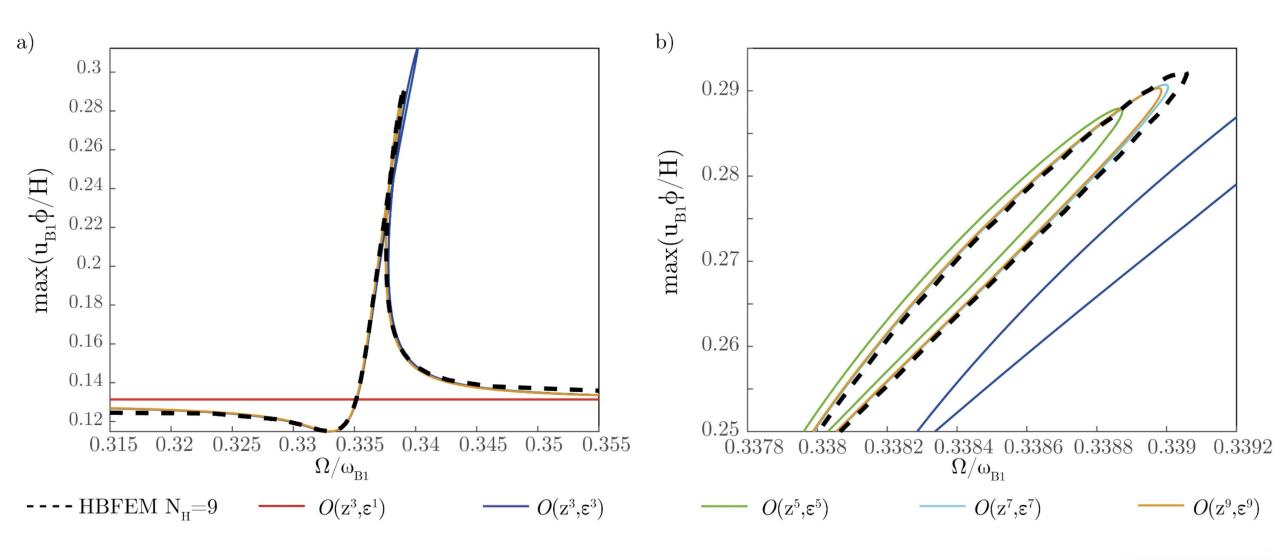
Cantilever
Beam in Large
amplitude
Vibration

Convergence with the Order

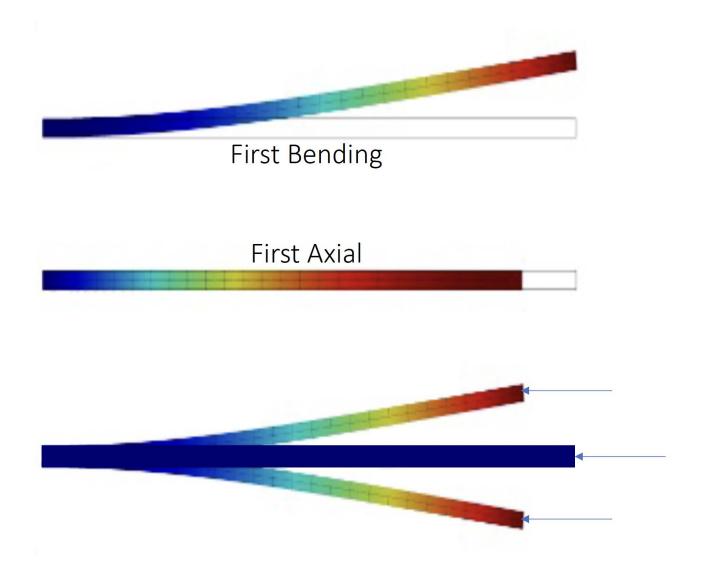


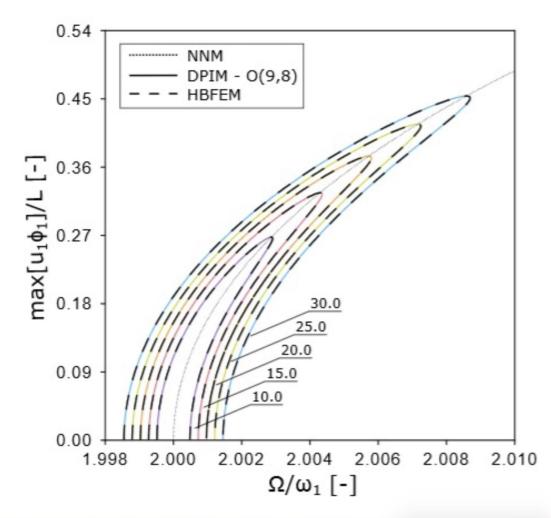


### Application to super-harmonic resonance



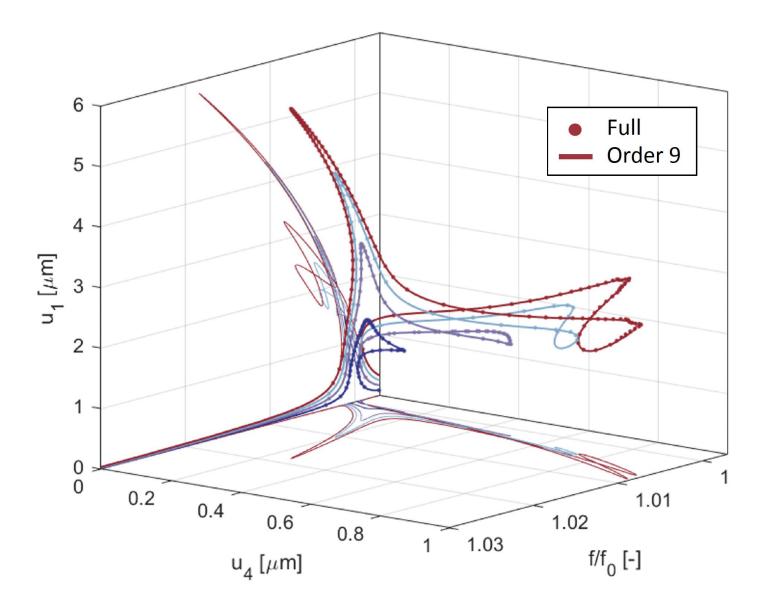
### Application to parametric resonance





## Application to internal resonance

1:3 internal resonance
between modes
captured
extremely accurately
by 2 oscillators ROM

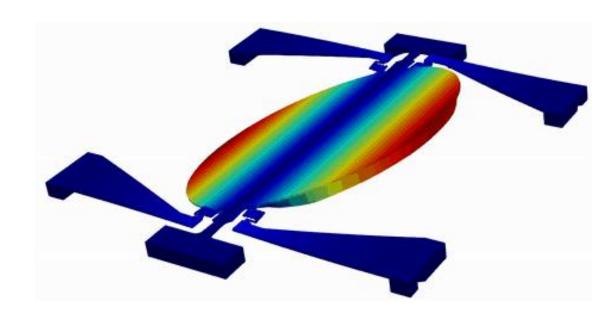


## Industrial Application: MEMS micromirror

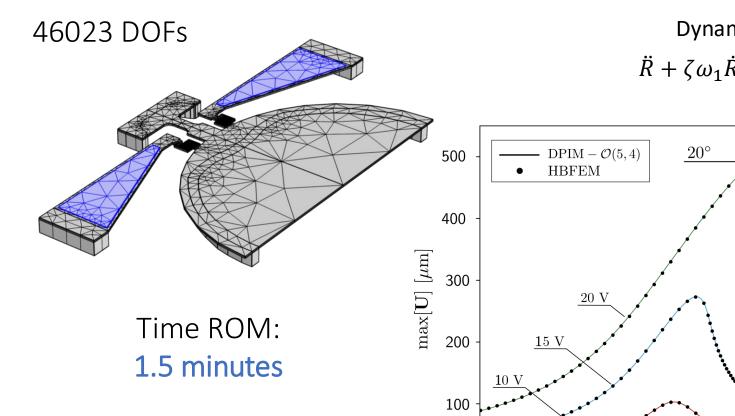
High precision device for LeddarTech



First Linear Mode at frequency ≈ 2 kHz

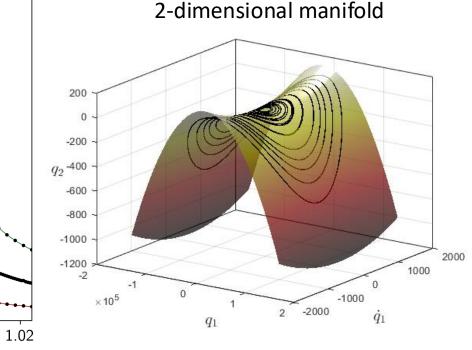


### Industrial Application: MEMS micromirror



Dynamics of a single oscillator:

$$\ddot{R} + \zeta \omega_1 \dot{R} + \omega_1^2 R + A R^3 + B R \dot{R}^2 = F$$



Time Full: 2 days

0.99

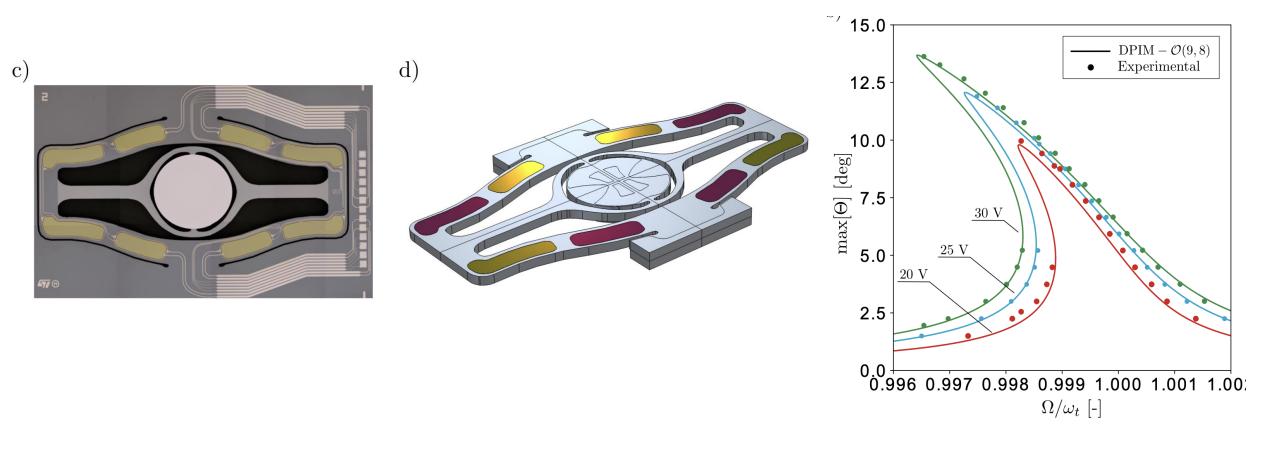
0.98

1.00

 $\Omega/\omega_{t}[-]$ 

1.01

## Industrial Application: MEMS micromirror



### Still a lot to do

#### ROM used for:

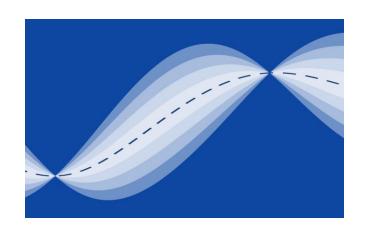
- Parametric ROMs
- Sensitivity & UQ
- Design optimisation

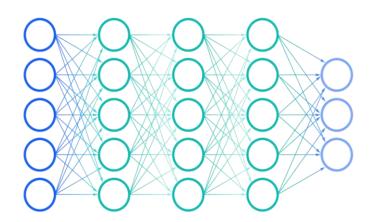
#### Coupled with data:

- Physics informed
- Bayesian inference
- Better Data (DoE)

#### Whole Framework:

- Complex Systems
- Composability
- Digital Twins







# Thank you for your attention