

# PCE VS RSM

This example is with known exact solution. Compared with fitting between PCE and RSM

## 1 - INITIALIZE UQLAB

```
clc;clear all;close all;  
clearvars  
rng(100,'twister')  
uqlab
```

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This is UQLab, version 2.0

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C:\NY2023\D\_document\UQLab\_Rel2.0.0\LICENSE.

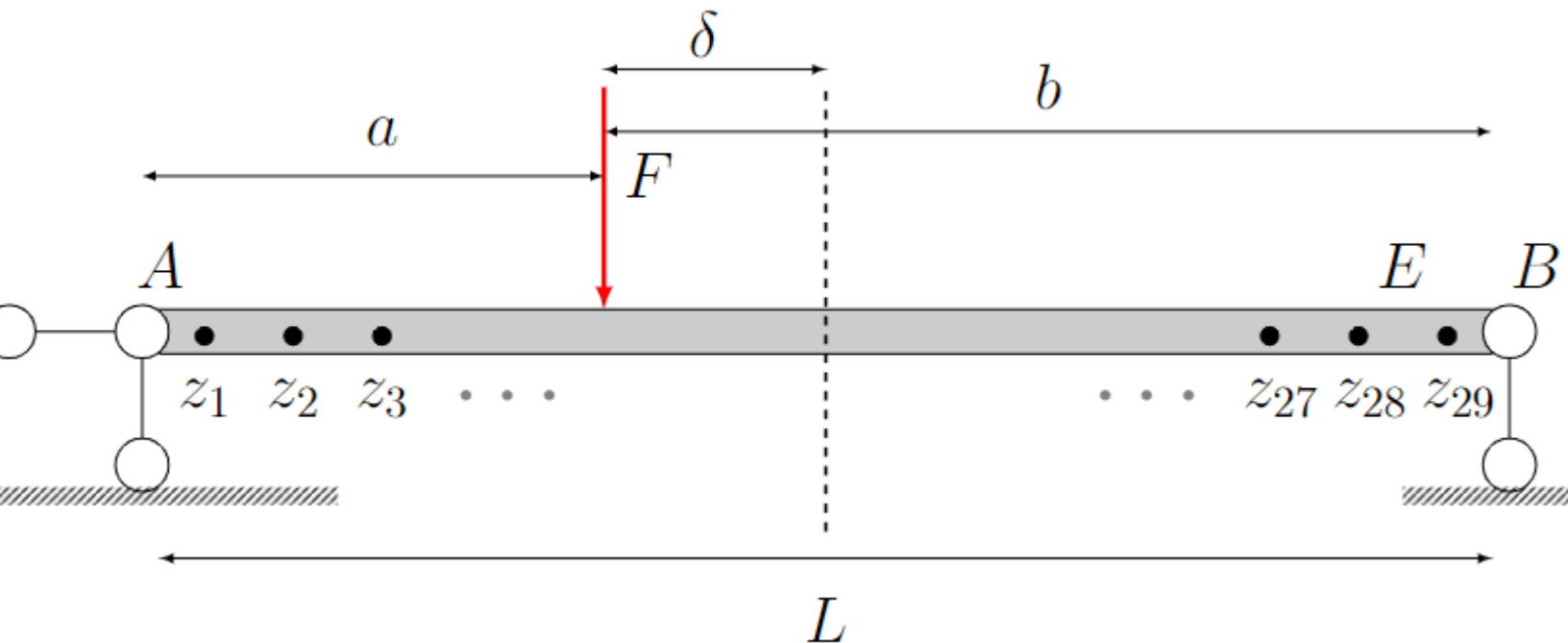
To request special permissions, please contact:

- Stefano Marelli (marelli@ibk.baug.ethz.ch).

Useful commands to get started with UQLab:

uqlab -doc	- Access the available documentation
uqlab -help	- Additional help on how to get started with UQLab
uq_citation help	- Information on how to cite UQLab in publications
uqlab -license	- Display UQLab license information

## 2 - COMPUTATIONAL MODEL



b\_b = 0.15; % beam width (m)

b\_h = 0.3; % beam height (m)

a % distance from the point A (m)

b % distance from the point B (m)

$L = 30$ ; % beam length (m)

$F = 43000$ ; % Concentrated force (N)

**Computational model:**

$$a = \frac{L}{2} + \delta; b = \frac{L}{2} - \delta$$

$$\mathcal{M}(E, \delta, z) = \frac{Fbz[(L^2 - b^2) - z^2]}{6LEI} \quad z \leq a$$

$$\mathcal{M}(E, \delta, z) = \frac{Fb[\frac{L}{b}(z - a)^3 + (L^2 - b^2)]}{6LEI} \quad z > a$$

Calculate the Mean-square-error data for surrogate

$$r(\vec{\theta}, \vec{z}) = \frac{1}{N} \sum_{i=1}^N (Y_i - \mathcal{M}(\vec{\theta}, \vec{z}))^2$$

$$\vec{\theta} = [E, \delta]; \vec{z} = [z_1, z_2, \dots, z_{28}, z_{29}];$$

$r$  is residual;  $\vec{x}$  is parameters of interests;  $E$  is elastic modulus;  $\delta$  is the loading position

$\vec{z}$  is the different measurement points along the beam;

$\mathcal{M}$  is the FE model;  $Y_i$  is the measurement data;  $N$  is the number of experiment expNum.

Create a MODEL from the function file:

```
ModelOpts.mFile = 'Analytical_Beam_Solution';  
  
myModel = uq_createModel(ModelOpts);
```

### 3 - PROBABILISTIC INPUT MODEL

$E \sim u(19e9, 31e9)$ ;  $\delta \sim u(-10, 10)$

```
% Young's modulus  
InputOpts.Marginals(1).Type = 'Uniform';  
InputOpts.Marginals(1).Parameters = [10e9 30e9];  
%InputOpts.Marginals(1).Bounds = [10e9 35e9];  
  
% Concentrated load loading position  
InputOpts.Marginals(2).Type = 'Uniform';  
InputOpts.Marginals(2).Parameters = [-15 15];  
%InputOpts.Marginals(2).Bounds = [-15 15];  
  
myInput = uq_createInput(InputOpts);
```

## 4 - POLYNOMIAL CHAOS EXPANSION (PCE) METAMODELS $\tilde{\mathcal{M}}(r)$

Calculate the polynomial chaos expansion (PCE) coefficients.

Select PCE as the metamodeling tool in UQLab:

```
metaopts.Type = 'Metamodel';  
metaopts.MetaType = 'PCE';
```

Select the sparse-favouring least-square minimization LARS for the

PCE coefficients calculation strategy:

```
metaopts.Method = 'LARS';
```

Select the PCE options and create the PCE model:

```
metaopts.Degree = 1:20;
```

Experimental design

```
metaopts.ExpDesign.NSamples = 150;  
metaopts.ExpDesign.Sampling = 'LHS';
```

Assign the beam function model as the full computational model of the PCE metamodel:

```
metaopts.FullModel = myModel;
```

Calculation

```
myPCE = uq_createModel(metaopts);  
  
--- Calculating the PCE coefficients by regression. ---  
The estimation of PCE coefficients converged at polynomial degree 12 and qNorm 1.00 for output variable 1  
Final L00 error estimate: 1.176465e-06  
--- Calculation finished! ---
```

## 5 - Results

Print a summary of the resulting PCE metamodel:

```
uq_print(myPCE)  
  
%----- Polynomial chaos output -----%  
Number of input variables:    2  
Maximal degree:              12  
q-norm:                      1.00  
Size of full basis:          91  
Size of sparse basis:        78  
Full model evaluations:      150  
Leave-one-out error:          3.7794039e-08  
Modified leave-one-out error: 1.1764647e-06  
Mean value:                  1.2002
```

Standard deviation:	1.4708
Coef. of variation:	122.544%
%-----%	

Create a validation sample of size from the input model:

```
Xval = uq_getSample(1e4);
```

Evaluate the full model response at the validation sample points:

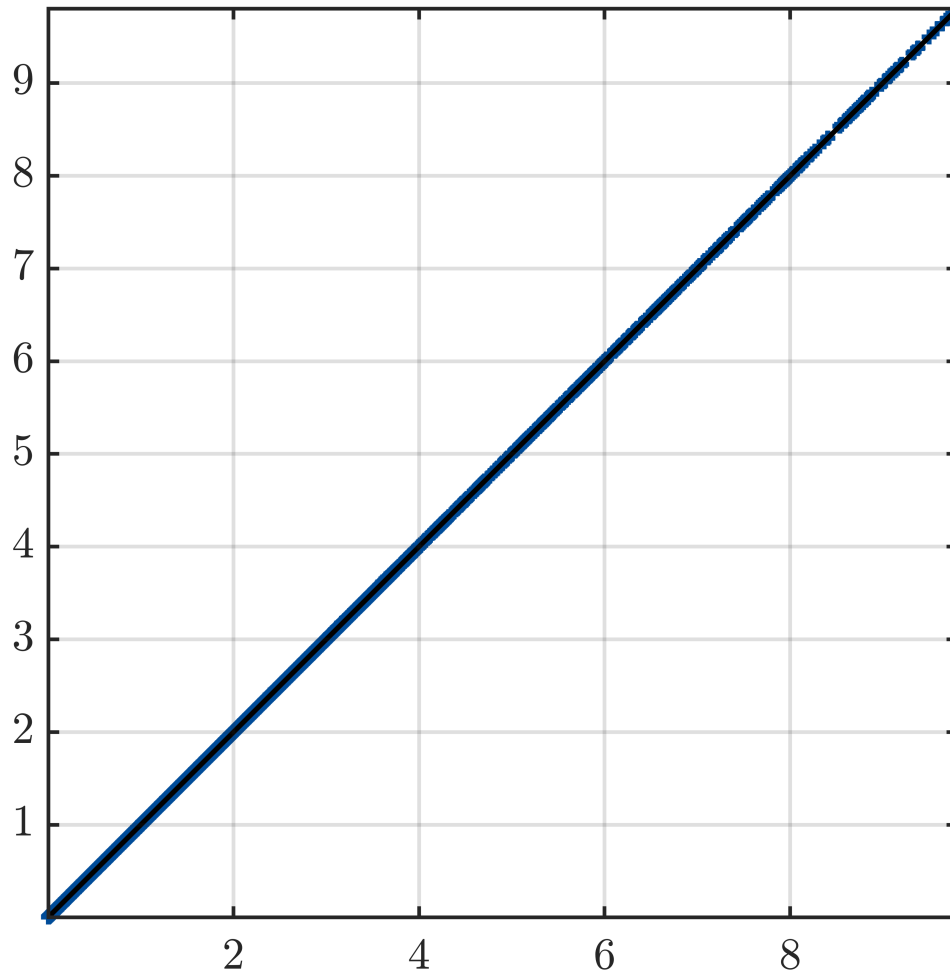
```
Yval = uq_evalModel(myModel,Xval);
```

Responses for PCE

```
YPCE = uq_evalModel(myPCE,Xval);
```

True vs predicted plot

```
close all;
uq_figure
uq_plot(Yval, YPCE, '+')
hold on
uq_plot([min(Yval) max(Yval)], [min(Yval) max(Yval)], 'k')
hold off
axis equal
axis([min(Yval) max(Yval) min(Yval) max(Yval)])
```



Export the PCE structure

```
save myPCE
```

## 6 - Define the priors for $E$ , $\delta$ and discrepancy $\sigma$

By default, UQlab assumes an independent and identically distributed discrepancy

$$\varepsilon \sim \mathcal{N}(0, \mu_y^2), \text{ with } \mu_y = \frac{1}{N} \sum_{i=1}^N y_i$$

synthetic ground truth

```
E = 25e9; delta = -3; noise = 0;
```

```
Measurement = Deflection(25e9, -3, 0);
```

priors

```

%Priors on E and p
PriorOpts.Marginals(1).Name = 'E'; % Young's modulus
PriorOpts.Marginals(1).Type = 'Gaussian';
PriorOpts.Marginals(1).Moments = [25e9 5e9]; % (N/m^2)
PriorOpts.Marginals(1).Bounds = [10e9 35e9];

PriorOpts.Marginals(2).Name = 'delta'; % Concentrated load loading
position
PriorOpts.Marginals(2).Type = 'Gaussian';
PriorOpts.Marginals(2).Moments = [0 5]; % (N/m)
PriorOpts.Marginals(2).Bounds = [-10 10];

PriorOpts.Marginals(3).Name = 'sigma2'; % variance
PriorOpts.Marginals(3).Type = 'Uniform';
sigma2 = mean(Measurement(:, :), "all");
PriorOpts.Marginals(3).Parameters = [0 sigma2^2];

myPriorDist = uq_createInput(PriorOpts);

```

## 7 - Define the custom-loglikelihood and measurement data for UQlab calculation

$$\log \mathcal{L}(\Theta) = \sum_{i=1}^N \left( -\frac{1}{2} \left( r_i(\vec{x}, \vec{z}) \right)^T \Sigma(\epsilon)^{-1} \left( r_i(\vec{x}, \vec{z}) \right) \right) - \frac{3N}{2} \log(2\pi) - \frac{N}{2} \log(\det(\Sigma(\epsilon)))$$

Monitored data  $Y_i$  for beam deflection have been used in PCE surrogate model. No measurements available for Bayesian inference: Pass zeros to measurement  $Y_i$  just for calculation, which equals:

$$r(\vec{x}, \vec{z}) \sim (0 - r(\vec{x}, \vec{z})) \sim (Y_i - \mathcal{M}(\vec{x}, \vec{z}))$$

$$r(\vec{x}, \vec{z}) \text{ dim } 248 \times 1 \sim (Y_i - \mathcal{M}(\vec{x}, \vec{z})) \text{ dim } 248 \times 29$$

Also, measurement data for  $Y_{10 \times 29}$  changed into  $Y_{10 \times 1}$

```

y = zeros(1,1);
myData.y = y;
myData.Name = 'Zeros vector measurement for Bayesian inference';

```

Loglikelihood still follows the Gaussian discrepancy criteria

```

myLogLikeli = @(params,y) myLogLikeli2(params,y);

```

## 8 - Solver options

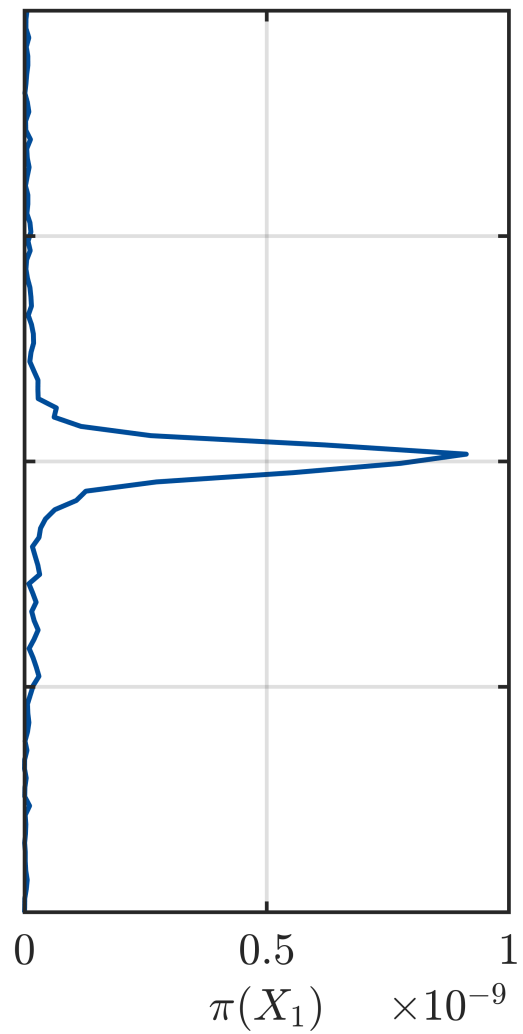
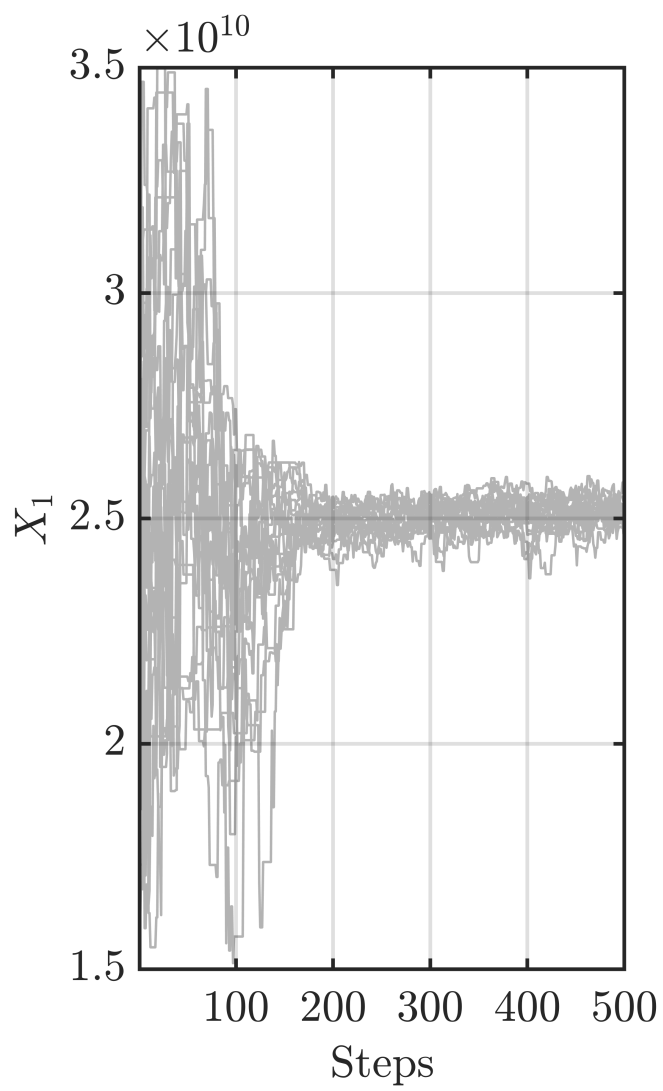
```
Solver.Type = 'MCMC';  
Solver.MCMC.Visualize.Parameters = [1 2];  
Solver.MCMC.Visualize.Interval = 10;  
Solver.MCMC.Sampler = 'AIES';  
Solver.MCMC.Steps = 500;  
Solver.MCMC.NChains = 20;  
Solver.MCMC.Proposal.PriorScale = 1e-3;
```

## 9 - Bayesian inference

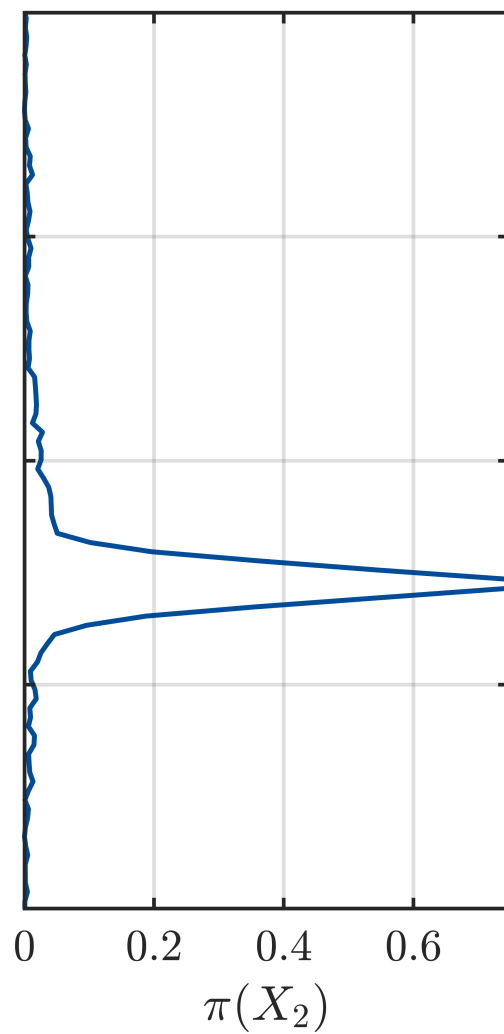
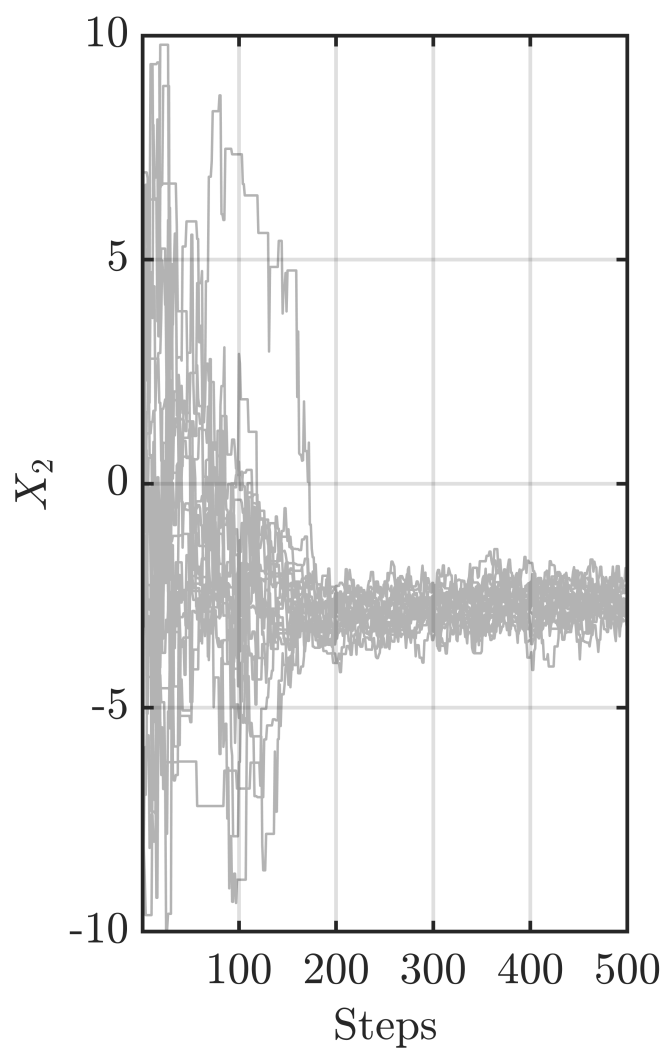
```
BayesOpts.Data = myData;  
BayesOpts.LogLikelihood = myLogLikeli;  
BayesOpts.Type = 'inversion';  
BayesOpts.Solver = Solver;  
BayesAnalysis = uq_createAnalysis(BayesOpts);
```

Starting AIES...

#		1.80% #		3.60% ##		6
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Finished AIES!