WindTrue: Sensitivity analysis applied to DANAERO wind turbine

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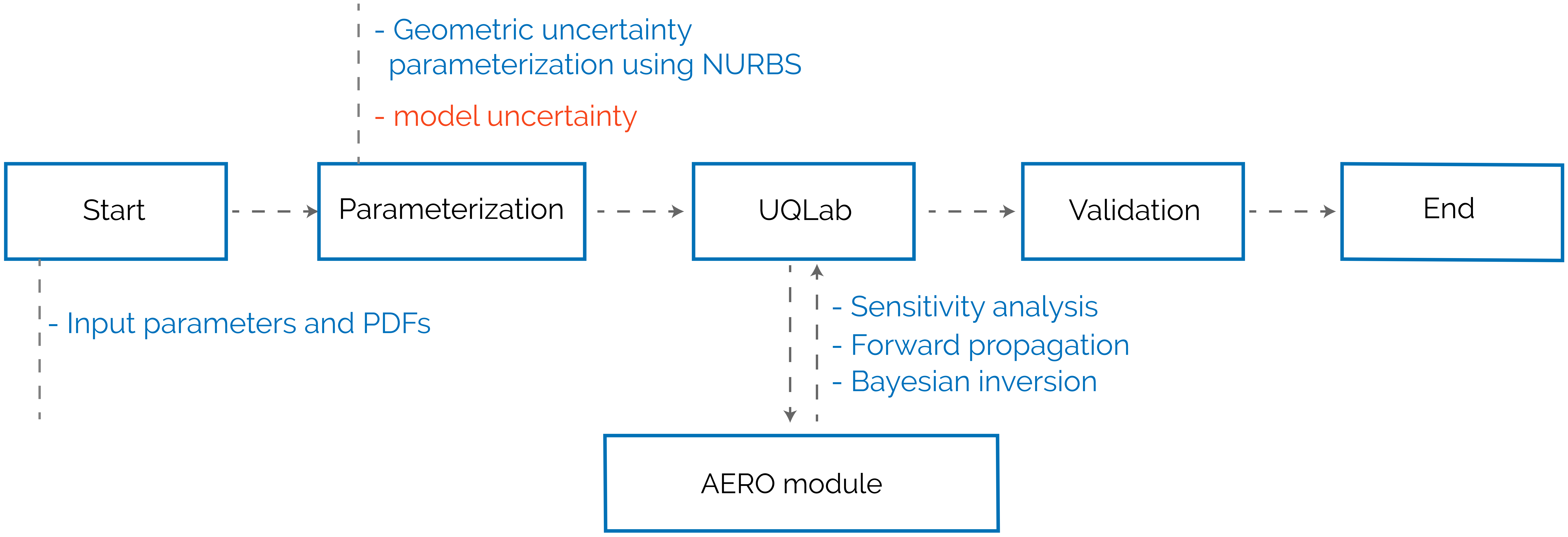
CWI

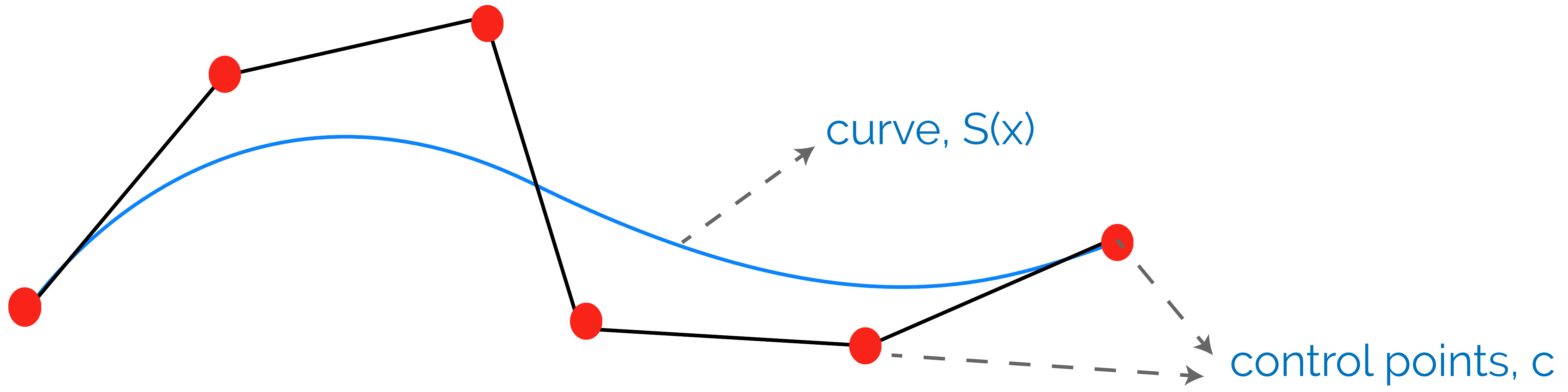
Workflow



- Geometric uncertainty
parameterization using NURBS
- model uncertainty
Start
Parameterization
UQLab
Validation
End
- Input parameters and PDFs
- Sensitivity analysis
- Forward propagation
- Bayesian inversion
AERO module

NURBS based parametrization

Non-Uniform Rational Basis Spline (NURBS)



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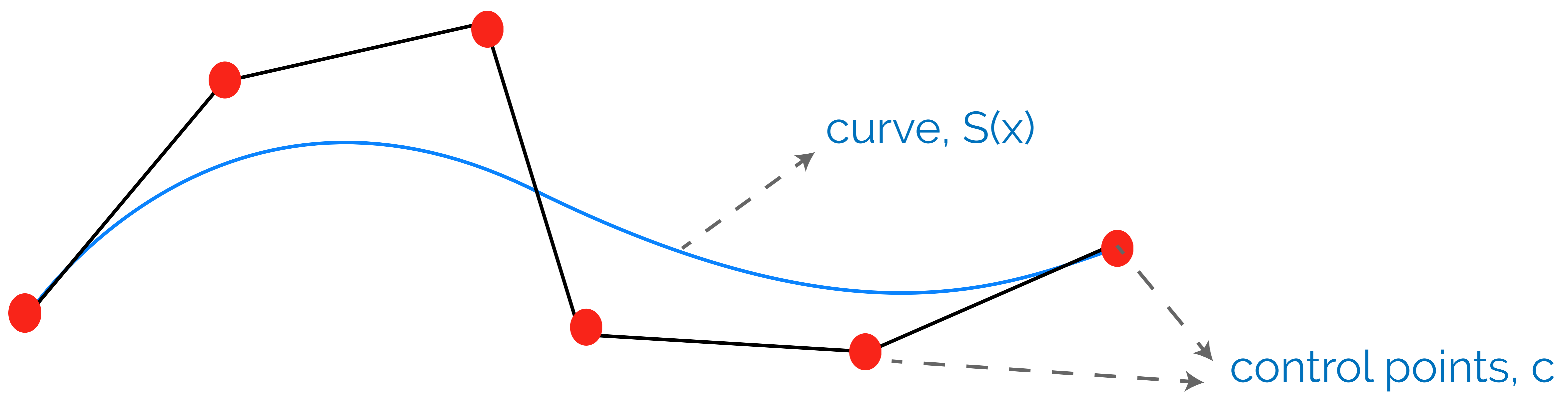

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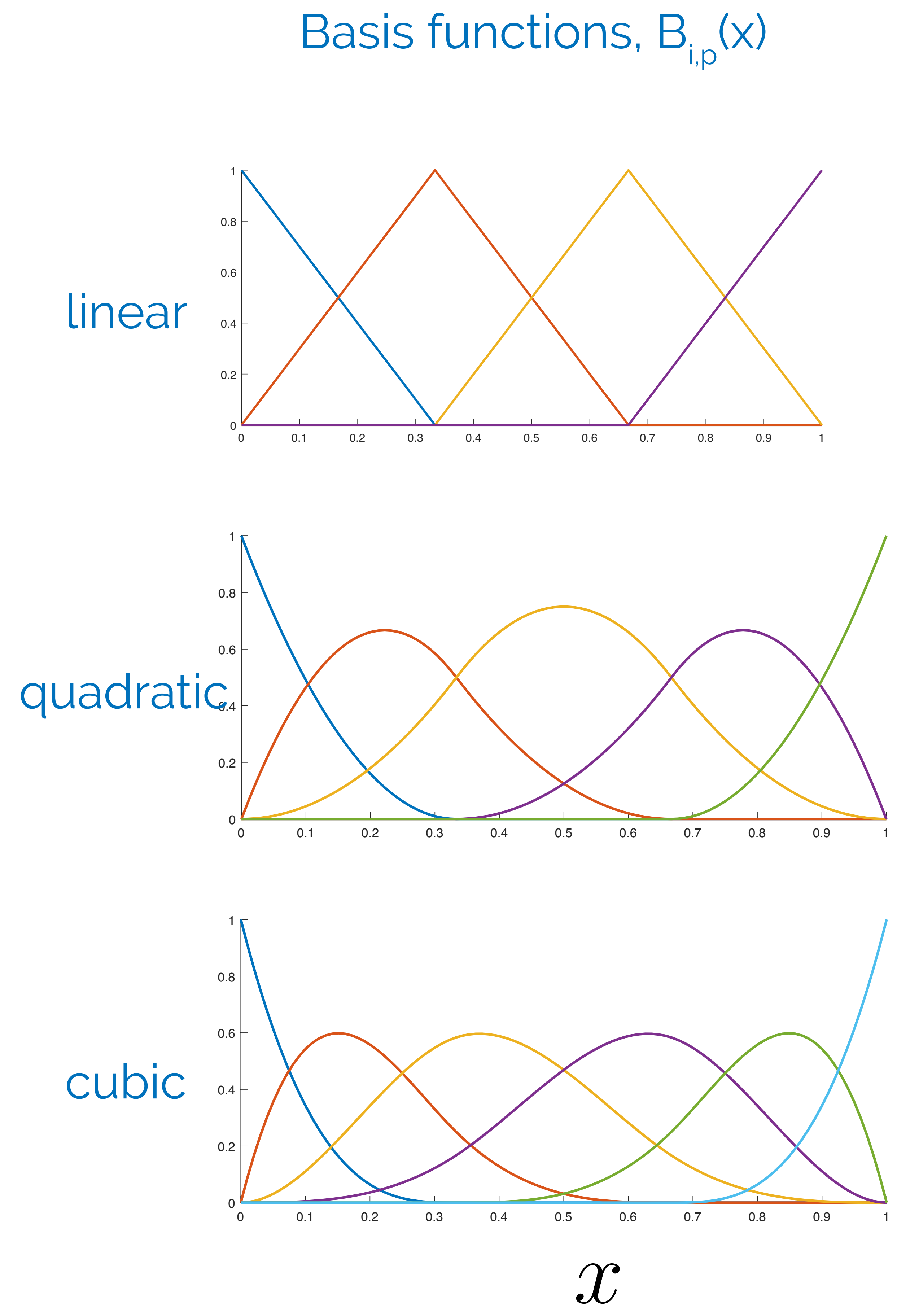


Why NURBS?

-> Represent complex shapes with very few points

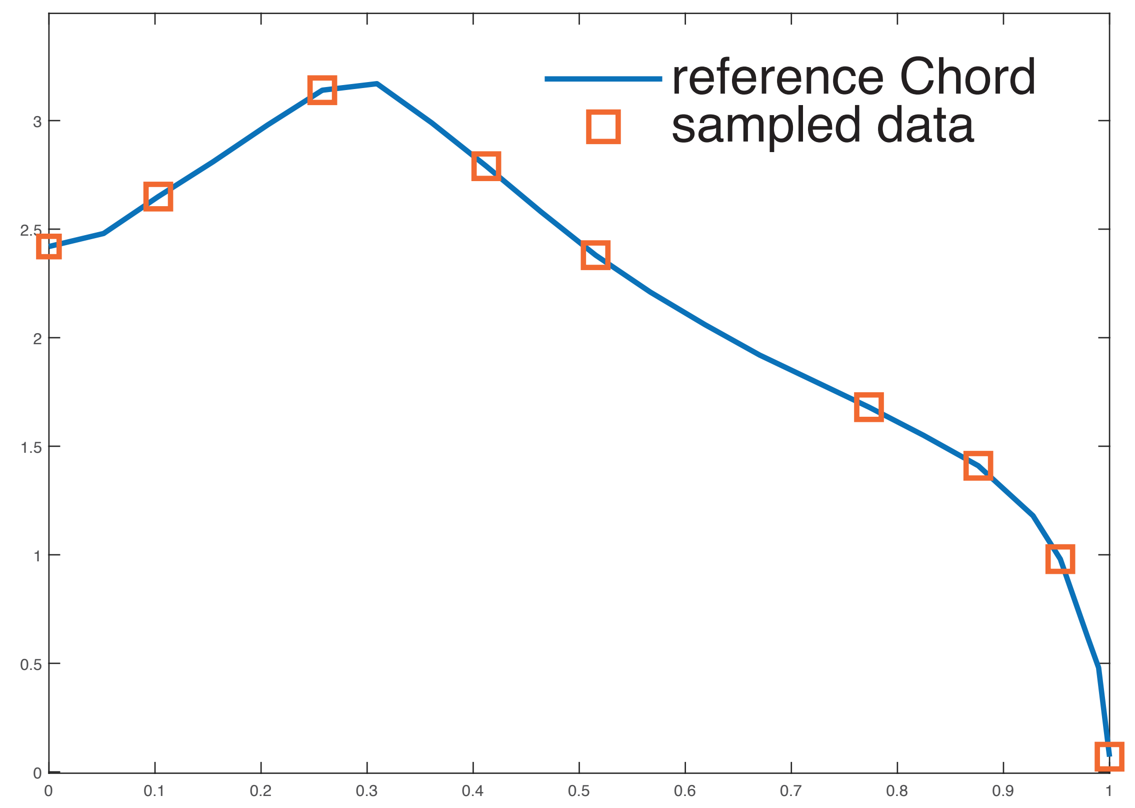
-> Flexibility to design a large variety of shapes

-> Easy to obtain high-order polynomials

Parameterization using NURBS

Goal: Obtain perturbed chord/twist from a given reference curves

Step 1: Sample locations from the reference curve



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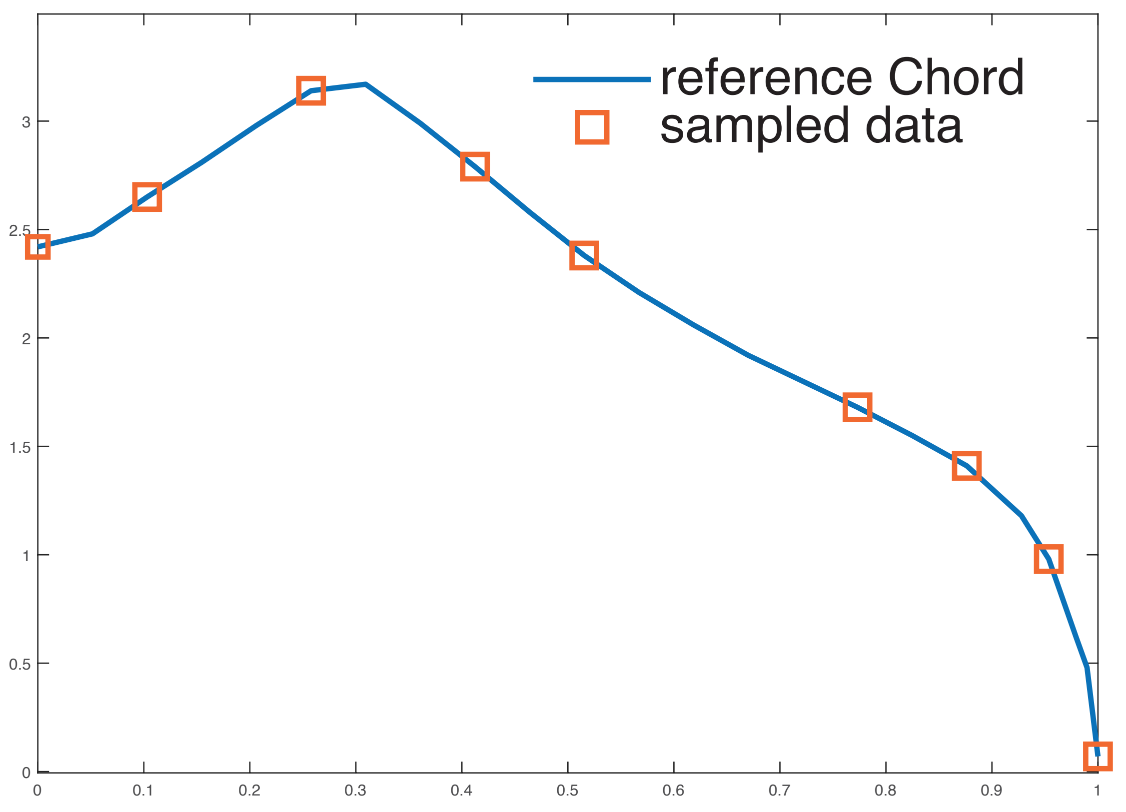

Step 2: Compute control points at sampled location via inversion

$$\underbrace{S(x)}_{\text{known}} = \sum_{i=0}^{N-1} c_i \underbrace{B_{i,p}(x)}_{\text{known}} \implies \mathbf{B}\mathbf{c} = \mathbf{S}$$

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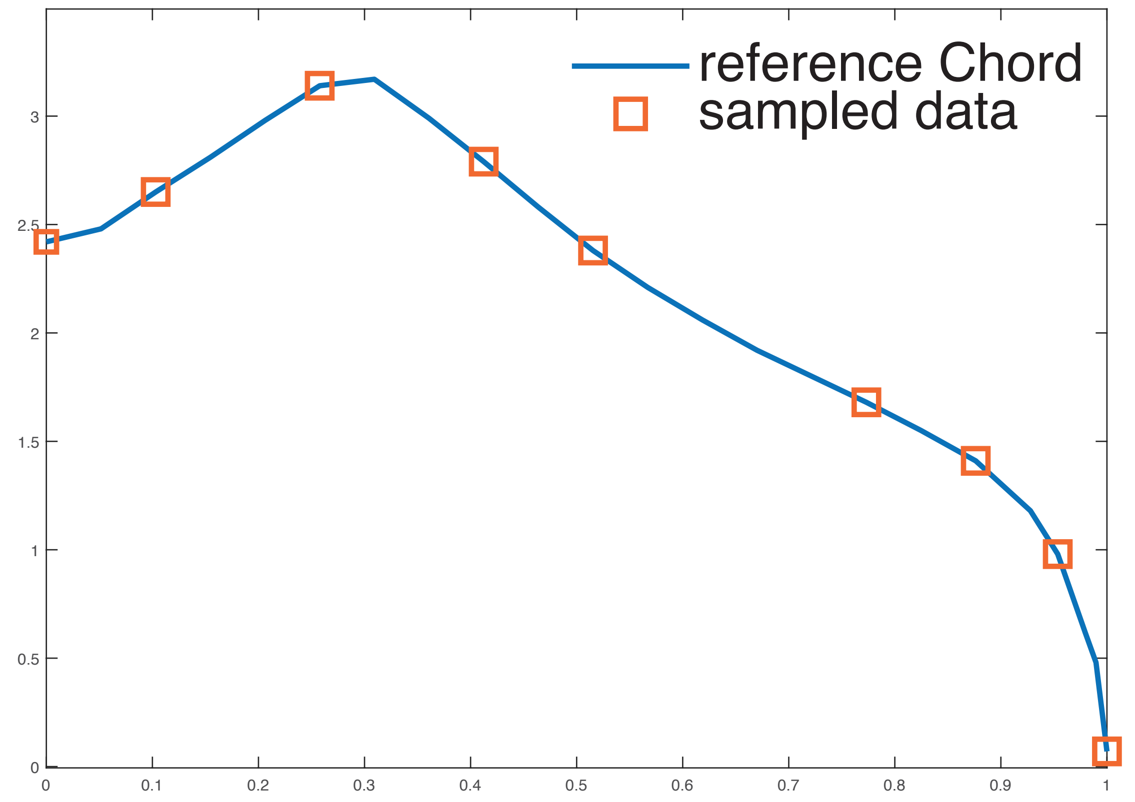

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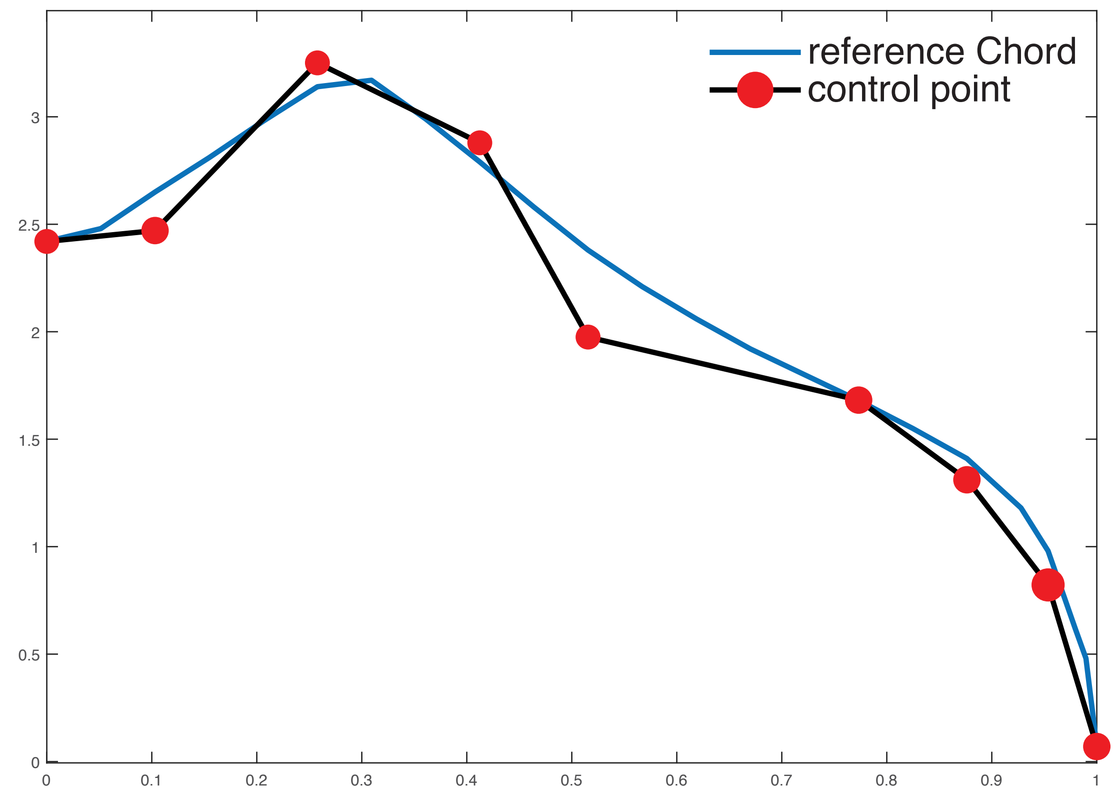

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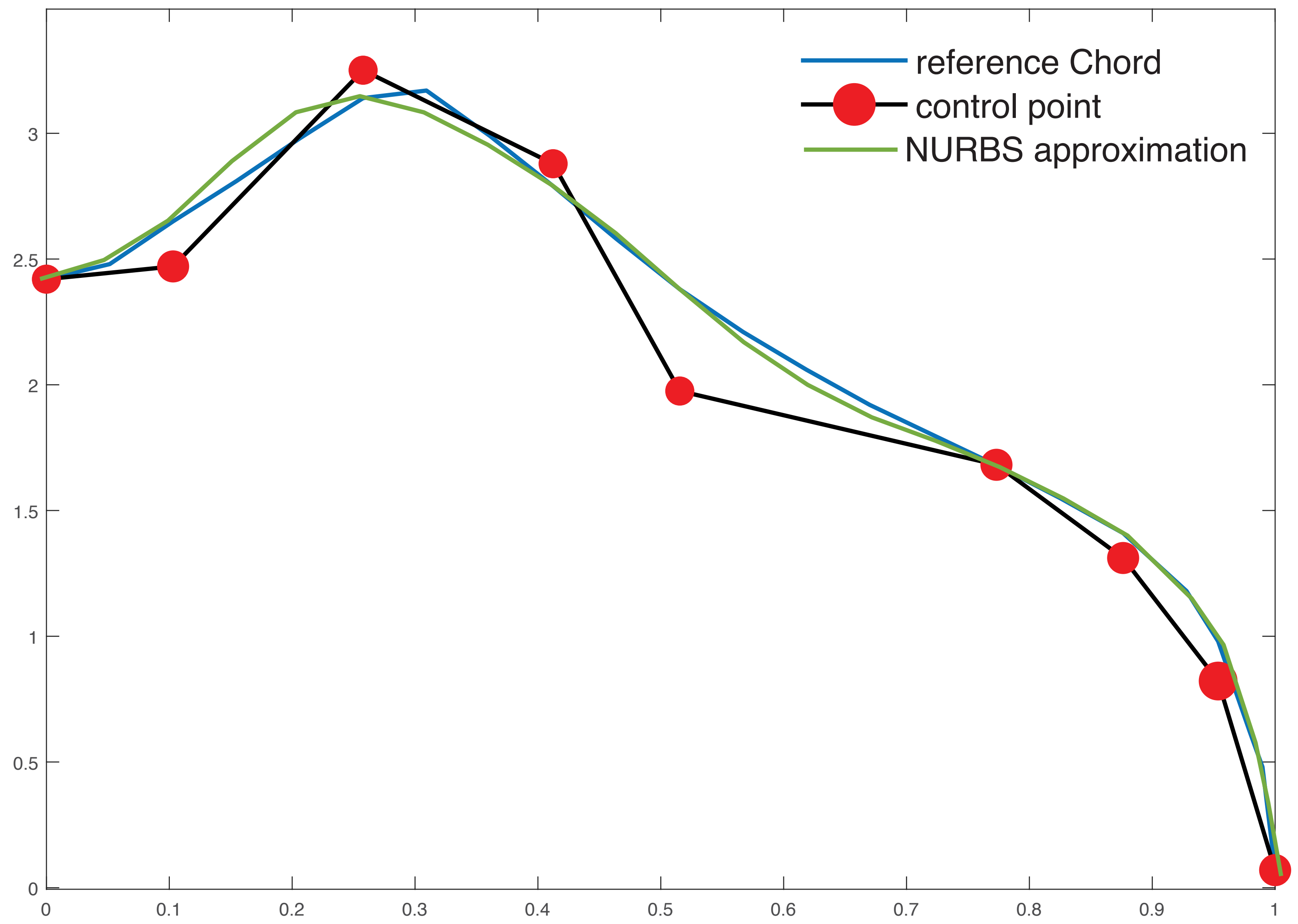
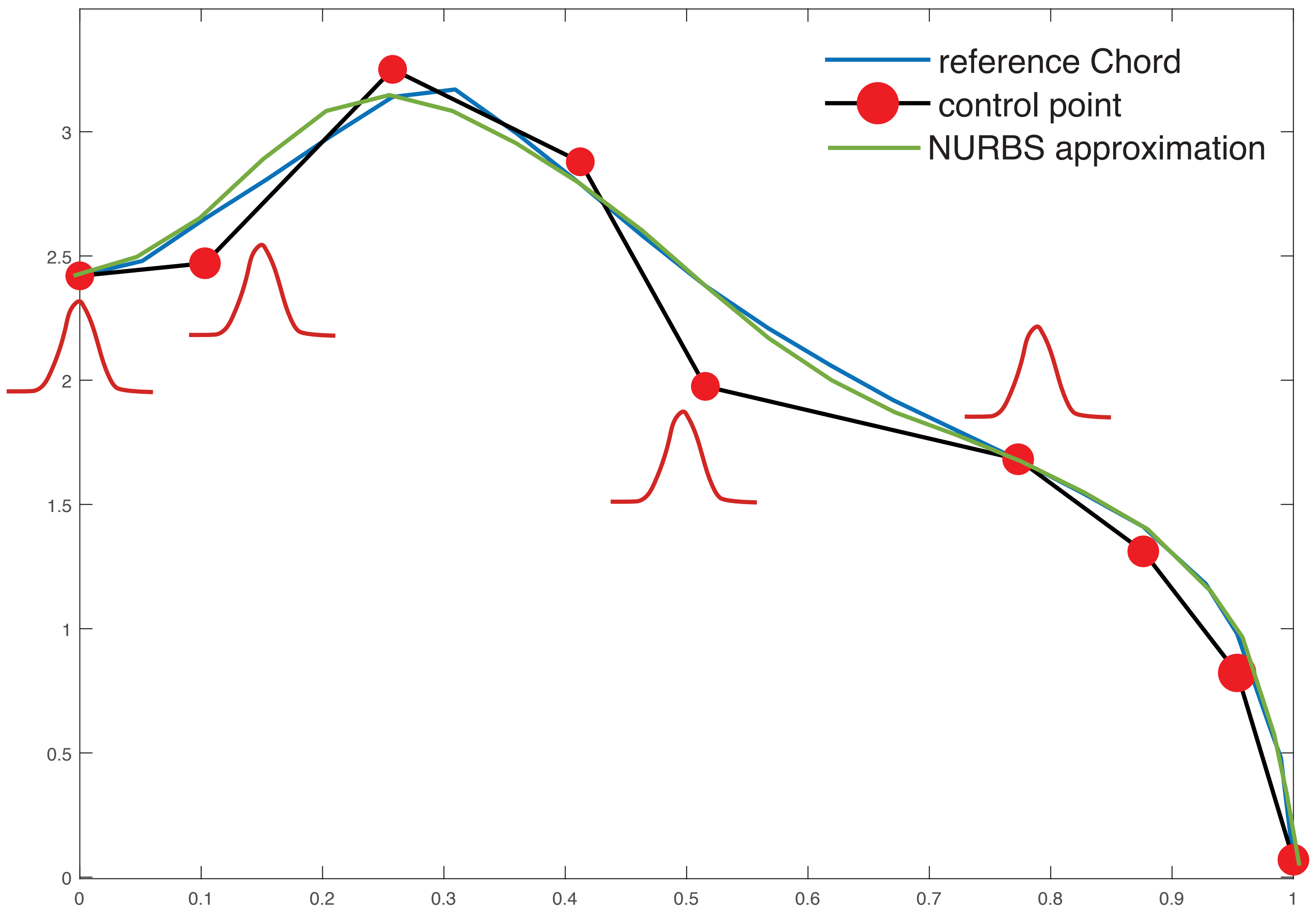


Parameterization using NURBS

Step 3: Perturb control point values using some PDF



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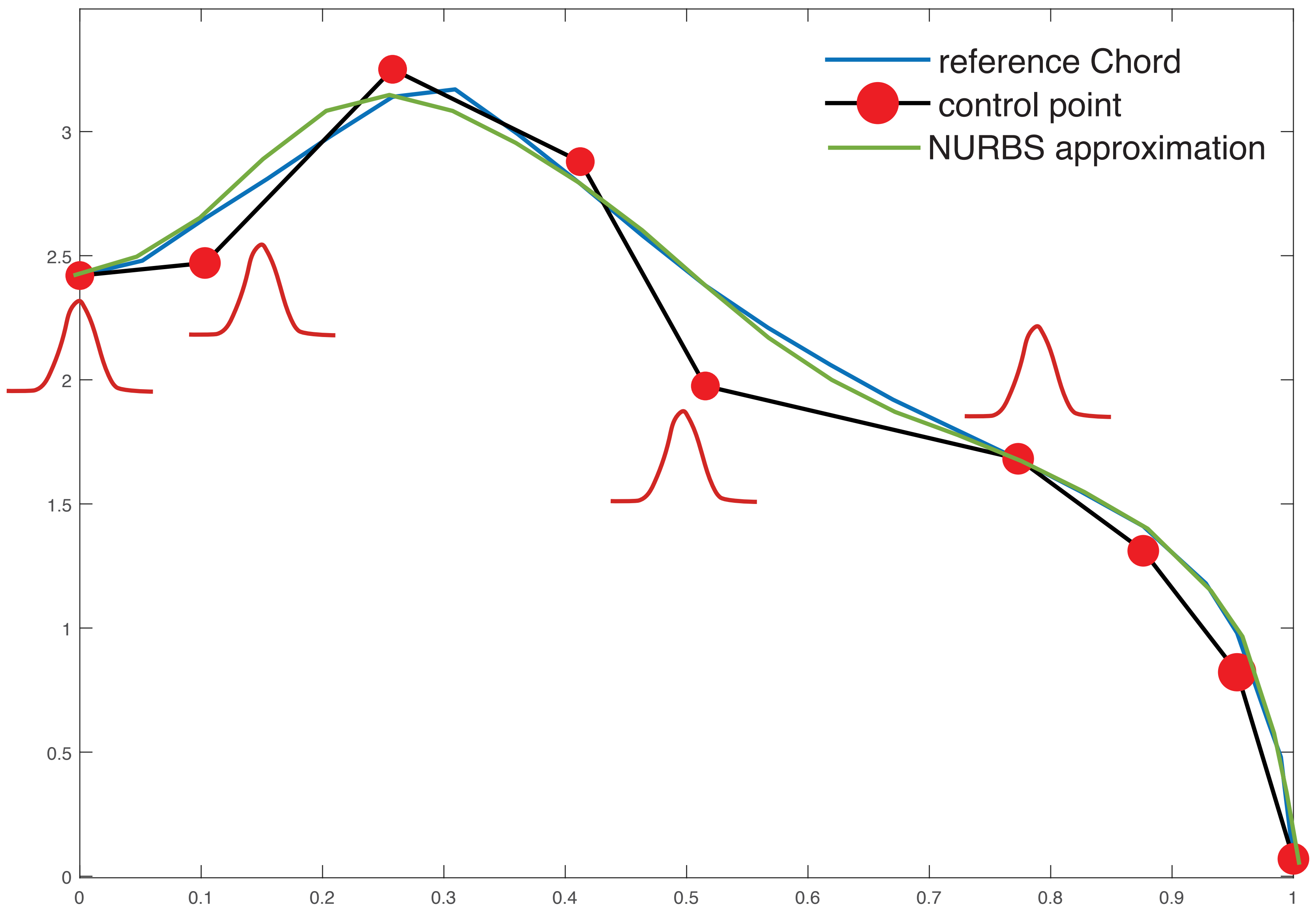
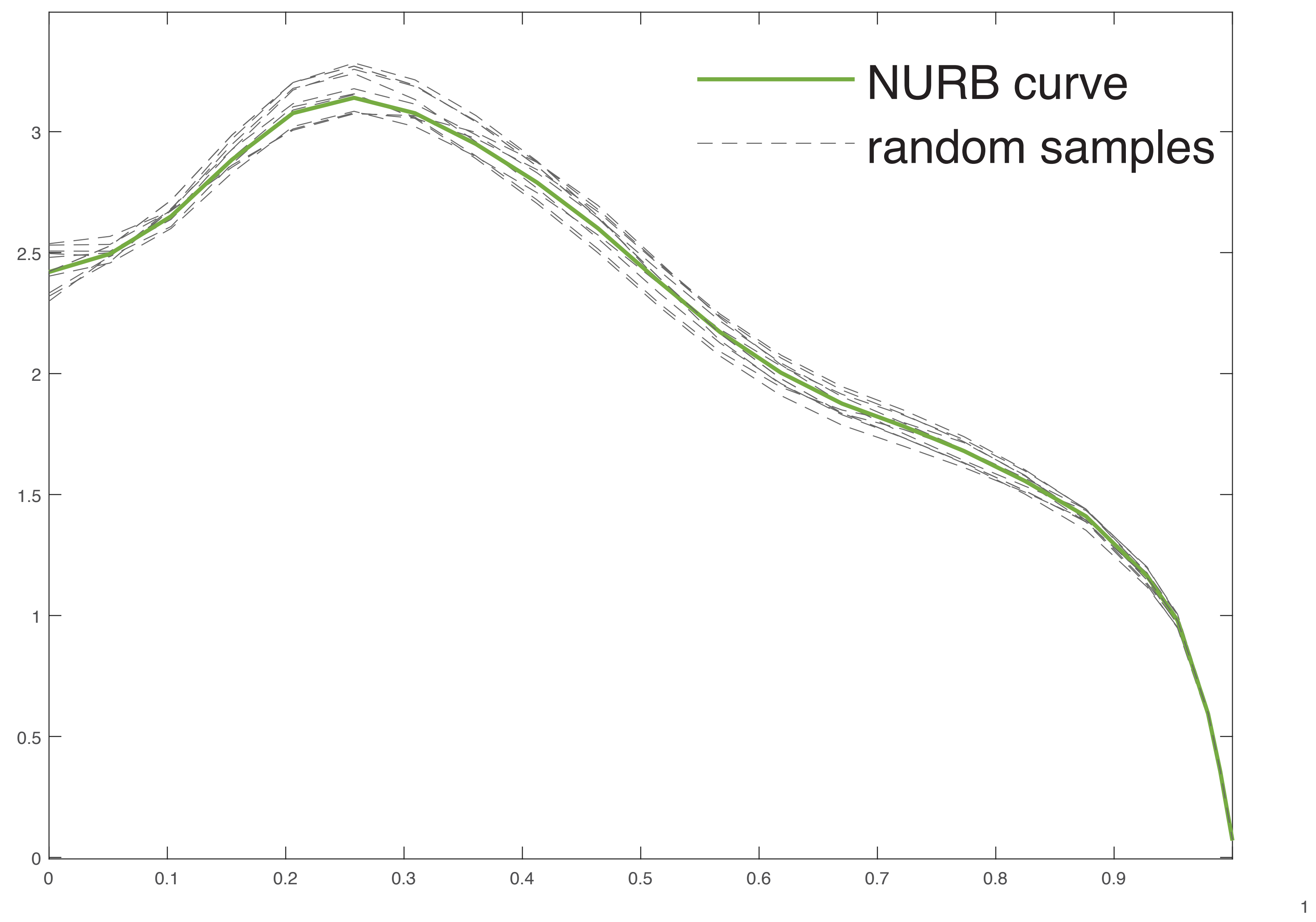


Step 4: Sample perturbed curves



Global sensitivity analysis

Global sensitivity analysis

-> Goal is to rank the uncertain parameters in the order of importance

-> Global approaches cover the uncertainty spaces more exhaustively

-> Better able to capture uncertainty in the model output

Sobol sensitivity indices

Main idea: Decompose the variance of model output in terms of contribution from individual input parameters and their combinations.

$$V(y) = \sum_i V_i + \sum_{i,j} V_{i,j} + \text{higher order terms}$$

First order indices

$$S_1 = \frac{V_1}{V}, S_2 = \frac{V_2}{V}, \ldots$$

Second order indices

$$S_{1,2} = \frac{V_{1,2}}{V}, S_{1,3} = \frac{V_{1,3}}{V}, \ldots$$

Polynomial Chaos Expansion (PCE)

To compute individual variances, we use PCE based methods

Three variants of PCE:

1) Quadrature (PCE_QUAD) $\Longrightarrow$ Deterministic sampling, fixed in degree

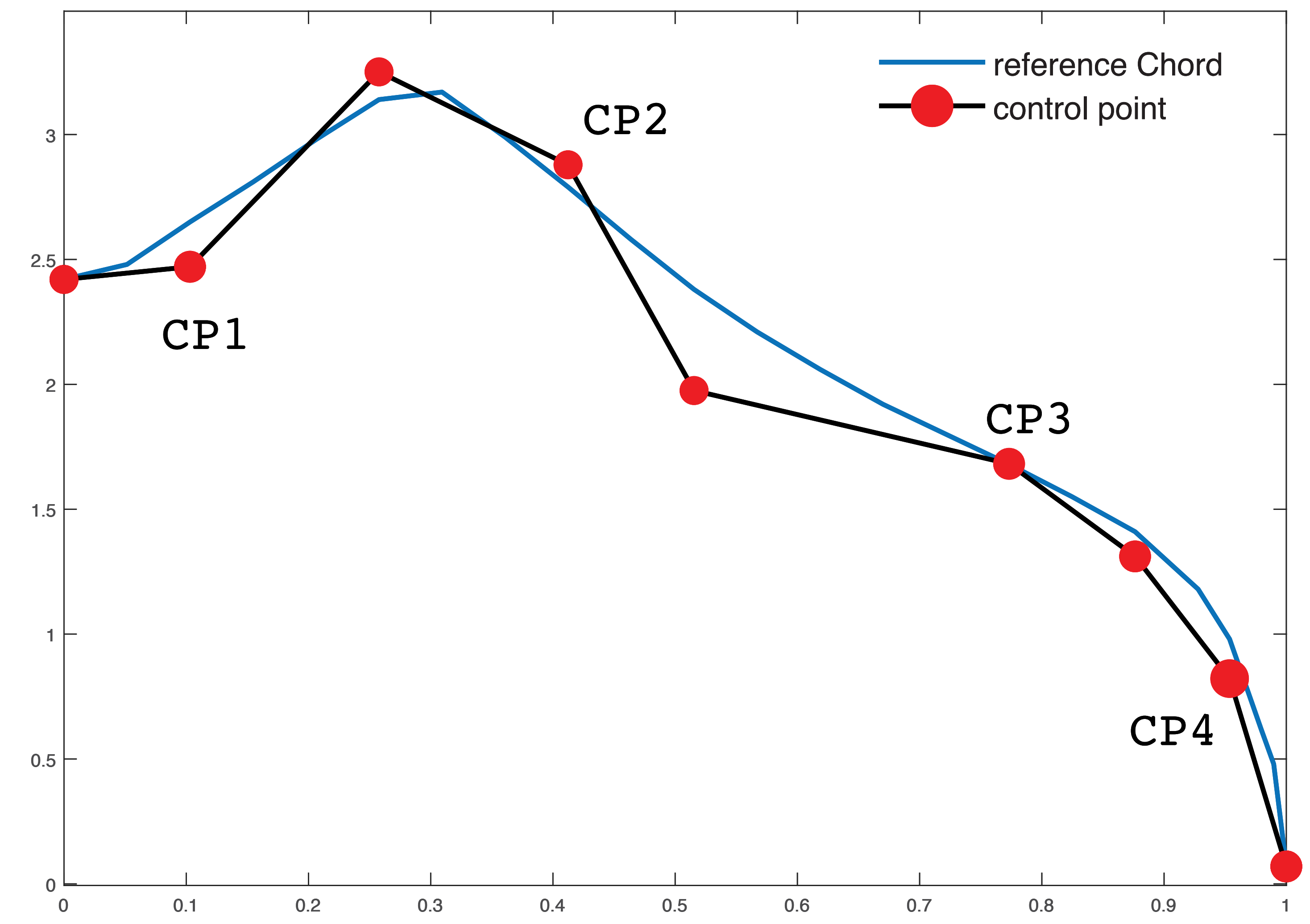
2) Ordinary Least square (OLS) $\Longrightarrow$ Random sampling, adaptive in degree

3) Least Angle Regression (LAR) $\Longrightarrow$ Random sampling, adaptive in degree

Sensitivity analysis results

Output quantity: Average power output of turbine

Uncertainty: Introduce 10% (uniform) uncertainty in 4 control points for Chord



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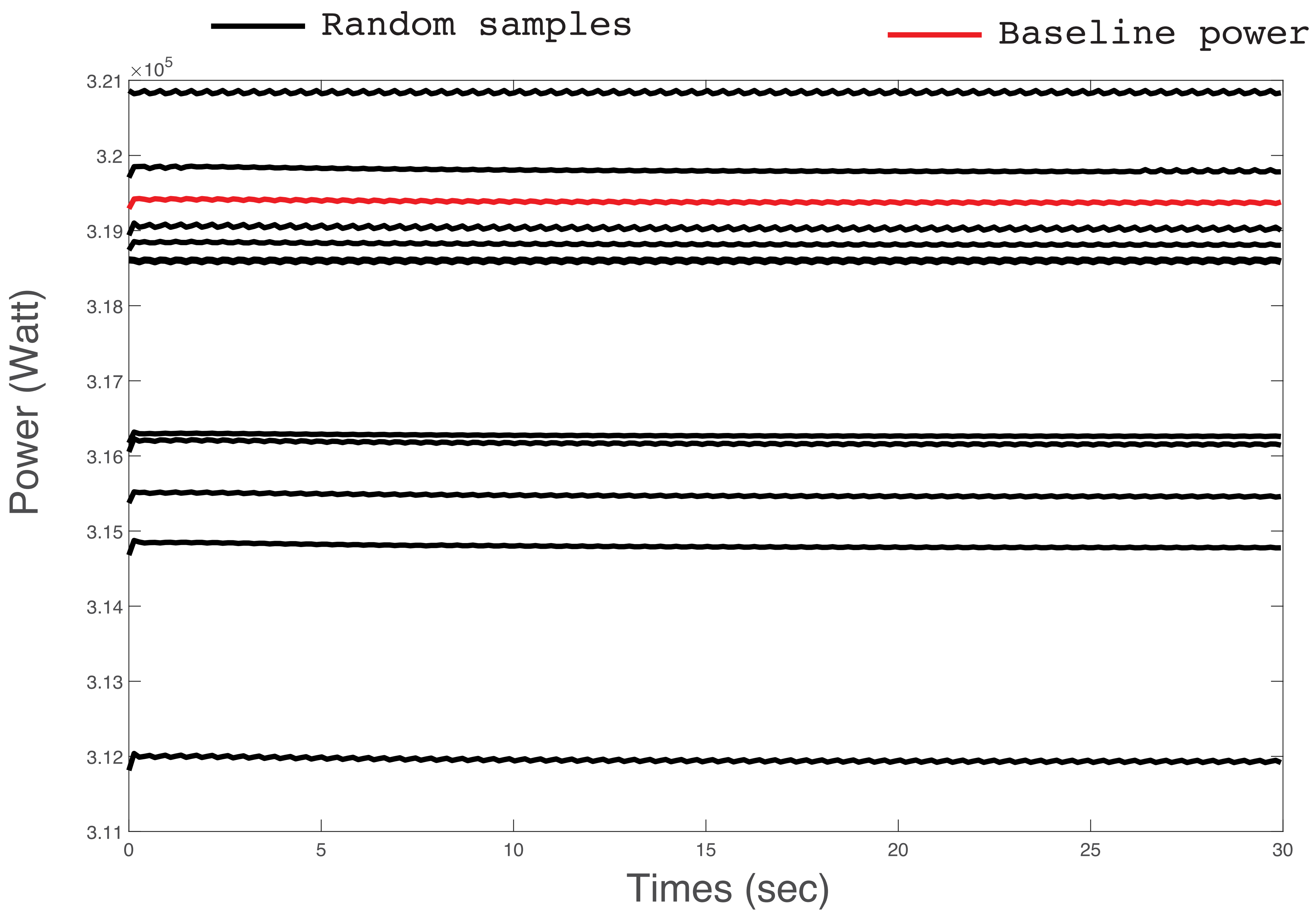

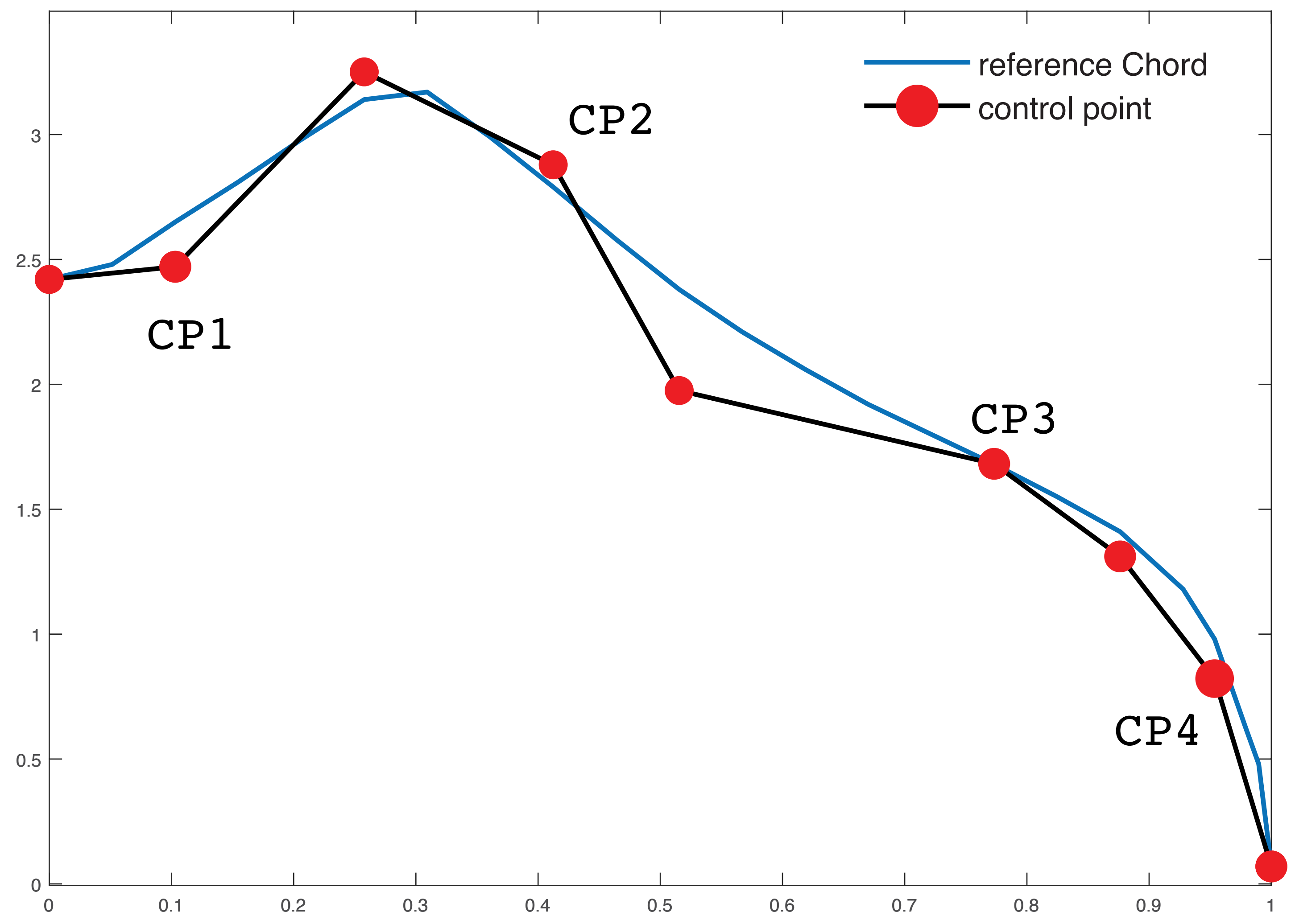

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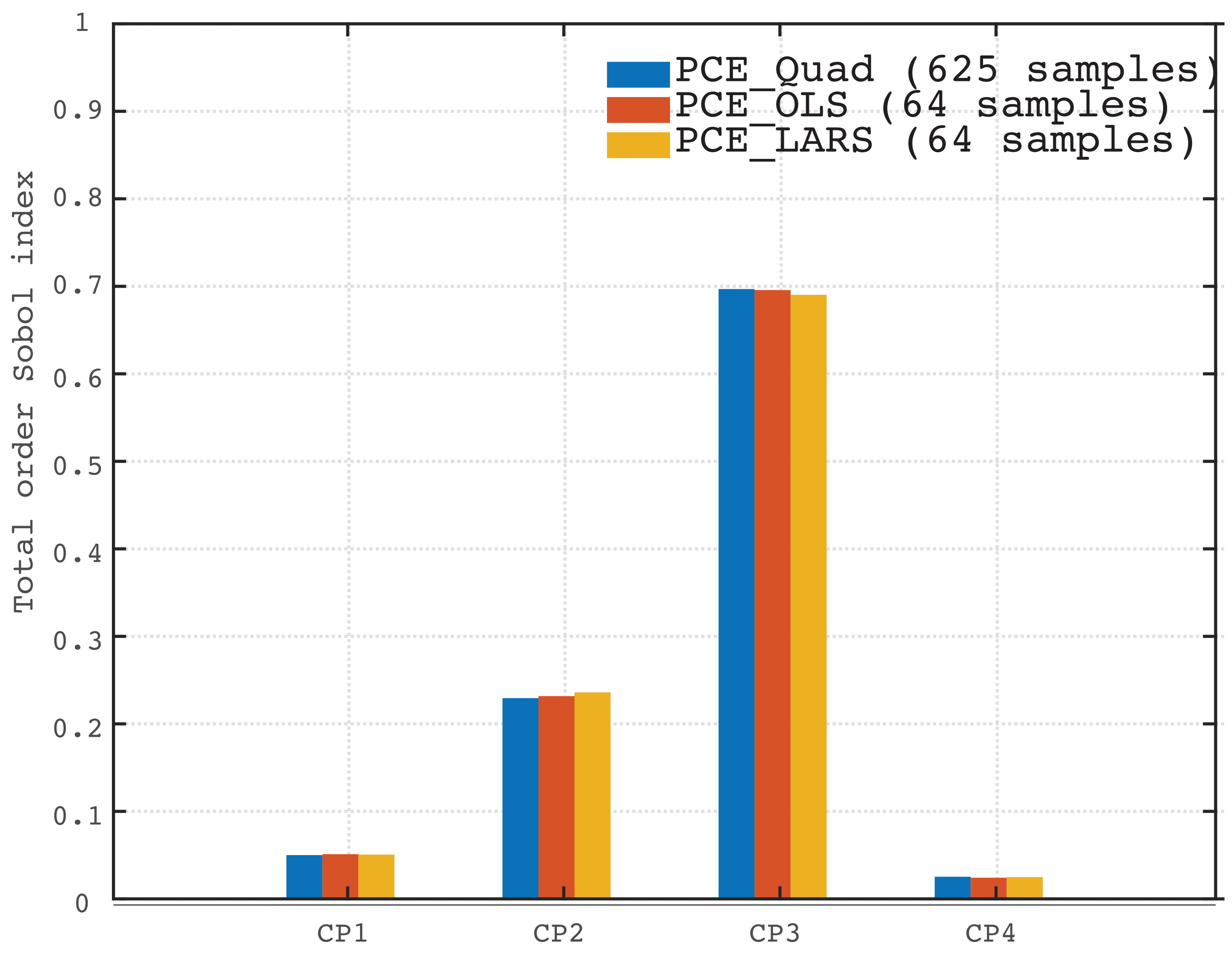
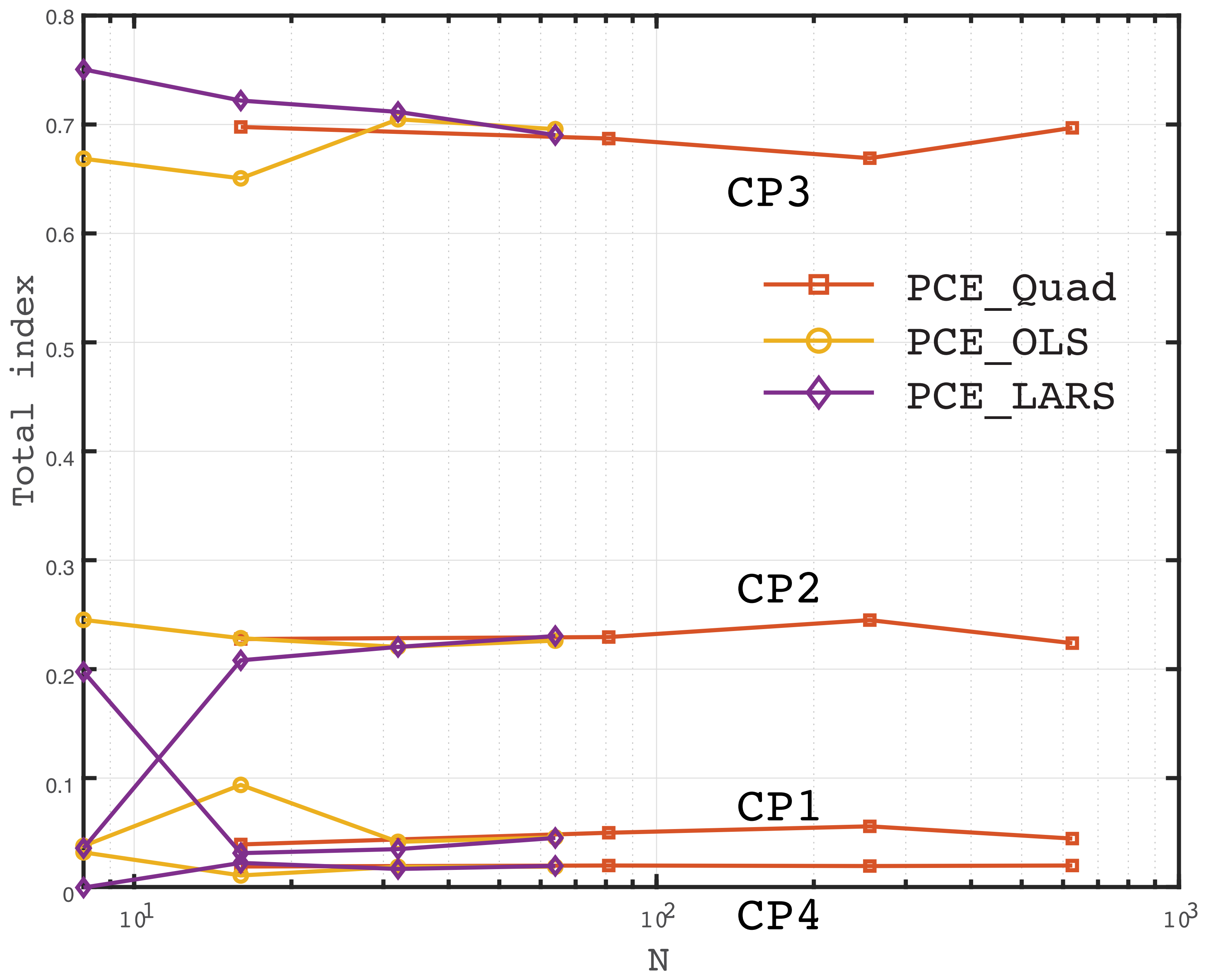


Comparison of total Sobol indices



Convergence

Conclusions

-> CP3 is the most important parameter

-> 64 samples using LARS and OLS is able to achive similar accuracy as PCE_QUAD with 625 samples

-> LARS and OLS are more suitable for models with a large number of uncertain inputs

Next steps:

-> Parameterization of other random inputs

-> Determine realistic amount of perturbations for uncertain parameters

-> Include Bladed in the workflow and compare with AERO module results