Reconstruction of extreme events in aeroelastic structures

Background

The failure of the aeroelastic structures (e.g. wind turbine blades) under extreme wind conditions can be attributed to a variety of factors from structural parameters to dynamic phenomena like flutter. These phenomena can be realized numerically using fluid structure interaction (FSI). We explore effects of uncertainty in structural and aerodynamic parameters on the response of the system.

Failure of a wind turbine blade

Objectives

- Develop robust ROMs to be used in lieu of flow solver in aeroelastic problems
- Develop efficient UQ techniques for aeroelastic problems
- Find applications of Bayesian data-assimilation in aeroelasticity, such as reconstruction of gusts from wind turbine sensor data
- Develop efficient computational tools for these inverse problems such as real-time gust monitoring tools for wind farms

Reduced Order Model (ROM)

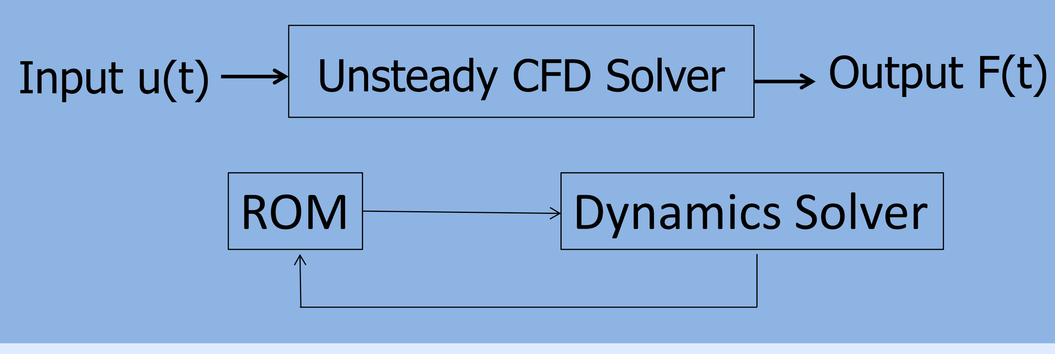
Prediction of range for dynamic instabilities (e.g. flutter) can be costly even with parallel computing facilities. Solving an aeroelastic system requires coupling of aerodynamic (responsible for bulk of the processing time) and structural solvers. Replacing the aerodynamic with a cheap solver is required, wherein reduced order modelling approaches are applied.

a. Projection based approach:

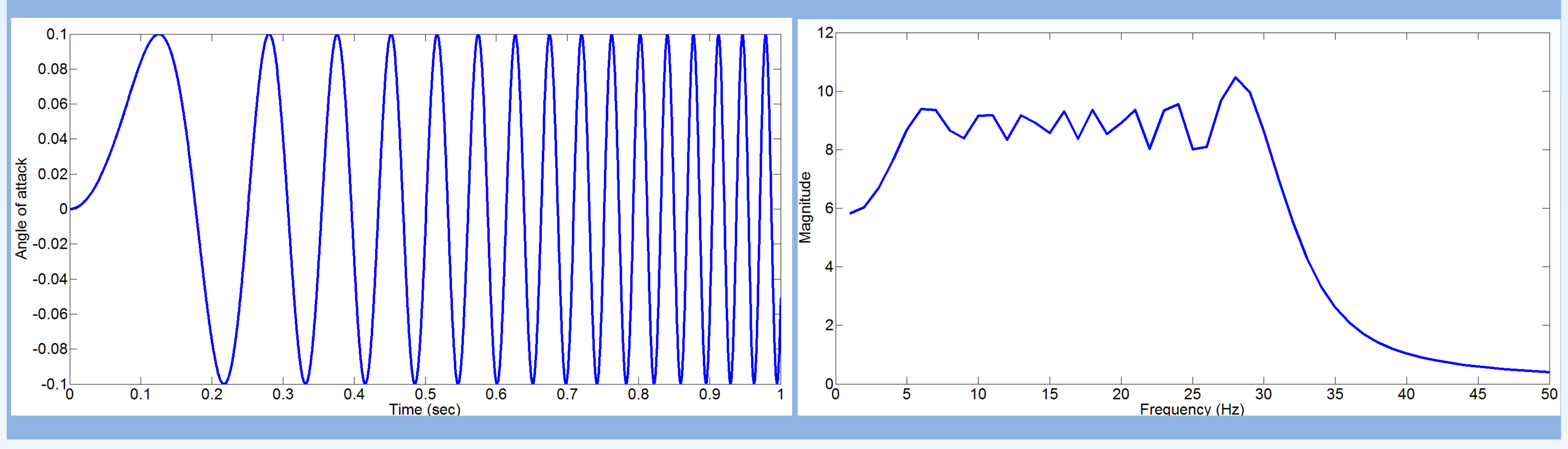
- Construction of low-dimensional subspace of the high dimensional system
- Projection of high dimensional model of interest onto the constructed subspace

b. System identification:

- Identification of the mapping relating input and output of the system
- Training of the base system for obtaining best possible approximation for the map



- Selection of "best" training signal for exciting entire frequency range of interest
- Model order optimization for error minimization

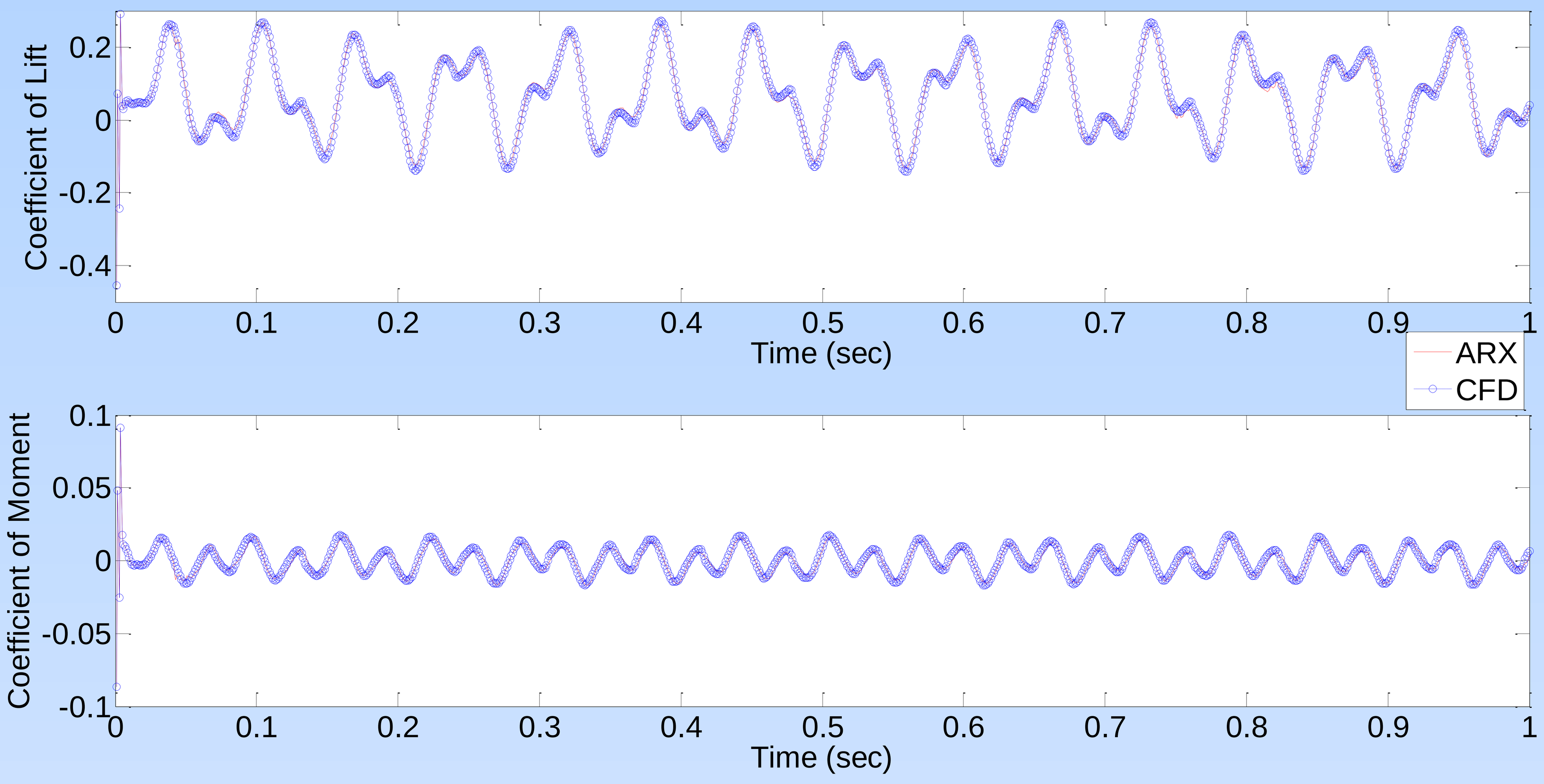


Autoregressive with exogenous input (ARX) model

$$x(s)=\sum_{i=1}^{p}a_i x(s-i)+\sum_{j_1=1}^{q_1}b_{j_1}y_1(s-j_1)+\cdots\cdots+\sum_{j_h=1}^{q_h}b_{j_h}y_h(s-j_h)$$

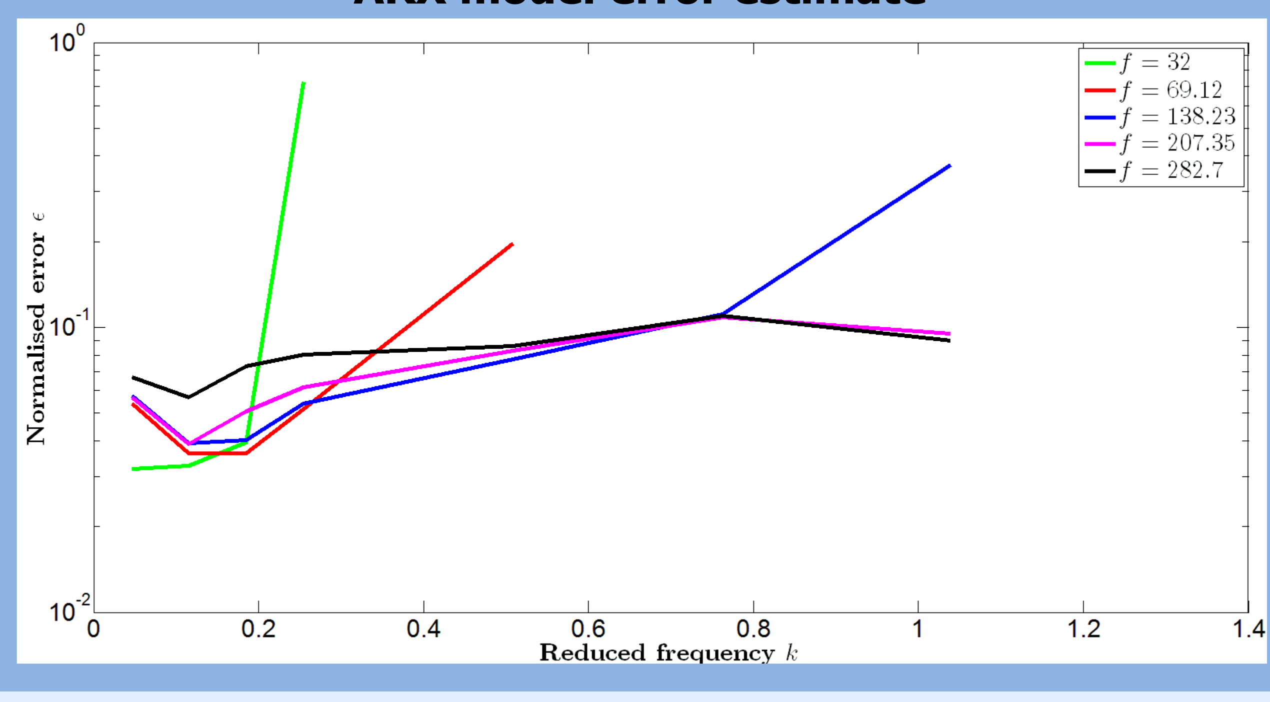
$$\hat{C}_L(t^{n+1})=\sum_{i=0}^{n}a_i C_L(t^{n-i})+\sum_{j=0}^{n}b_i\alpha(t^{n-j})+\sum_{k=0}^{n}c_k h(t^{n-k})$$

$$\hat{C}_M(t^{n+1})=\sum_{i=0}^{n}d_i C_M(t^{n-i})+\sum_{j=0}^{n}e_i\alpha(t^{n-j})+\sum_{k=0}^{n}f_k h(t^{n-k})$$

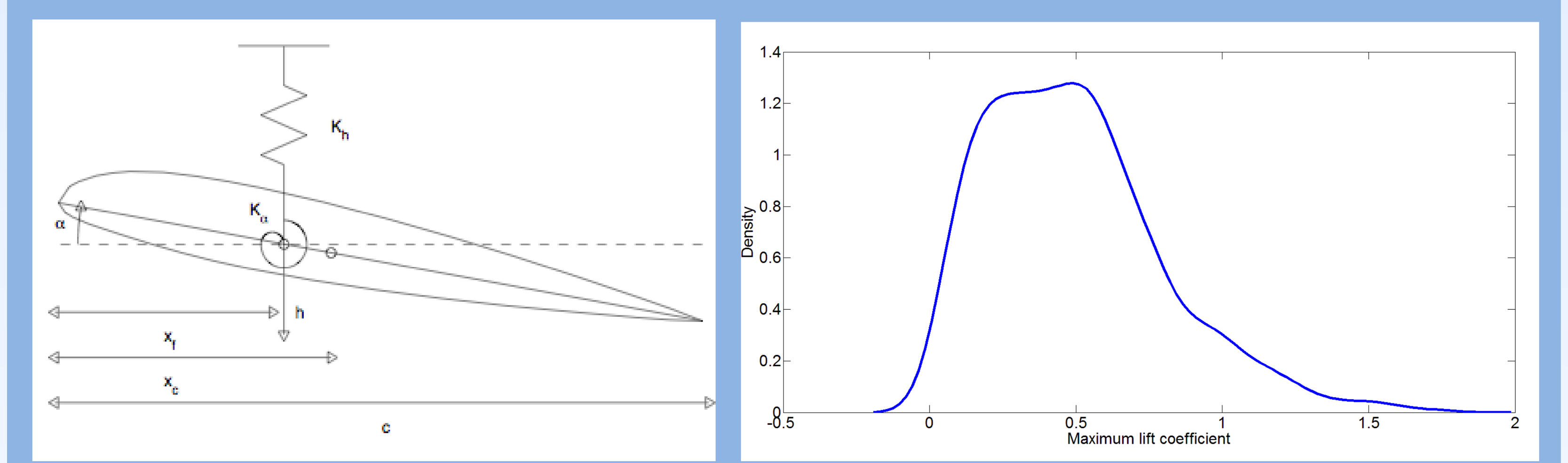


Reconstruction of lift and moment coefficient for pitch-plunge airfoil

ARX model error estimate



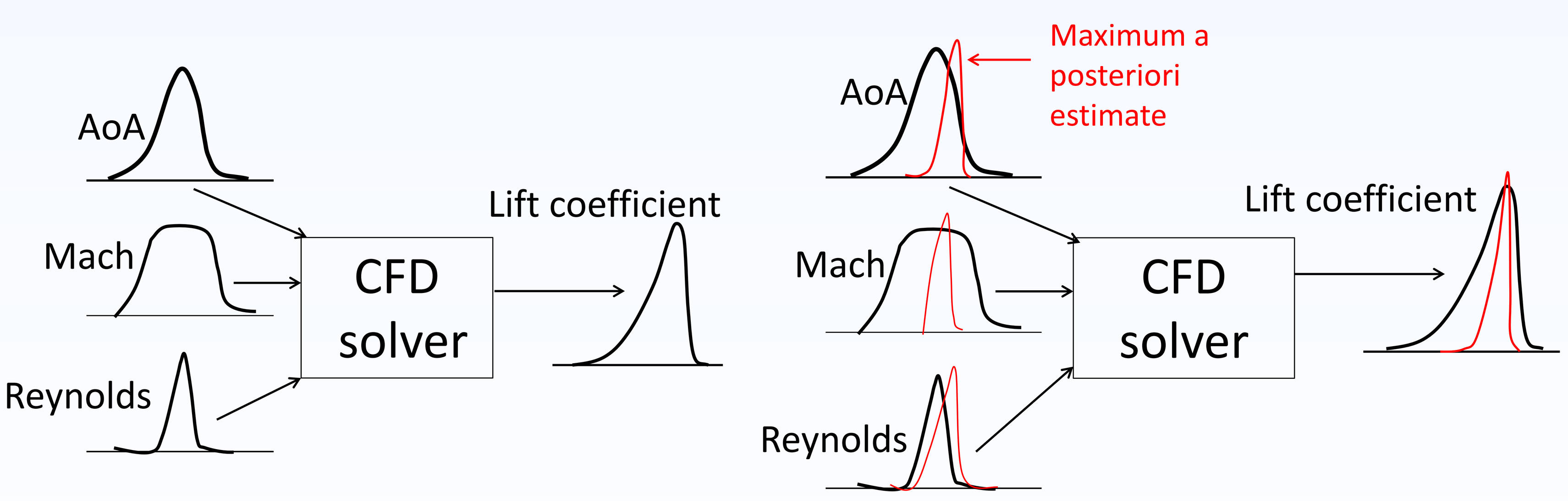
Uncertainty quantification - Brute Force Monte Carlo



- Angle of attack ~ U (0.5° - 8°)
- Reduced frequency ~ U (0.118 – 1.039)

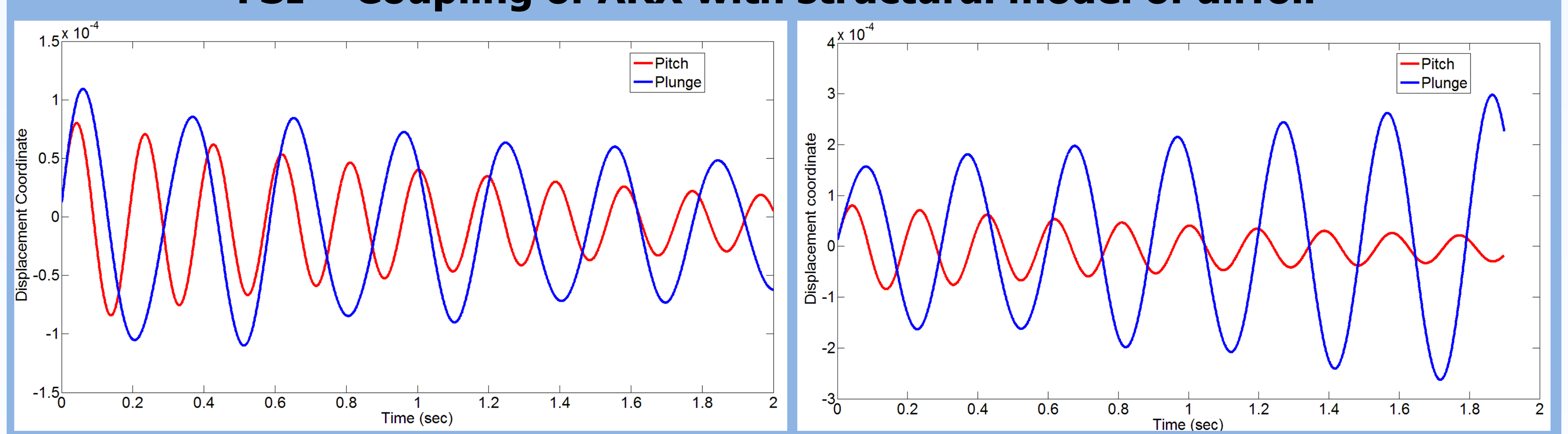
Uncertainty quantification

- Computationally intensive, may require hundreds of simulations for obtaining probabilistic estimates when traditional methods like Monte Carlo , etc. are used.
- Application of efficient UQ techniques such as probabilistic collocation method
- Bayesian data assimilation



$$P(A|B)\propto P(A)P(B|A)$$

FSI – Coupling of ARX with structural model of airfoil



$$m\ddot{h}+S\ddot{\alpha}+C_h\dot{h}+K_h h=Q_h$$

$$S\ddot{h}+I_\alpha\ddot{\alpha}+C_\alpha\dot{\alpha}+K_\alpha\alpha=Q_\alpha$$

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