SEAFLOWER: on the use of metamodels in offshore geotechnical engineering

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for floating wind energy

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Strategies to Exploit Anchors for FLoating Offshore Wind Energy Reaping

The Marie Skłodowska-Curie Actions (MSCA) are funding programmes provided by the Research Executive Agency of the EU Commission and which objective is to support researchers' careers through mobility across borders and exposure to different sectors and disciplines.

https://marie-sklodowska-curie-actions.ec.europa.eu/

SEAFLOWER is an **Individual Fellowship** (IF, Global Fellowship type) of the MSCA granted in the 2019 call (H2020-MSCA-IF-GF)

now

HE 2021 - 2027
5 types of MSCA

- **Post-Doctoral Fellowship (PF)**
- Doctoral Networks (DN)
- COFUND
- Staff Exchanges (SE)
- MSCA and Citizens

European Postdoctoral Fellowships. They are open to researchers moving within Europe or coming to Europe from another part of the world to pursue their research career. These fellowships take place in an EU Member State or Horizon Europe Associated Country and can last between 1 and 2 years. Researchers of any nationality can apply.

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Global Postdoctoral Fellowships. They fund the mobility of researchers outside Europe. The fellowship lasts between 2 to 3 years, of which the first 1 to 2 years will be spent in a non-associated Third Country, followed by a **mandatory return phase** of 1 year to an organisation based in an EU Member State or Horizon Europe Associated Country. Only nationals or long-term residents of the EU Member States or Horizon Europe Associated Countries can apply.

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MSCA-IF-GF 2019 → 3 years = 1.5y outgoing + 0.5y secondment + 1y return

INSTITUTES

TEAM

BENEFICIARY

Laura Govoni

Non-EU PARTNER

THE UNIVERSITY OF WESTERN AUSTRALIA

Christophe

Phil

SECONDMENT

INRAE

Franck Bourrier

t = 1.5 years

t = 2 years

t = 3 years

starting date
June/July 2020

INRAE
secondment

THE UNIVERSITY OF WESTERN AUSTRALIA
outgoing

return

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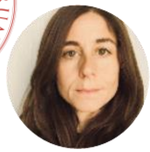

Non-EU PARTNER

THE UNIVERSITY OF WESTERN AUSTRALIA

Christophe

Phil

SECONDMENT

INRAE

Franck Bourrier

15 March 2021

July 2021

April 2022

March 2023

March 2024

INRAE

secondment

THE UNIVERSITY OF WESTERN AUSTRALIA

THE UNIVERSITY OF WESTERN AUSTRALIA

outgoing

return

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the proposal: MSCA-IF-GF

1. Excellence

Threshold: 0/5.00; Weight: 50%

4.2/5.0

- Quality and credibility of the research/innovation project; level of novelty, appropriate consideration of inter/multidisciplinary and gender aspects
- Quality and appropriateness of the training and of the two way transfer of knowledge between the researcher and the host
- Quality of the supervision and of the integration in the team/institution
- Potential of the researcher to reach or re-enforce professional maturity/independence during the fellowship

2. Impact

Threshold: 0/5.00; Weight: 30%

5.0/5.0

- Enhancing the future career prospects of the researcher after the fellowship
- Quality of the proposed measures to exploit and disseminate the project results
- Quality of the proposed measures to communicate the project activities to different target audiences

3. Implementation

Threshold: 0/5.00; Weight: 20%

4.8/5.0

- Coherence and effectiveness of the work plan, including appropriateness of the allocation of tasks and resources
- Appropriateness of the management structure and procedures, including risk management
- Appropriateness of the institutional environment (infrastructure)

91.2/100.0

SEAFLOWER - on the use of metamodels in offshore geotechnical engineering

- Introduction
  - the concept
  - the procedure
- Case study 1: plate in clay
  - Polynomial Chaos Expansion - PCE
  - PCE exploitation
- Case study 2: pile in sand
  - Sobol indices
- Concluding remarks

the concept

The need
Floating offshore wind turbines are in the pre-commercial development. User-friendly tools would aid the preliminary design (PD) of the anchors.

Effective solutions from O&G industry, but FOWT has different requirements

transfer of technologies

reduced information at this design stage

(soil conditions, anchor type, floater, etc.)

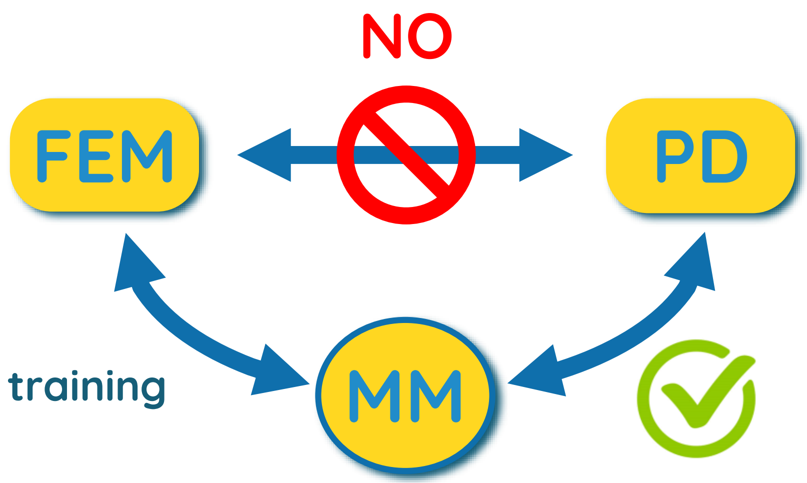
inadequate competences of the designer

(not always geotech for pilot design activities)

probabilistic approaches (Monte Carlo) should be used at this stage

(advanced numerical tools, like FEM, cannot be coupled with these methods)

The objective
Develop a numerical tool that is able to embed the response of the advanced FE model at a low computational cost.



The methodology
Use metamodels (MM) or emulation methods. Built on selected samples of the problem input, they are trained/calibrated with the data of a FE parametric test programme to estimate some of the model output at negligible computational cost, while retaining their accuracy.

the procedure

1. Define problem position

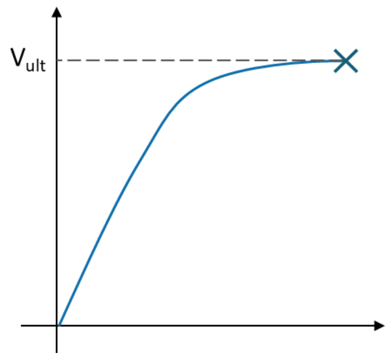
- foundation type
  - geometry — fixed / variable
  - FEM — Mesh /analysis type
- soil type
  - constitutive model — drained / undrained
  - heterogeneity — homogeneous / layering / random soil
  - interface — frictionless / penalty / user-defined
- boundary conditions
  - constraints — initial state
  - load type — monotonic / cyclic /combine or not

❖ selection of input (i.e., not deterministic parameters)

- realistic
- FE stability
- range of variation (MM works within the defined range)
- number (n < 20)

❖ identification of output

- representative of the problem
- normalised



the procedure

2. Sampling

Sample the selected input into their range of variations for a parametric test programme of size N

$$\boldsymbol{X} = \{\boldsymbol{x}^{(1)}, \dots, \boldsymbol{x}^{(N)}\}$$

Experimental Design (ED)

Run FEM for the created sample

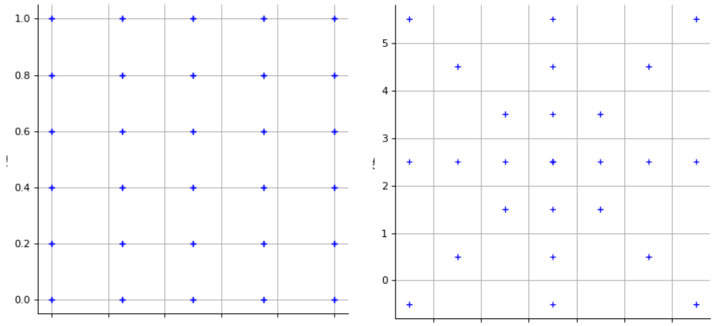
$$\boldsymbol{Y} = \{y_i = G(\boldsymbol{x}^{(i)}), i = 1, \dots, N\}$$

Model response vector

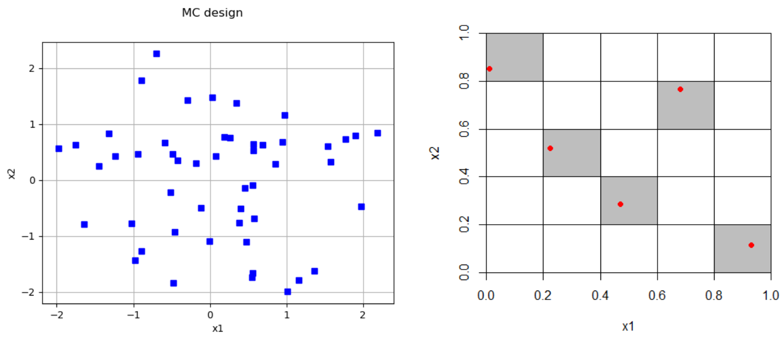
Input-output pairs are used to calibrate the MM, an analytical function that approximate the original computational model

$$\boldsymbol{Y} = G(\boldsymbol{X}) \cong \hat{G}(\boldsymbol{X})$$

metamodel



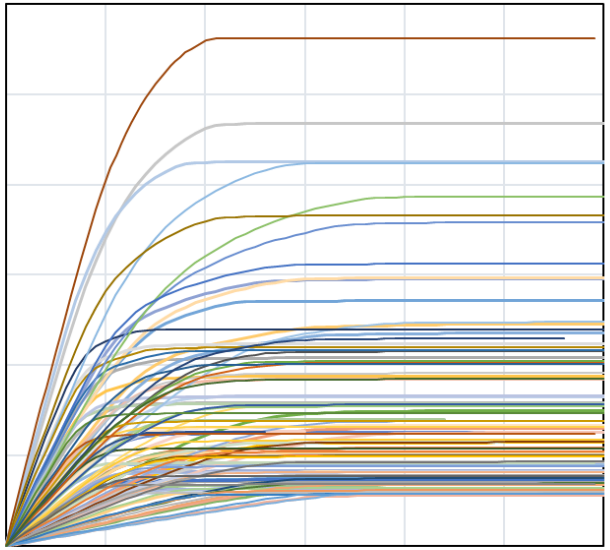
user-defined (box patterns; composite)



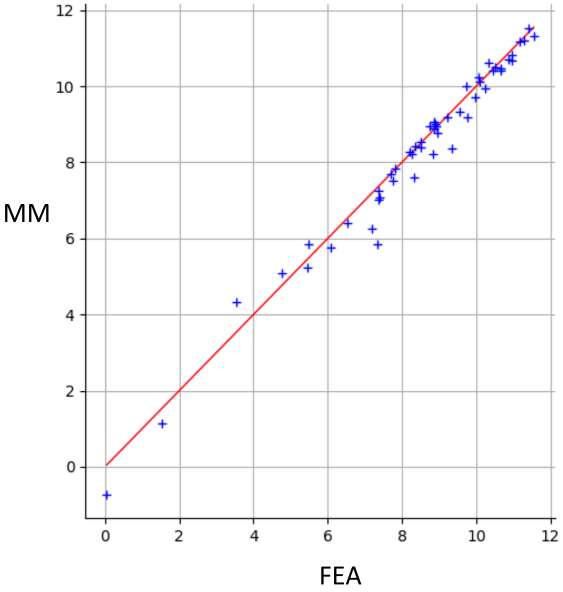
random (MC with normal distribution; LHS with uniform distribution)

sequential (Sobol, Halton; etc.)

3. FE test programme



4. MM calibration & validation



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case study 1 – plate in clay

1. Define problem position

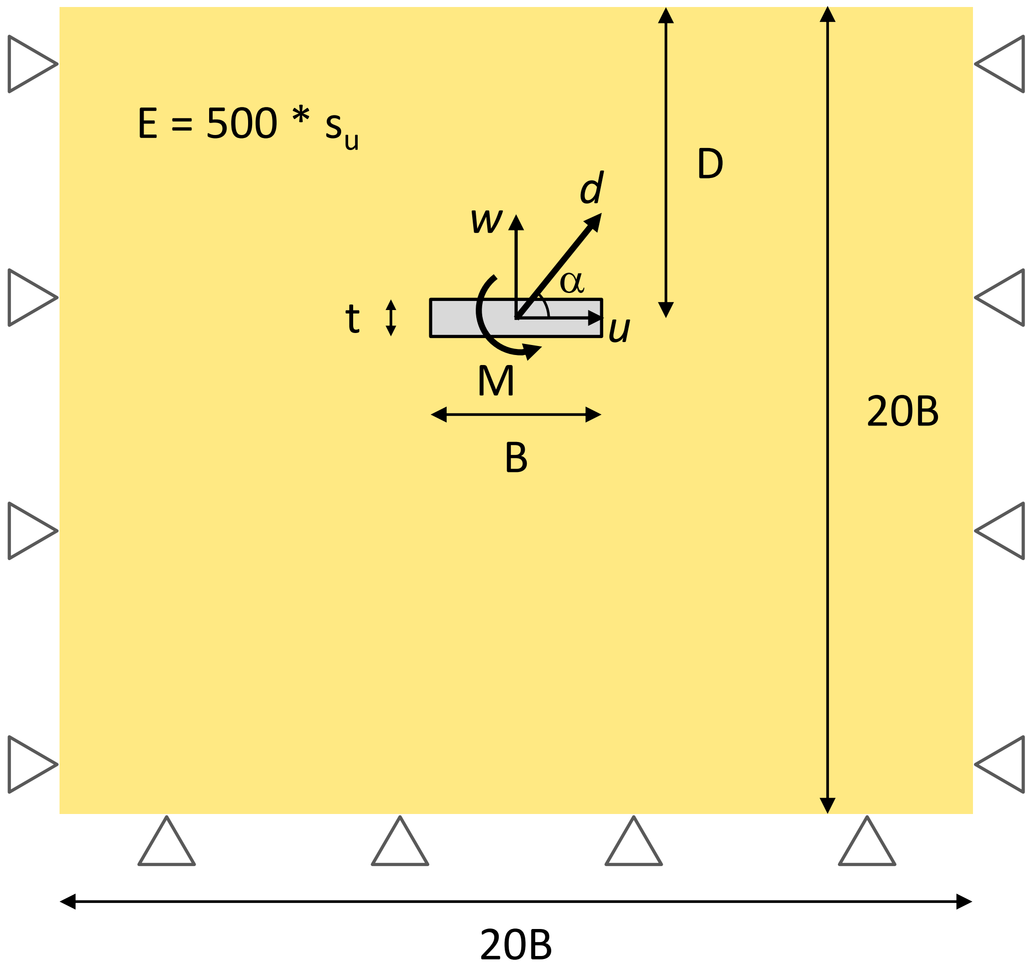


plate anchor — B = 1m; B/t = 20; D=6B

— 2DFEM mesh l_{min} = t/4

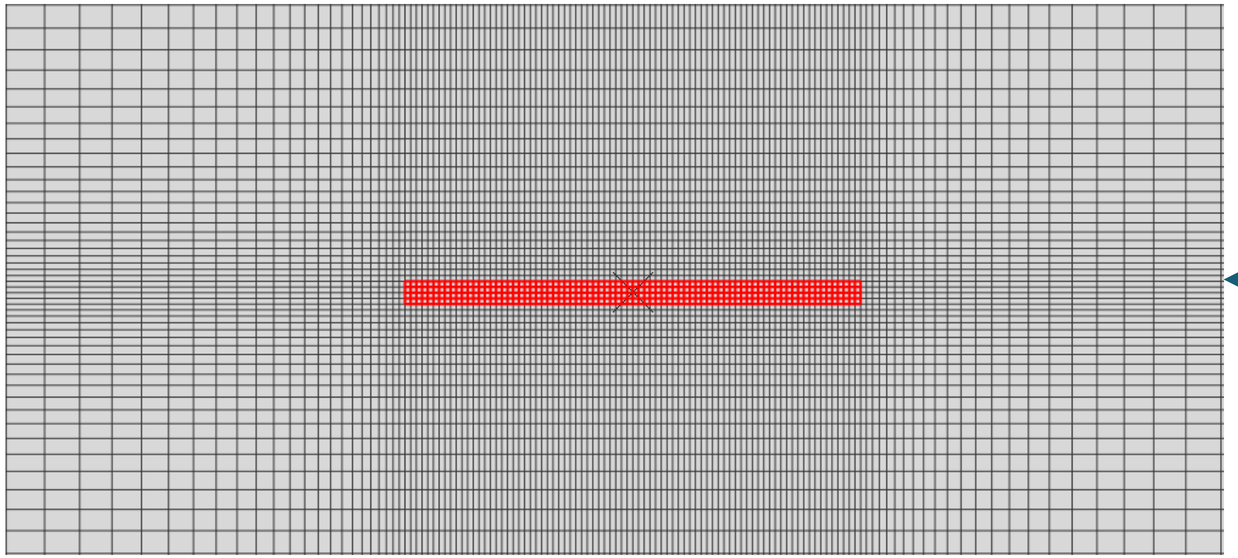
clay — linear elastic; Tresca

— homogeneous

— fully bonded

boundary conditions — Constraints; no installation

— undrained V-H-M



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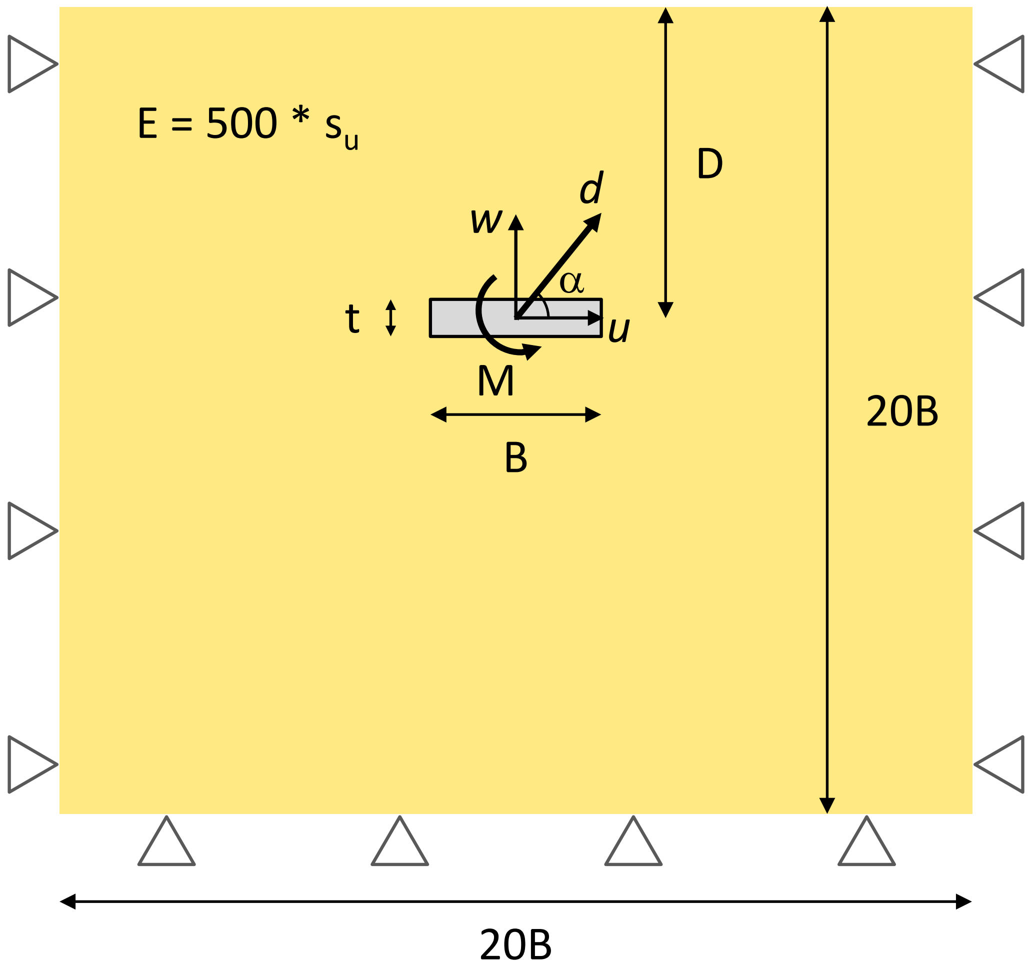

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clay	linear elastic; Tresca
	homogeneous
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boundary conditions	constraints
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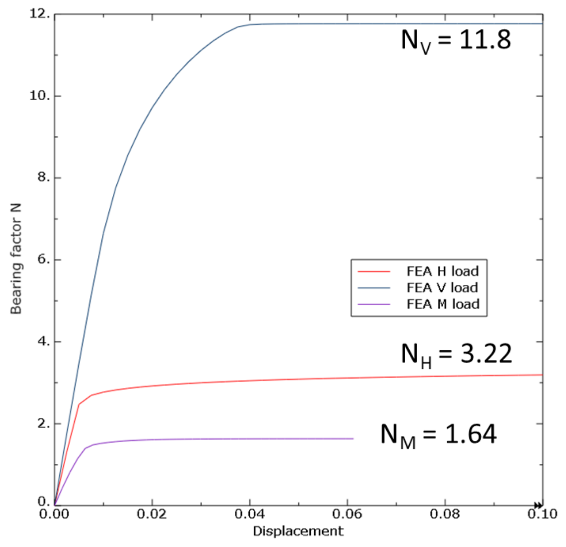
step 1

$M = x_M * M_u$

$M_u = N_M * B * s_u$



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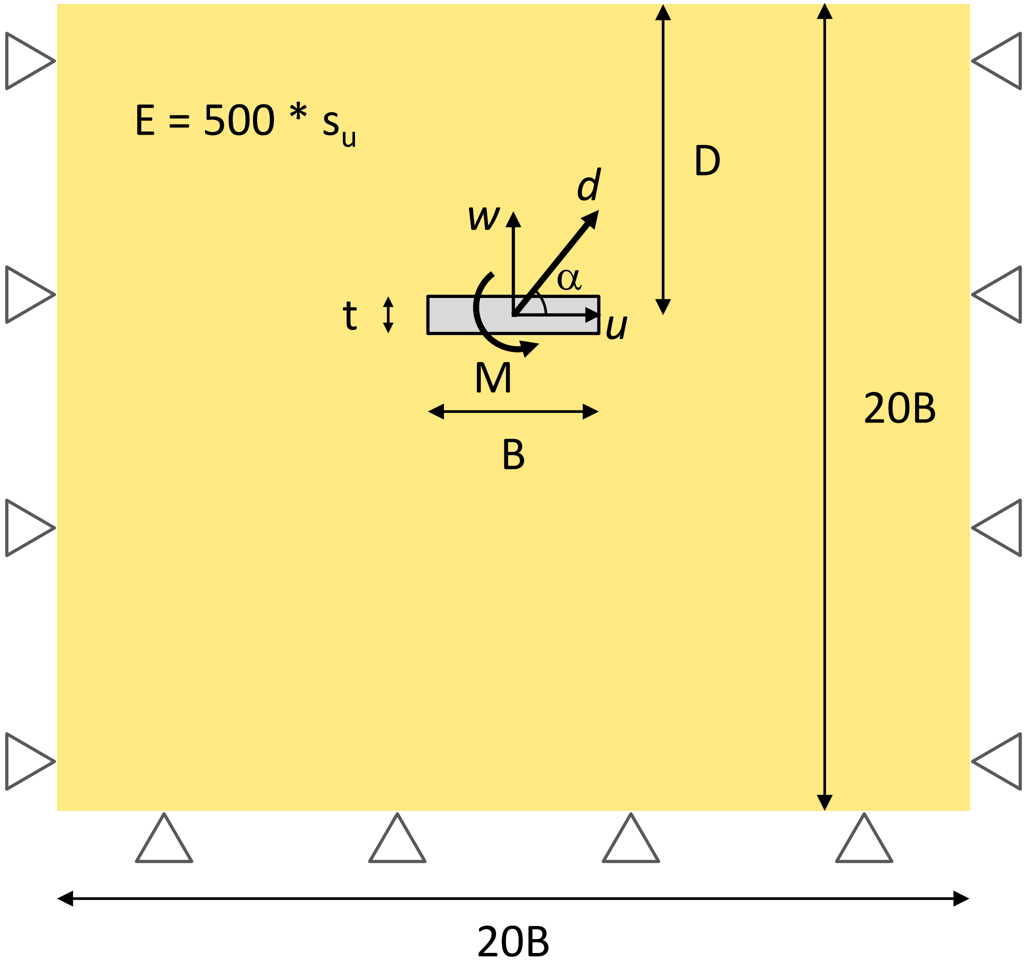

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boundary conditions — constraints

— undrained V-H-M

❖ selection of input

step 1

$M = x_M * M_u$

$M_u = N_M * B * s_u$

step 2

$\alpha = x_\alpha * \pi/2$

$u = d * \cos(\alpha)$

$w = d * \sin(\alpha)$

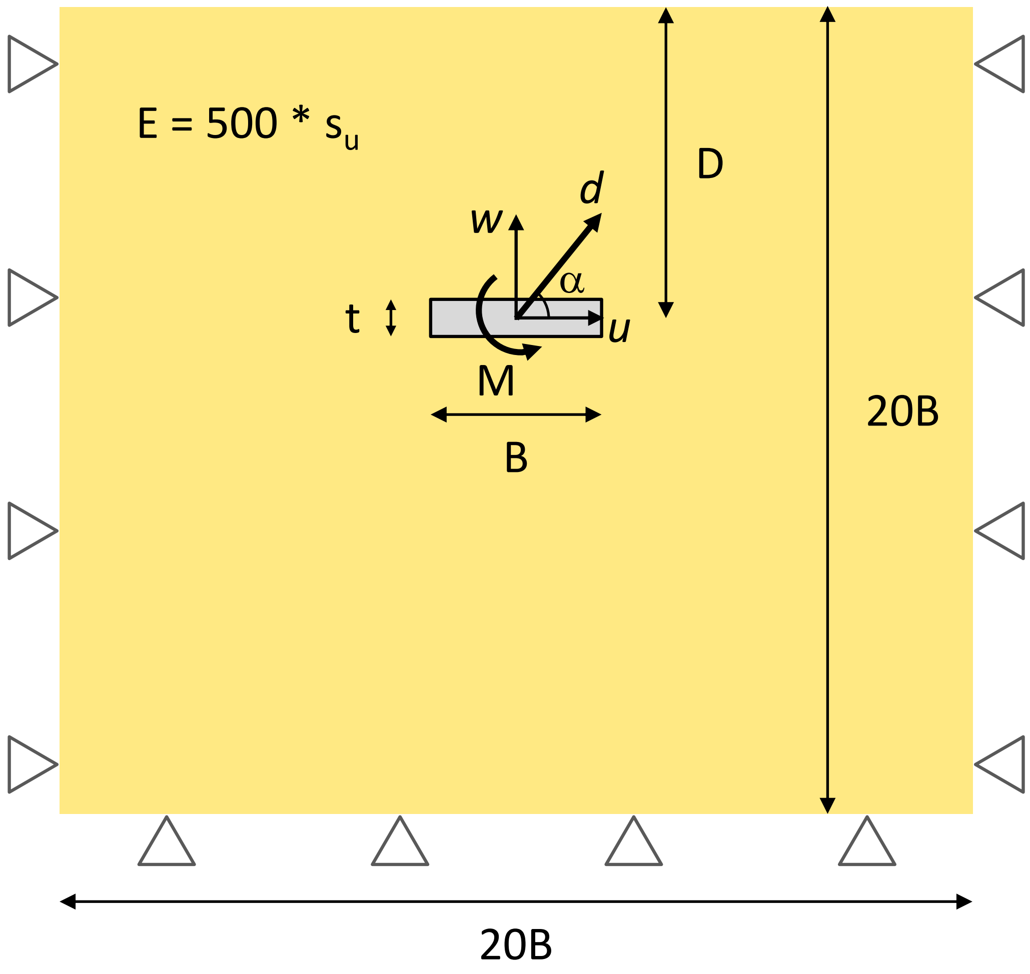
$$x_M \in \mathbb{R}: 0 \leq x_M \leq 1$$

$$x_\alpha \in \mathbb{R}: 0 \leq x_\alpha \leq 1$$

$$\boldsymbol{x}^{(i)} = \left\{x_M^{(i)}, x_\alpha^{(i)}\right\}$$

case study 1 – plate in clay

1. Define problem position



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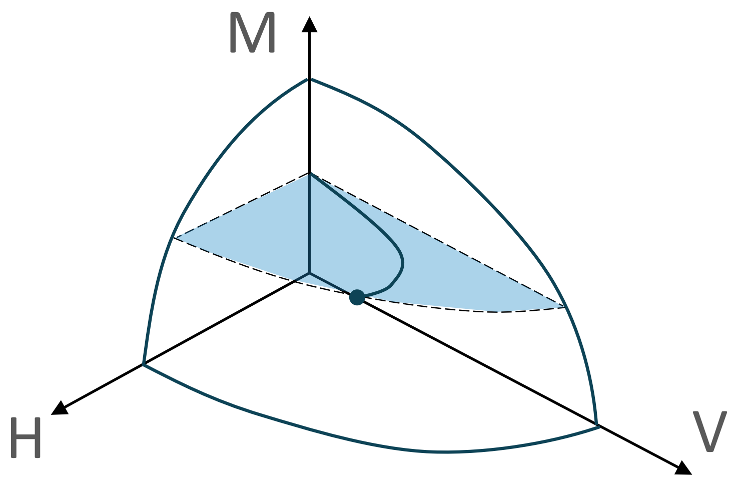
clay	linear elastic; Tresca
	homogeneous
	fully bonded
boundary conditions	constraints
	undrained V-H-M

❖ identification of output



$$\boldsymbol{y}^{(i)} = \left\{N_H^{(i)}, N_V^{(i)}\right\}$$

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case study 1 – plate in clay

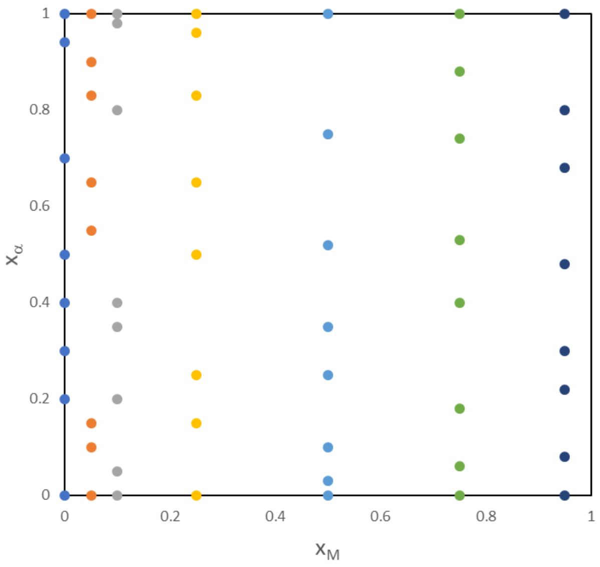
2. Sampling

user-defined sample

x_M = [0.0; 0.05; 0.10; 0.25; 0.50; 0.75; 0.95] → i = 7

x_α = [0; random; 1] → j = 8

N = sample size = i * j = 56 pairs



ED of size *N*

$$\boldsymbol{X} = \{\boldsymbol{x}^{(i)}, \ldots, \boldsymbol{x}^{(N)}\}$$

$$\boldsymbol{x}^{(i)} = \{x_M^{(i)}, x_\alpha^{(i)}\}$$

case study 1 – plate in clay

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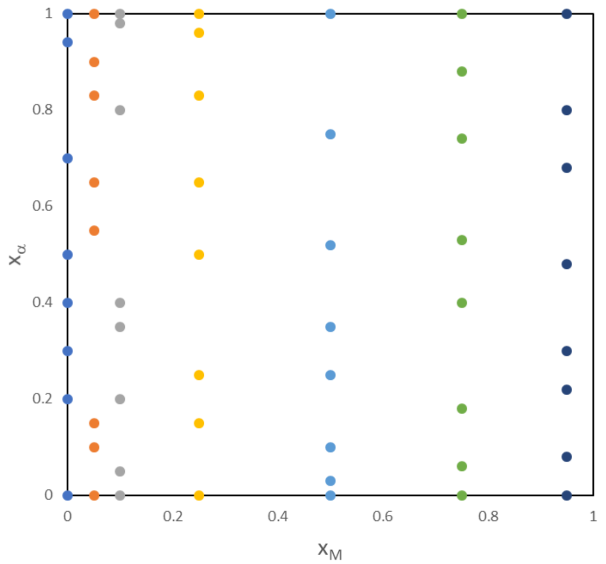
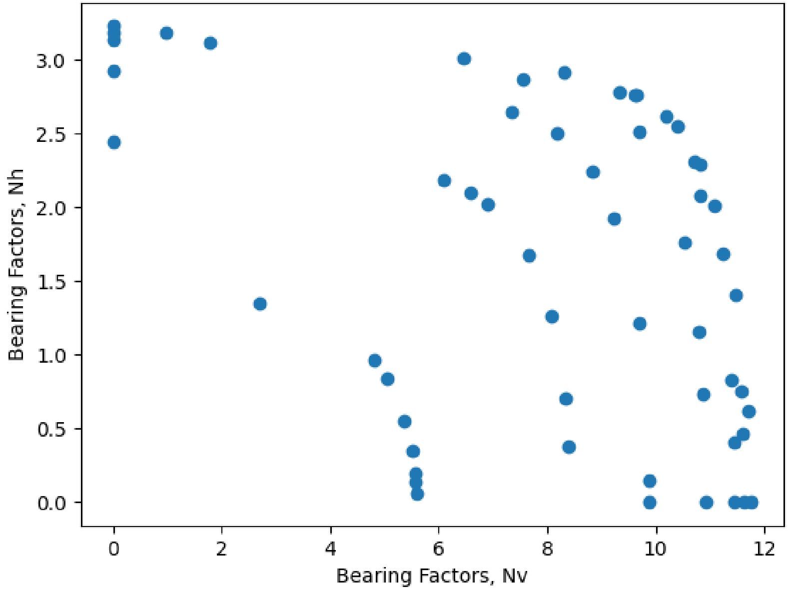


3. FE test programme



$$\boldsymbol{Y} = \{\boldsymbol{y}^{(i)}, \ldots, \boldsymbol{y}^{(N)}\}$$

Model response vector

$$\boldsymbol{y}^{(i)} = \{N_H^{(i)}, N_V^{(i)}\}$$

case study 1 – plate in clay

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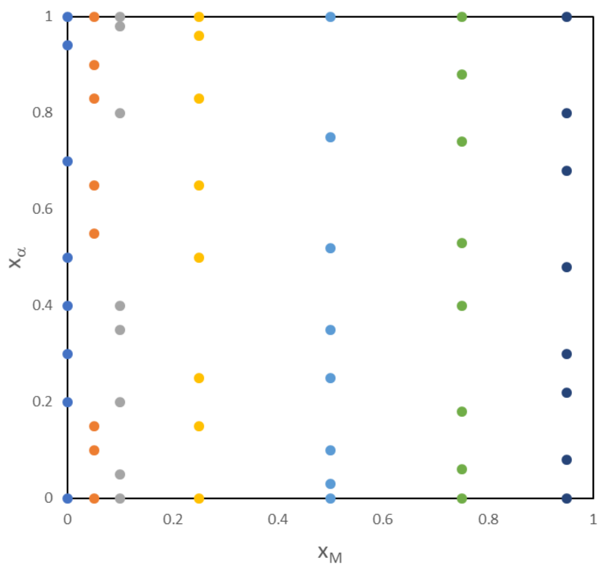

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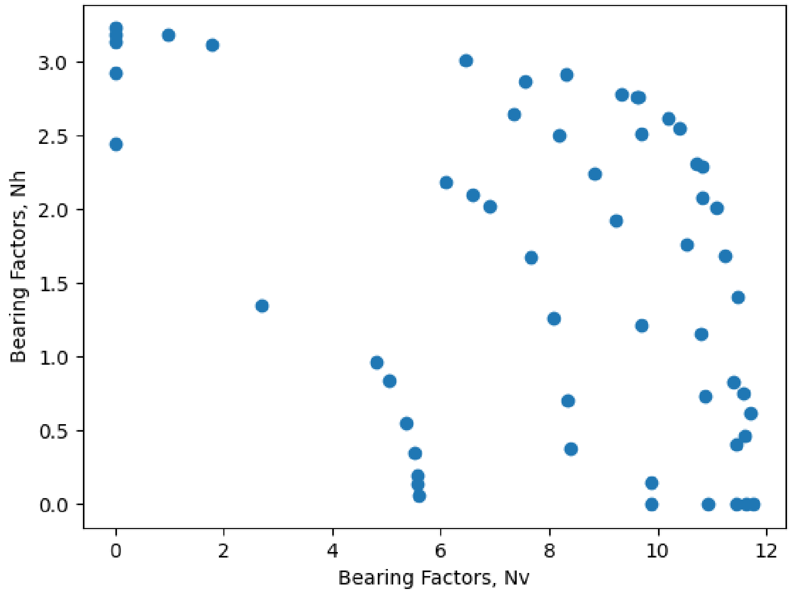

4. MM calibration & validation

Polynomial Chaos Expansion (PCE); Gaussian Process (GP); Kriging; Neural Networks; Support Vector Machine (SVM); boosting regression trees; etc.

Bertrand Iooss, Paul Lemaître, 2015. A review on global sensitivity analysis methods.

Polynomial Chaos Expansion – PCE

THE HOMOGENEOUS CHAOS.

By Norbert Wiener.

1938

Ghanem, R., and Spanos, P. D. (March 1, 1990). "Polynomial Chaos in Stochastic Finite Elements." ASME. *J. Appl. Mech*. March 1990; 57(1): 197–202.

$$Y = G(\boldsymbol{X})$$

: G (i.e., the FEM) is a black-box function →

Assuming that Y has a finite variance, it belongs to the so-called Hilbert space of second order random variables, which allows for the spectral representation:

$$Y \cong \hat{G}(\boldsymbol{X}) = \sum_{k \in K} \alpha_k \Psi_k(\boldsymbol{Z})$$

- $\Psi_k(\boldsymbol{Z})$ are multivariate polynomials orthonormal basis of the Hilbert space in the input vector $\boldsymbol{Z}$
- $\boldsymbol{Z} = T(\boldsymbol{X})$ T is an isoprobabilistic transform applied to the ED, $\boldsymbol{X}$, to obtain standardised distribution forms
- $K \epsilon \mathrm{N}$ is the number of terms used in the expansion (i.e., max degree of polynomial basis)
- α_k are the coefficients corresponding to each polynomial

Polynomial Chaos Expansion – PCE

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By NORBERT WIENER.

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$$Y \cong \hat{G}(\boldsymbol{X}) = \sum_{k \in K} \alpha_k \Psi_k(\boldsymbol{Z})$$

- $\Psi_k(\boldsymbol{Z})$
- $\boldsymbol{Z} = T(\boldsymbol{X})$

} 1. selection of orthonormal basis

- $K \epsilon \mathrm{N}$ → 2. truncation scheme (i.e., max degree)
- α_k → 3. computation of coefficients

Polynomial Chaos Expansion – PCE

1. Selection of orthonormal basis

$$\Psi_k(Z) \qquad Z = T(X)$$

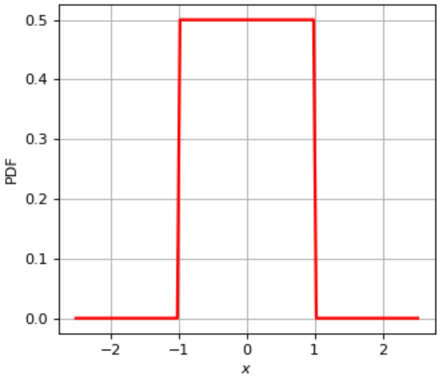
$$P_0 = 1$$

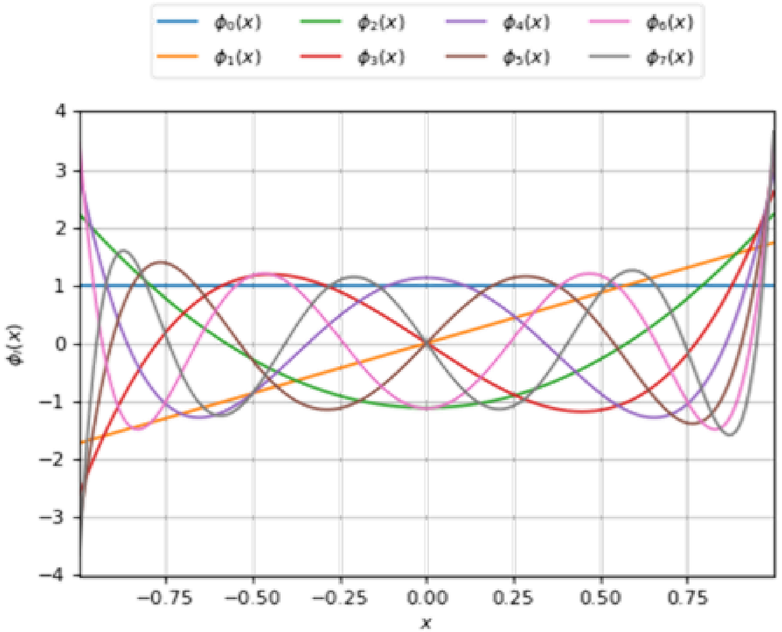
$$P_1 = \sqrt{3}x$$

$$P_2 = \frac{1}{2}\left(\sqrt{45}x^2 - \sqrt{5}\right)$$

For traditional distribution forms, the associated families of orthogonal polynomials – with enforced normalisation rule – that form a basis of an Hilbert space are well-known.

Standard distribution	Polynomial
Normal $\mathcal{N}(\mu = 0, \sigma = 1)$	HermiteFactory
Uniform $\mathcal{U}(a = -1, b = 1)$	LegendreFactory
Gamma $\Gamma(k = k_a + 1, \lambda = 1, \gamma = 0)$	LaguerreFactory
Beta $\mathrm{B}(r = \beta + 1, t = \alpha + \beta + 2, a = -1, b = 1)$	JacobiFactory
Poisson $\mathcal{P}(\lambda)$	CharlierFactory
Binomial $\mathcal{B}(n, p)$	KrawtchoukFactory
NegativeBinomial $\mathcal{B}^{-}(r, p)$	MeixnerFactory





$$P_{i+1} = (a_i x + b_i)P_i + c_i P_{i-1}, \quad 1 < i$$

$$\begin{aligned} a_i &= \frac{\sqrt{(2i+1)(2i+3)}}{i+1} \\ b_i &= 0 \\ c_i &= -\frac{i\sqrt{2i+3}}{(i+1)\sqrt{2i-1}} \end{aligned}, \quad 1 < i$$

Polynomial Chaos Expansion – PCE

2. Truncation scheme (i.e., max degree)

$$Y \cong \hat{G}(\boldsymbol{X}) = \sum_{k \in K} \alpha_k \Psi_k(\boldsymbol{Z})$$

It is natural to consider a truncated series of all the polynomials up to a maximum degree, *p*.

total degree of multivariate polynomial

$$|k| \overset{\text{def}}{=} \sum_{i=1}^{n} k_i$$

n = number of input variables

Standard truncation scheme (linear enumeration strategy)

Select all polynomials such that |k| is ≤ p

$$\text{card } K = \frac{(n+p)!}{n!\,p!}$$

- Hyperbolic enumeration strategy
- Anisotropic hyperbolic enumeration strategy
- Infinity norm enumeration strategy

https://openturns.github.io/

e.g. n = 3 ; p = 2 → card K = 10

i	k1	k2	k3	|**k**|
0	0	0	0	0
1	1	0	0	1
2	0	1	0	1
3	0	0	1	1
4	2	0	0	2
5	1	1	0	2
6	1	0	1	2
7	0	2	0	2
8	0	1	1	2
9	0	0	2	2

$$\hat{G}(\boldsymbol{Z}) = \alpha_o P_o + \alpha_1 P_1(z_1) + \alpha_2 P_1(z_2) + \alpha_3 P_1(z_3) +$$
$$+\alpha_4 P_2(z_1) + \alpha_5 P_1(z_1) P_1(z_2) + \alpha_6 P_1(z_1) P_1(z_3) +$$
$$+\alpha_7 P_2(z_2) + \alpha_8 P_1(z_2) P_1(z_3) + \alpha_9 P_2(z_3)$$

Polynomial Chaos Expansion – PCE

3. Computation of the coefficients, α_k

Least-square strategy

Once a truncation scheme is chosen, the series can be seen as the truncated one plus a residual.

$$Y = \hat{G}(\boldsymbol{X}) = \sum_{k \in K} \alpha_k \Psi_k(\boldsymbol{X}) + \varepsilon$$

Where ε corresponds to all those polynomials whose index k is not in the truncation set K.

The least-square minimisation approach consist in finding the set of coefficients $\alpha = \{\alpha_k, k \text{ e } K\}$ which minimizes the mean square error

$$\boldsymbol{\alpha} = argmin \frac{1}{N} \sum_{i=1}^{N} \left[G(\boldsymbol{X}) - \sum_{k \in K} \alpha_k \Psi_k(\boldsymbol{X}) \right]^2$$

$$\boldsymbol{X} = \left\{ \boldsymbol{x}^{(i)}, \dots, \boldsymbol{x}^{(N)} \right\}$$

$$\boldsymbol{Y} = G(\boldsymbol{X}) = \left\{ \boldsymbol{y}^{(i)}, \dots, \boldsymbol{y}^{(N)} \right\}$$

available after Sampling and FE test programme

[1] Géraud Blatman, 2009. Adaptive sparse polynomial chaos expansions for uncertainty propagation and sensitivity analysis. PhD thesis at Université Blaise Pascal - Clermont-Ferrand II

[2] Le Gratiet, L., Marelli, S., Sudret, B. 2017. Metamodel-Based Sensitivity Analysis: Polynomial Chaos Expansions and Gaussian Processes. Handbook of Uncertainty Quantification

[3] https://openturns.github.io/

[4] https://www.uqlab.com/

case study 1 – plate in clay

4. MM calibration & validation

ED with N = 56 + FE test programme → **X** and **Y**

training

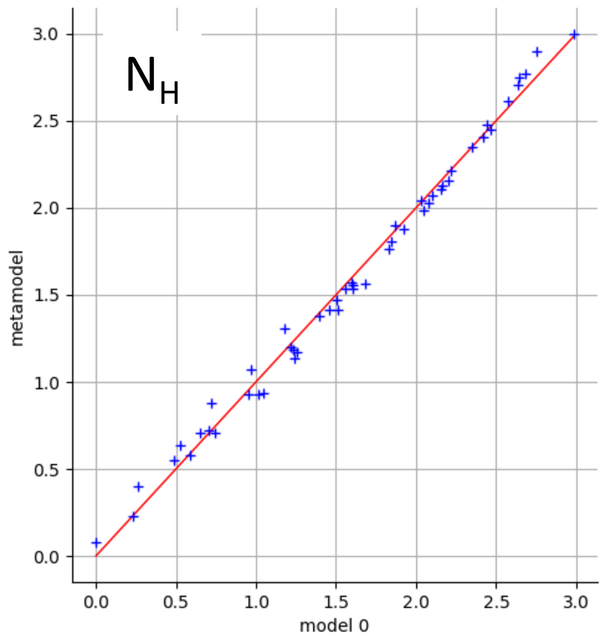
$$Y = \hat{G}(\boldsymbol{X}) = \sum_{k \in K} \alpha_k \Psi_k(\boldsymbol{X})$$

validating

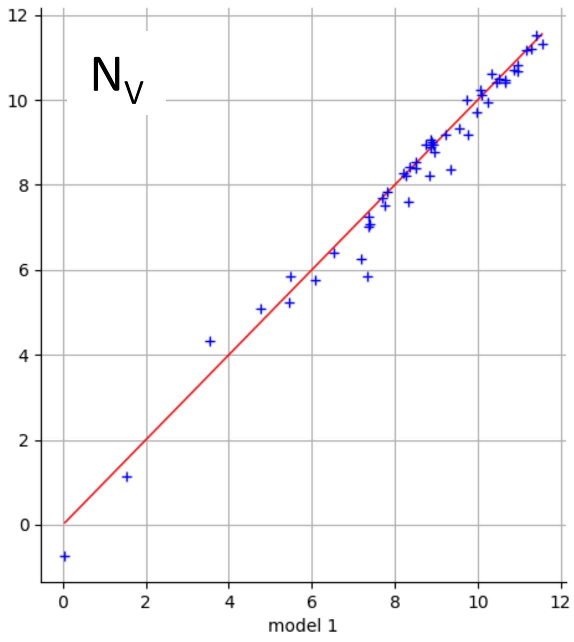
(random) validation sample size, M = 50

$$Q_2 = 1 - \frac{\sum_{i=1}^{M}\left[Y_i - \hat{G}(\boldsymbol{X}_i)\right]^2}{N \cdot Var(Y)}$$

Prediction capacity factor



$Q_2(N_H) = 0.991$



$Q_2(N_V) = 0.971$

case study 1 – plate in clay

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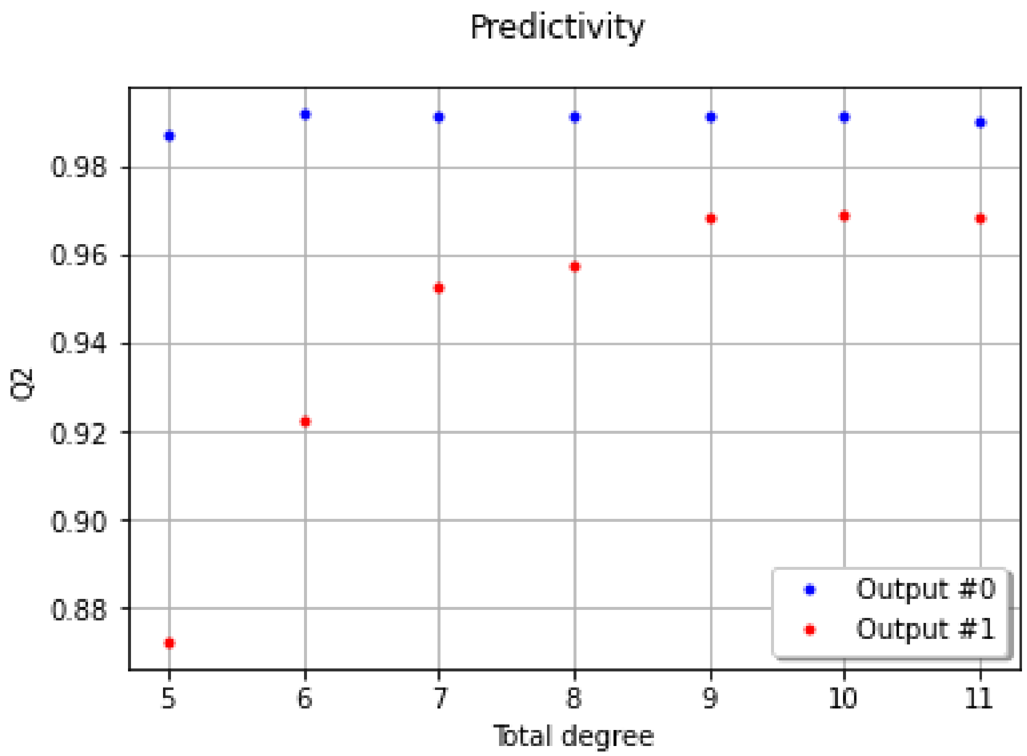
Prediction capacity factor

Sensitivity to polynomial degree



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case study 1 – plate in clay

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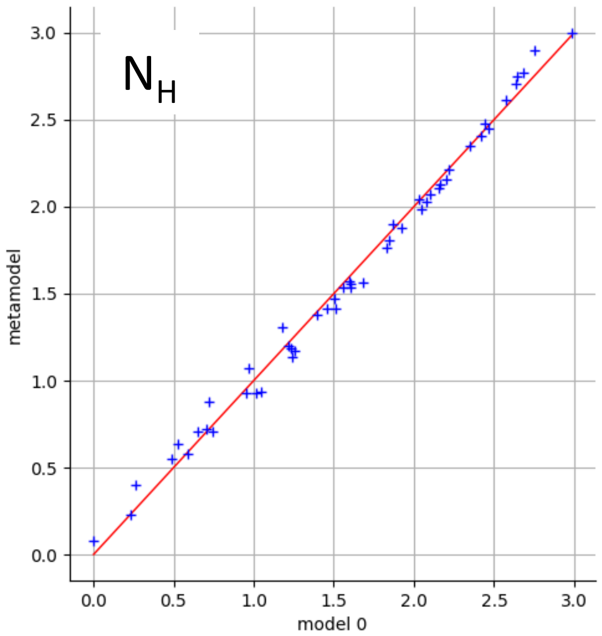
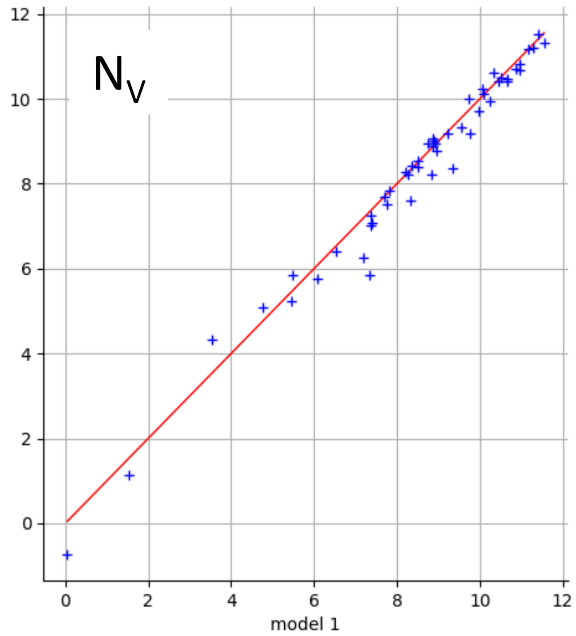
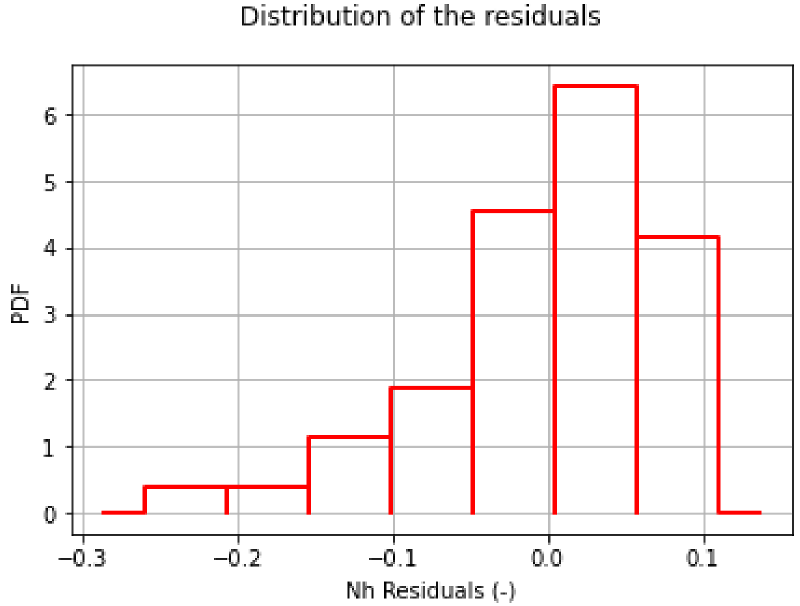
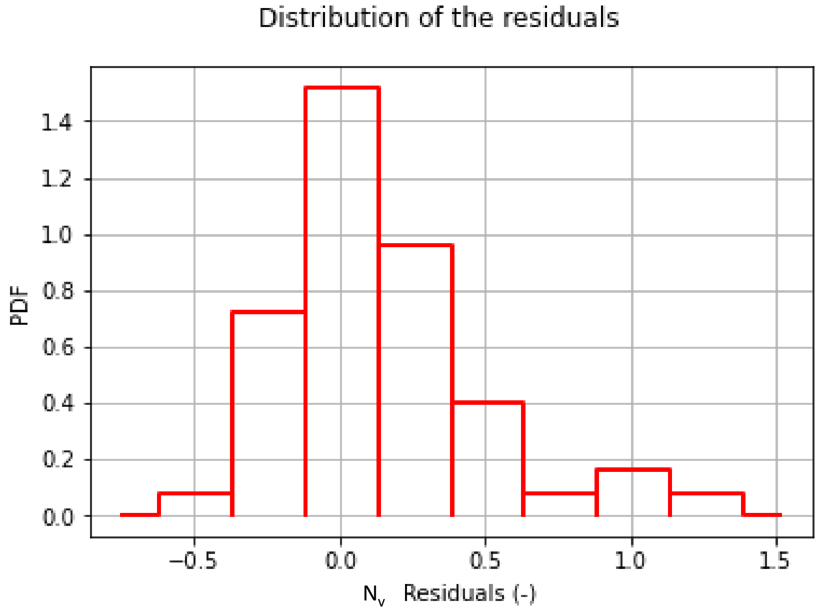




$$Q_2 = 1 - \frac{\sum_{i=1}^{M}\left[Y_i - \hat{G}(\boldsymbol{X}_i)\right]^2}{N \cdot Var(Y)}$$

Prediction capacity factor





case study 1 – plate in clay

4. MM calibration & validation

$Q_2(N_H) = 0.991$

$Q^2_{LOO}(N_H) = 0.992$

$Q_2(N_V) = 0.971$

$Q^2_{LOO}(N_H) = 0.968$

cross-validation technique

It consists in dividing the data sample into two subsample. A metamodel is built from one subsample (the training set) and its performance is assessed by comparing its prediction to the other subset (the test set).

Leave-One-Out - LOO

The PCE, $\hat{G}^{(-i)}$, is built from the ED $\mathbf{X} \backslash \{X^{(i)}\}$ i.e., removing the i-th observation

predicted residual → $$\Delta^{(i)} = G\left(X^{(i)}\right) - \hat{G}^{(-i)}\left(X^{(i)}\right)$$

LOO error → $$Err_{LOO} = \frac{1}{N}\sum_{i=1}^{N}\Delta^{(i)}$$

LOO relative error → $$\varepsilon_{LOO} = \frac{Err_{LOO}}{Var(Y)}$$

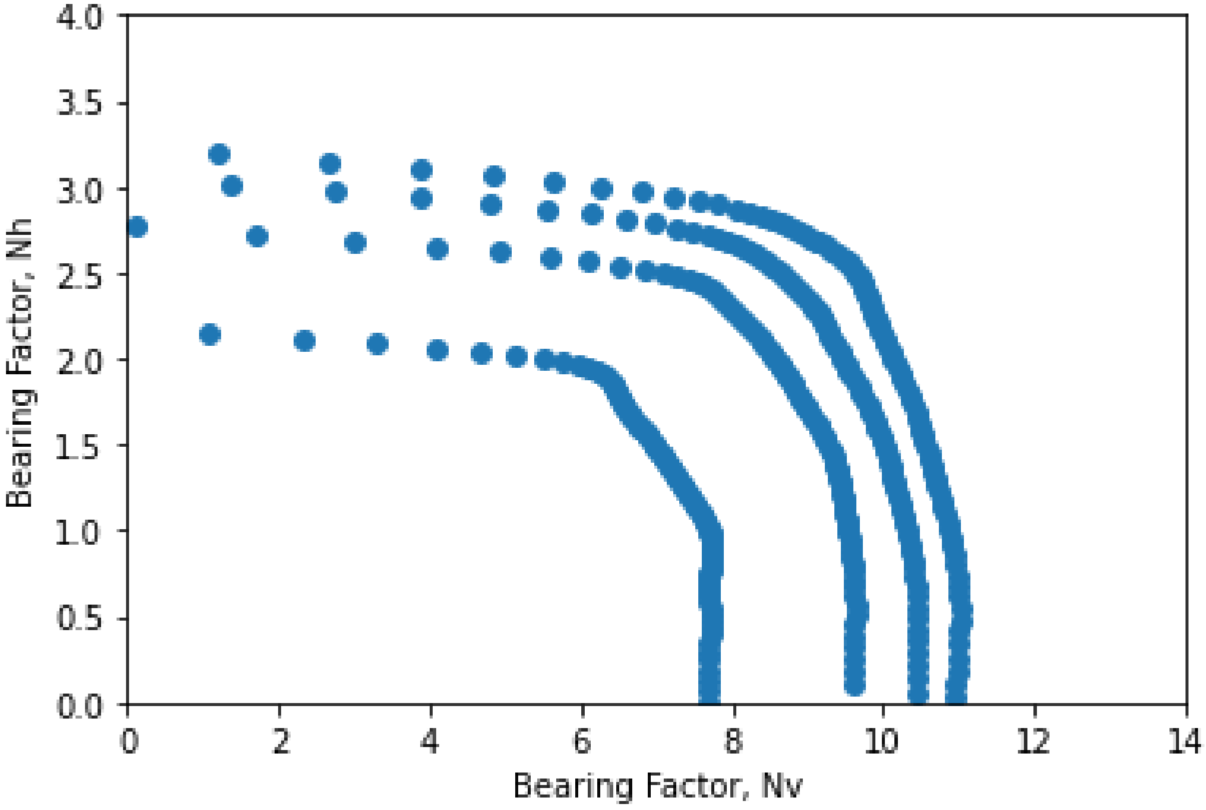
LOO predictivity factor → $$Q^2_{LOO} = 1 - \varepsilon_{LOO}$$

case study 1 – plate in clay

5. MM exploitation

Training dataset

x_M = [0.0; 0.05; 0.10; 0.25; 0.50; 0.75; 0.95]



x_M = [0.2; 0.4; 0.6; 0.8]

M = 20% M_u
M = 40% M_u
M = 60% M_u
M = 80% M_u

x_α = [random]

PCE trained with only 56 data!

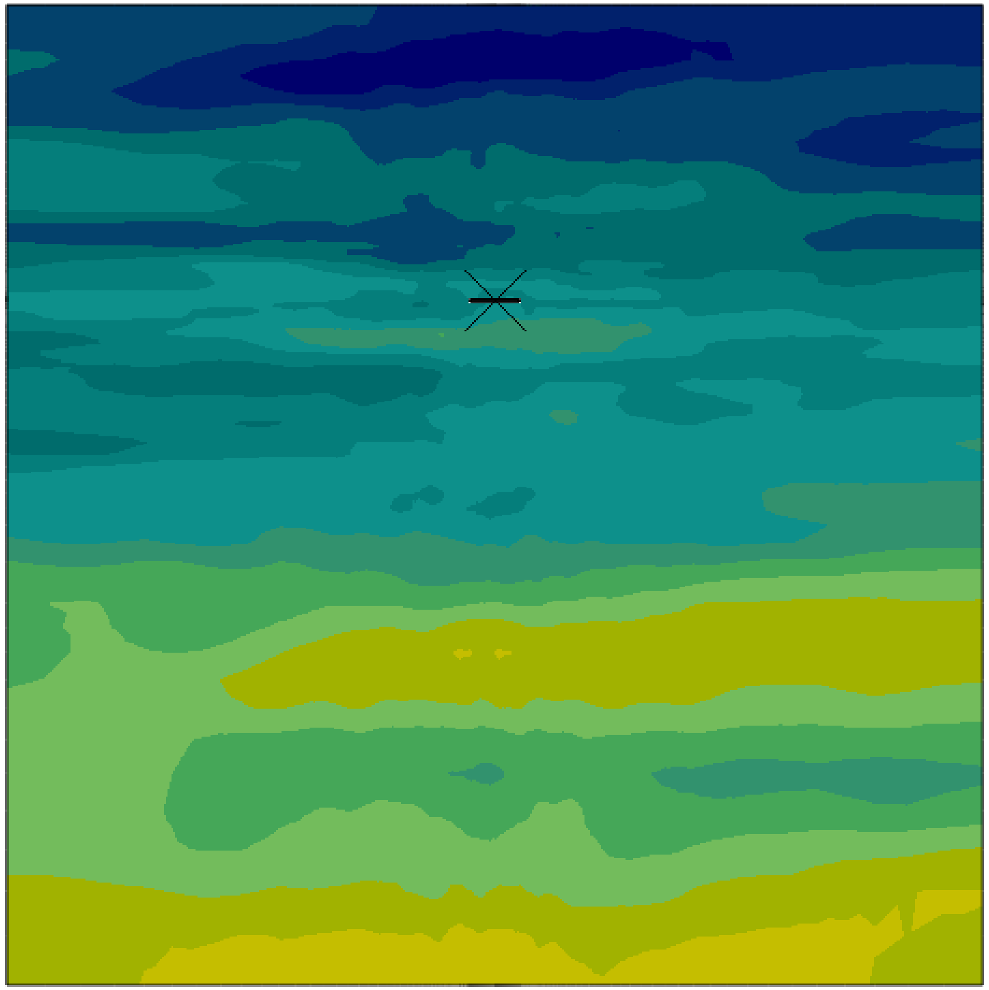
case study 1 – plate in clay

→ on-going activities

PCE of plate anchor in soil domain with random variable properties (i.e., s_u) and subjected to combined loading (VHM)

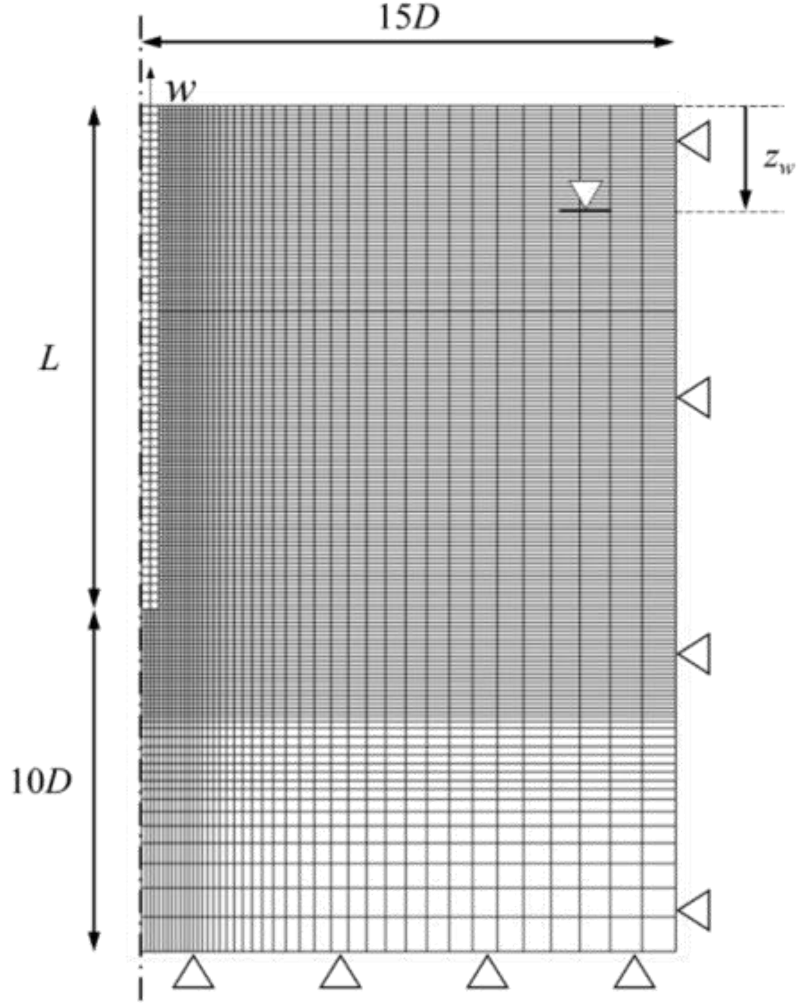
Prof. Yinghui Tian

THE UNIVERSITY OF MELBOURNE



case study 2 – pile in sand

1. Define problem position



❖ selection of input: 9 input

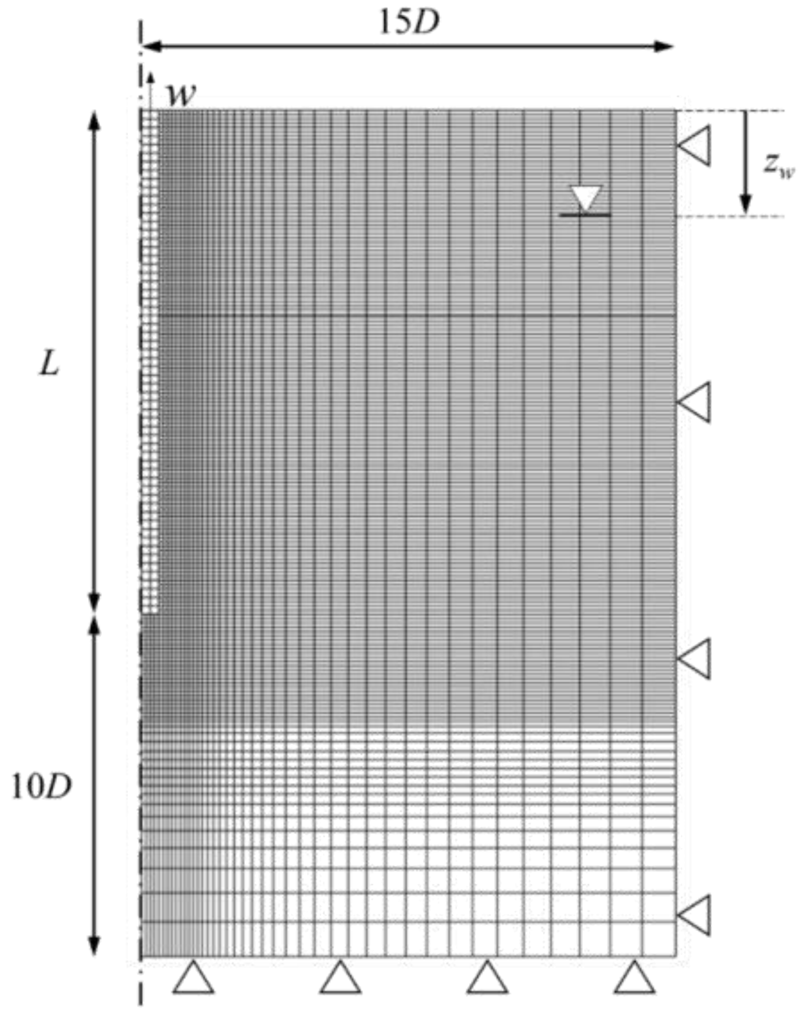
Input type	Input variable	Range
Geometry	Diameter, D [mm]	250 – 1000
	Slenderness ratio, L/D [-]	10 – 70
	Thickness ratio, D/t [-]	10 – 70
Soil property	Relative density, D_r [%]	40 – 100
	Soil behaviour type index, I_c [-]	1.31 – 2.05
	Critical state friction angle, ϕ'_{cv} [°]	28 – 40
Water level	Parameter for water level location, λ_w [-]	0.0 – 1.0
Interface	Parameter to define interface friction angle, λ_δ [-]	0.70 – 0.95
Earth pressure coefficient	Coefficient to define initial soil stress state, μ [-]	0.03 – 0.07

$$z_w = (L + 10D) \cdot \lambda_w \qquad \delta_{cv} = \phi'_{cv} \cdot \lambda_\delta$$

$$\boldsymbol{x}^{(i)} = \left\{ D, \frac{L}{D}, \frac{D}{t}, D_r, I_c, \phi'_{cv}, \lambda_w, \lambda_\delta, \mu \right\}$$

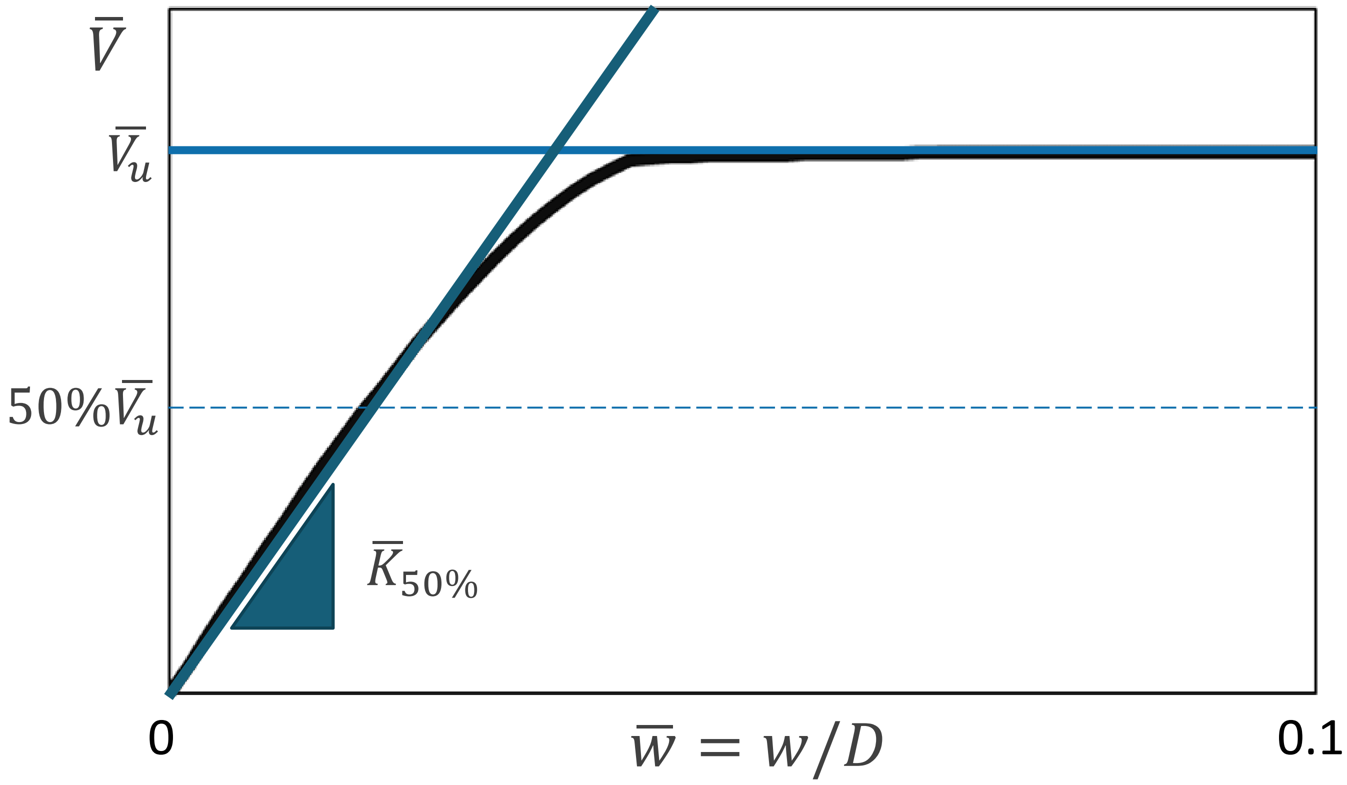
case study 2 – pile in sand

1. Define problem position



❖ selection of output

$$\boldsymbol{y}^{(i)} = \{\overline{V}_u, \overline{\boldsymbol{K}}_{50\%}\}$$

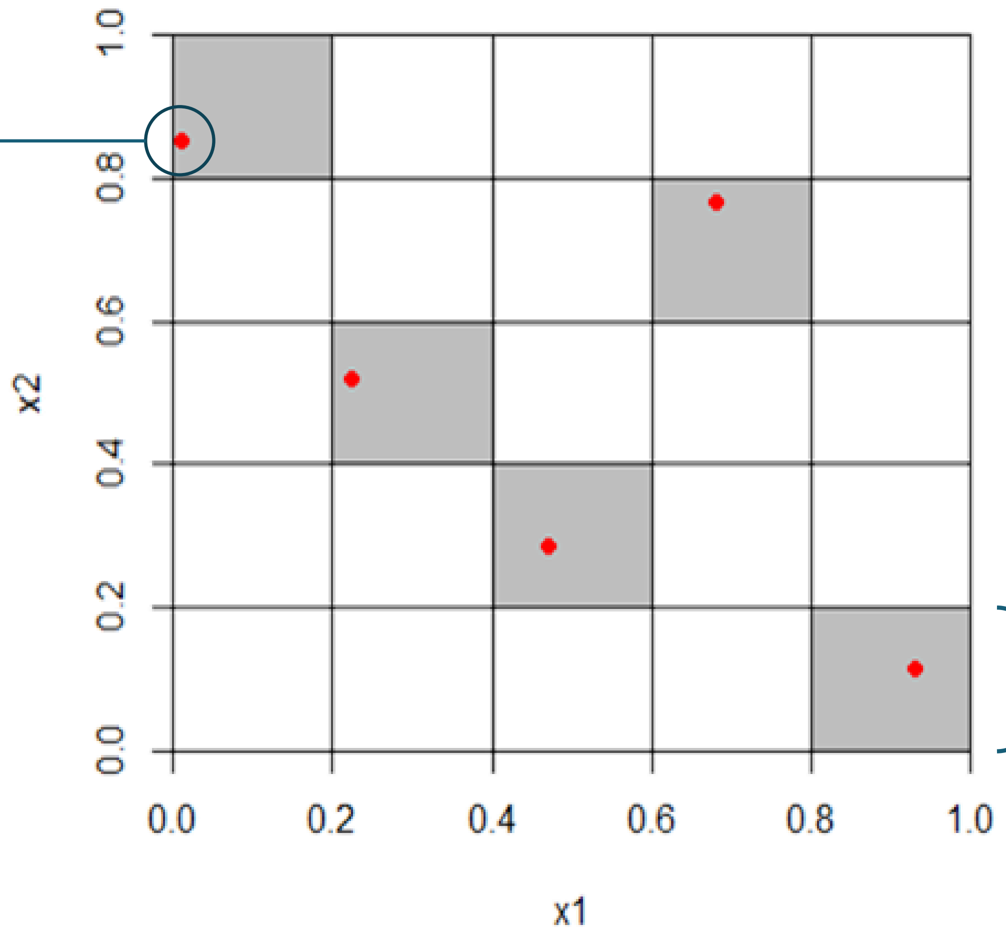


$$\overline{V}_u = \frac{V_u}{\gamma' D L^2}$$

2. Sampling

Latin Hypercube Sampling (LHS) technique

Input pairs randomly taken within the interval



Schematic of LHS

Sample size (ED): N = 5

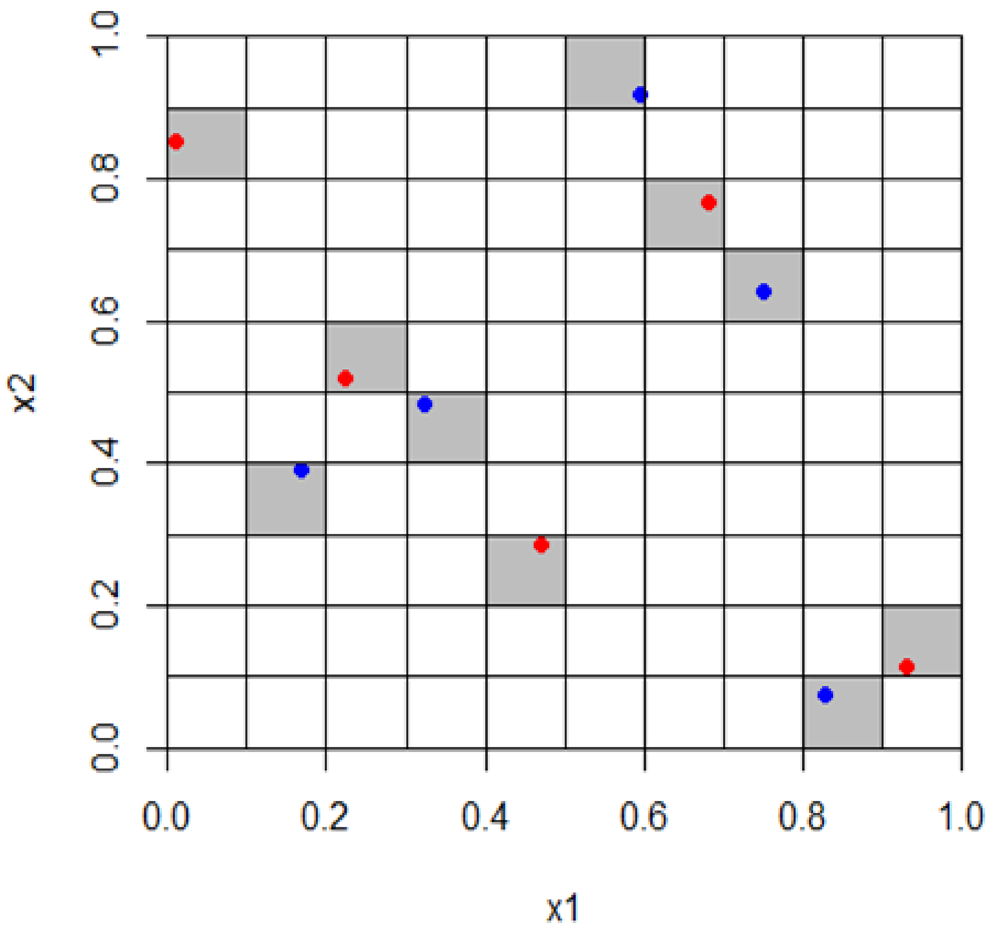
Number of variables: n = 2

Input variable range: [0, 1]

Intervals of equal probability, in the number of sample size N

2. Sampling

Latin Hypercube Sampling (LHS) technique



Advantages

- ❑ optimum coverage of the input variable domain;
- ❑ Sample can be augmented without losing LH property;
  → but $N_{aug} = 2 * N$
  → i.e., $N_{aug} = 5 * 2 = 10$

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case study 2 – pile in sand

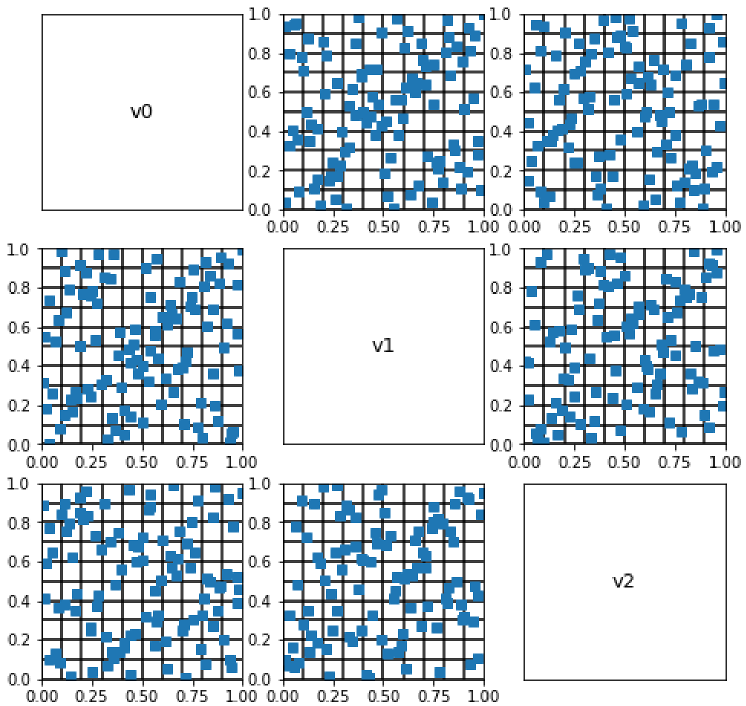
2. Sampling

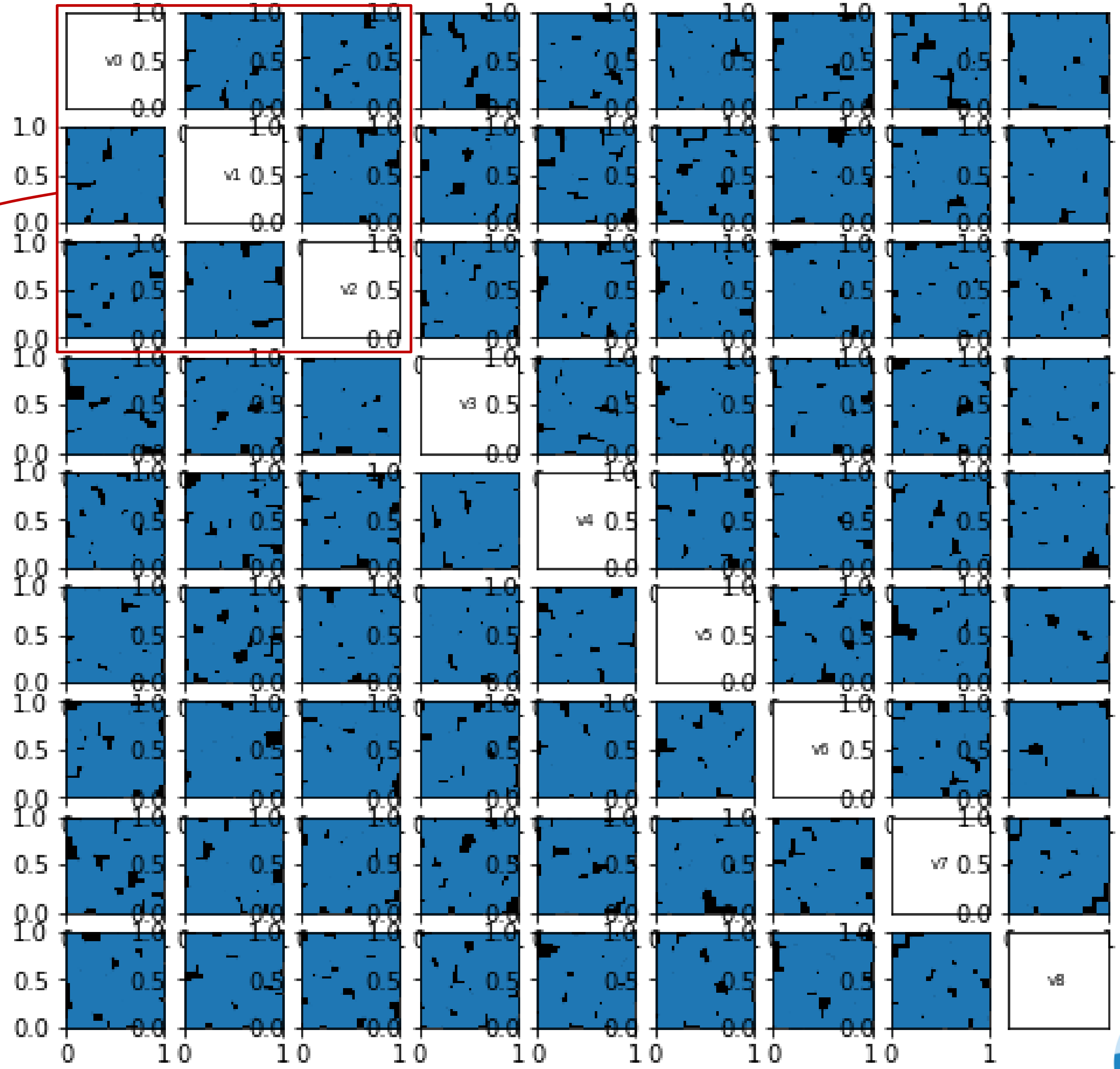
n = 9

N = 50; 100; 200; 400

$$\boldsymbol{X} = \{\boldsymbol{x}^{(i)}, \ldots, \boldsymbol{x}^{(N)}\}$$

Experimental Design (ED)





case study 2 – pile in sand

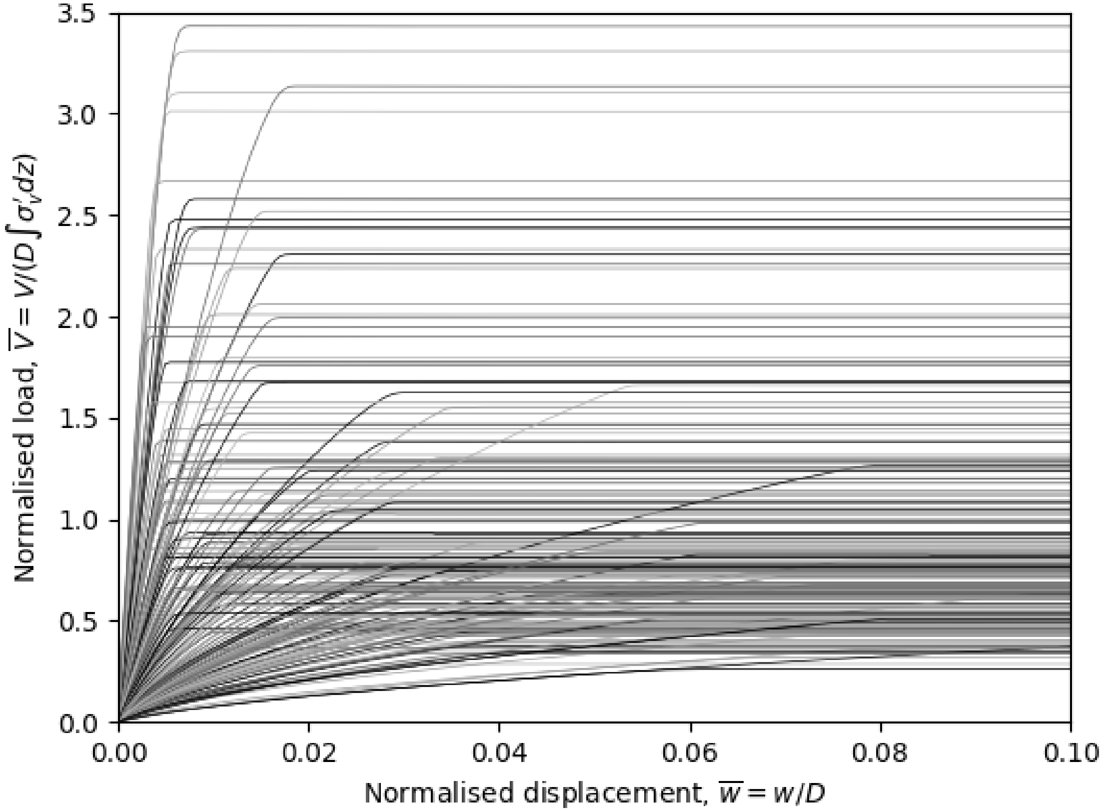
3. FE test programme

N = 200

$$\boldsymbol{Y} = \{\boldsymbol{y}^{(i)}, \ldots, \boldsymbol{y}^{(N)}\}$$

Model response vector

$$\boldsymbol{y}^{(i)} = \{\bar{V}_u, \bar{\boldsymbol{K}}_{50\%}\}$$



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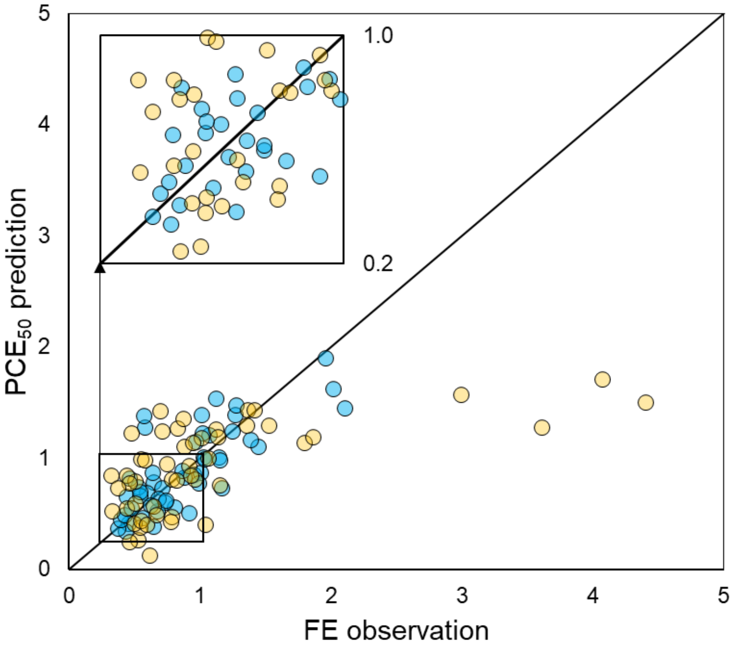
4. MM calibration & validation

LHS training sample size, N = 50

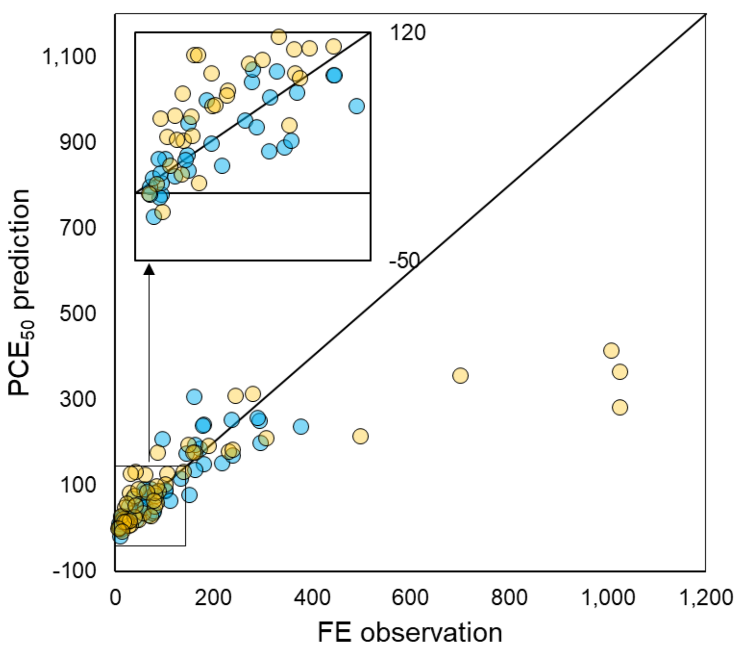
LHS validation sample size, M = 50; 100

Normalised ultimate capacity, $\bar{V}$



$Q^2(\bar{V}_u) = 0.373$

Normalised stiffness at 50%V_u, $\bar{K}_{50\%}$



$Q^2(K_{50\%}) = 0.845$

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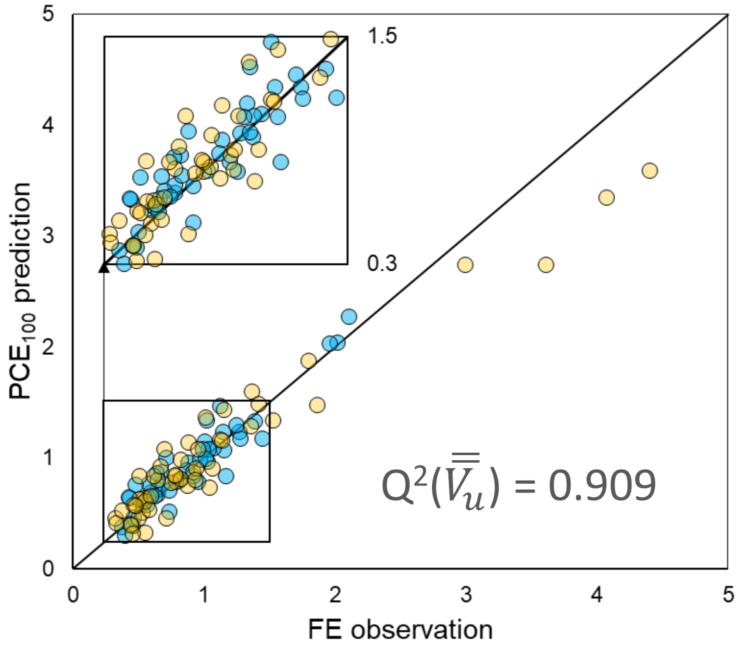
4. MM calibration & validation

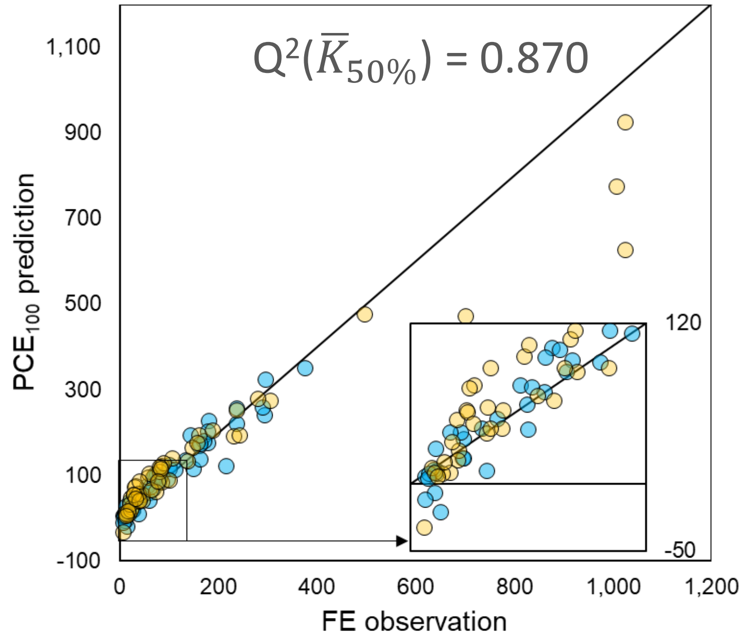
LHS training sample size, N = 100

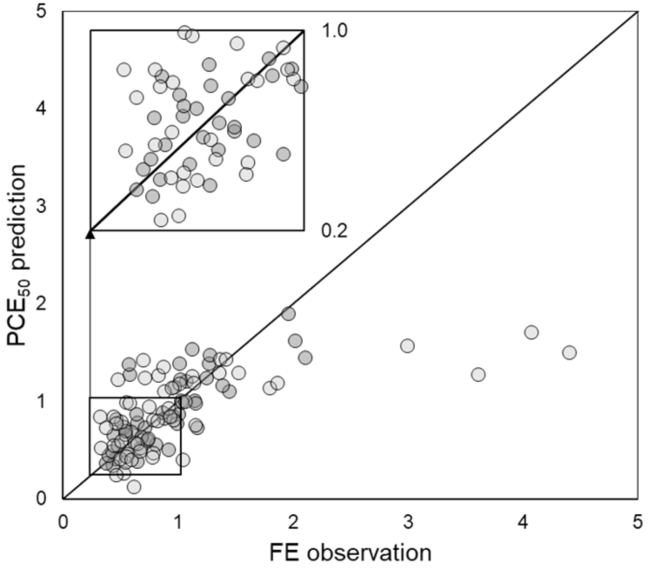
LHS validation sample size, M = 50; 100

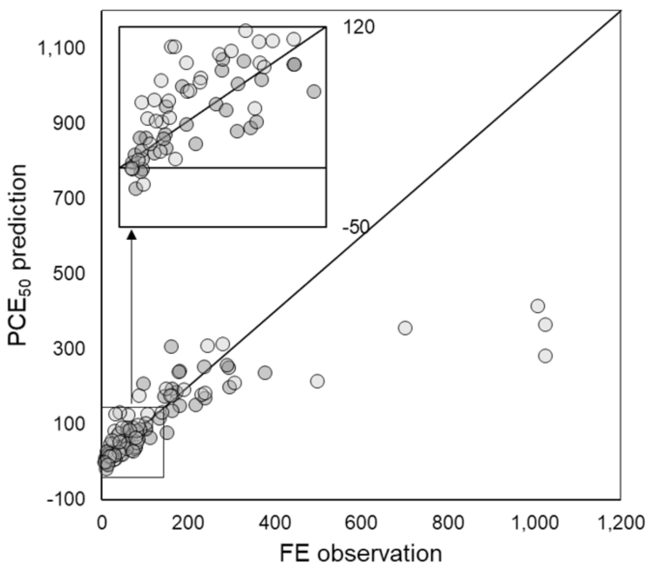
Normalised ultimate capacity, $\bar{V}$



Normalised stiffness at $50\%V_u$, $\bar{K}_{50\%}$







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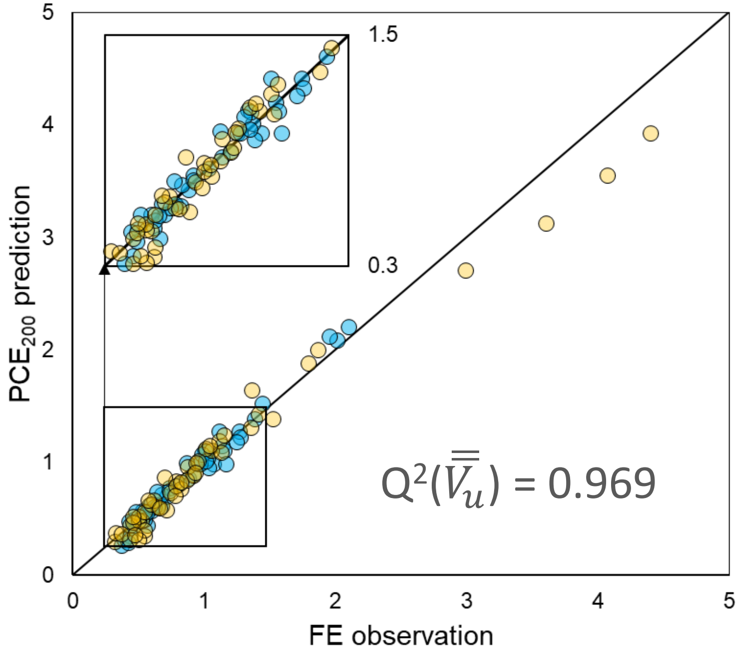
case study 2 – pile in sand

4. MM calibration & validation

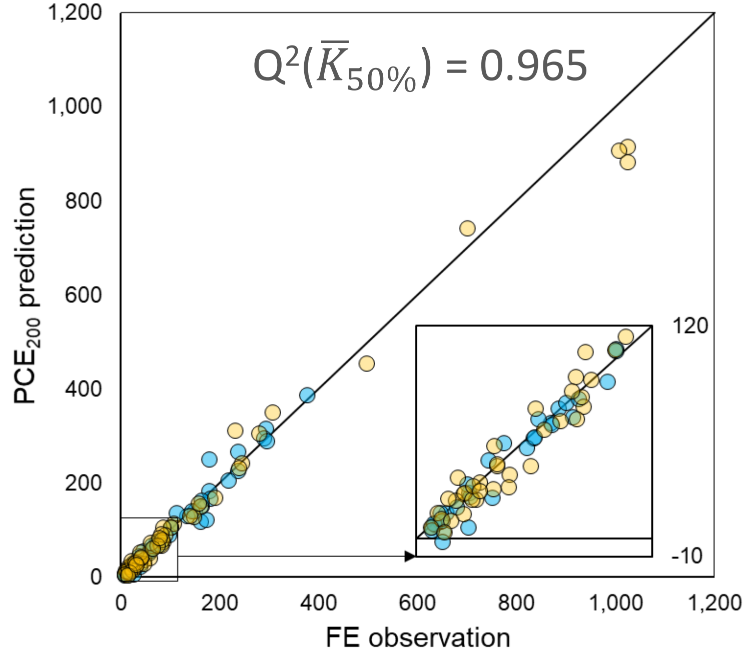
LHS training sample size, N = 200

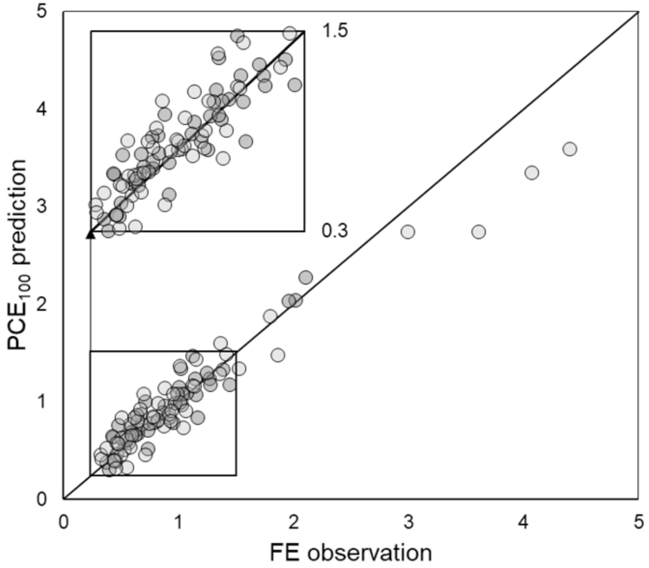
LHS validation sample size, M = 50; 100

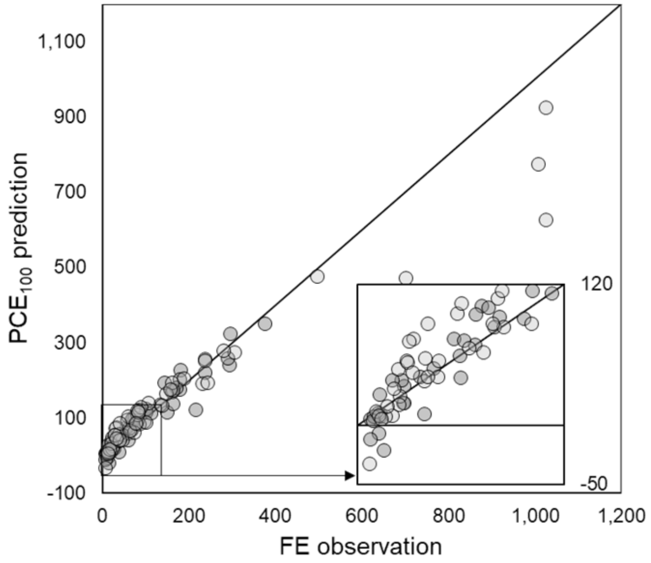
Normalised ultimate capacity, $\bar{V}$



Normalised stiffness at 50%V_u, $\bar{K}_{50\%}$







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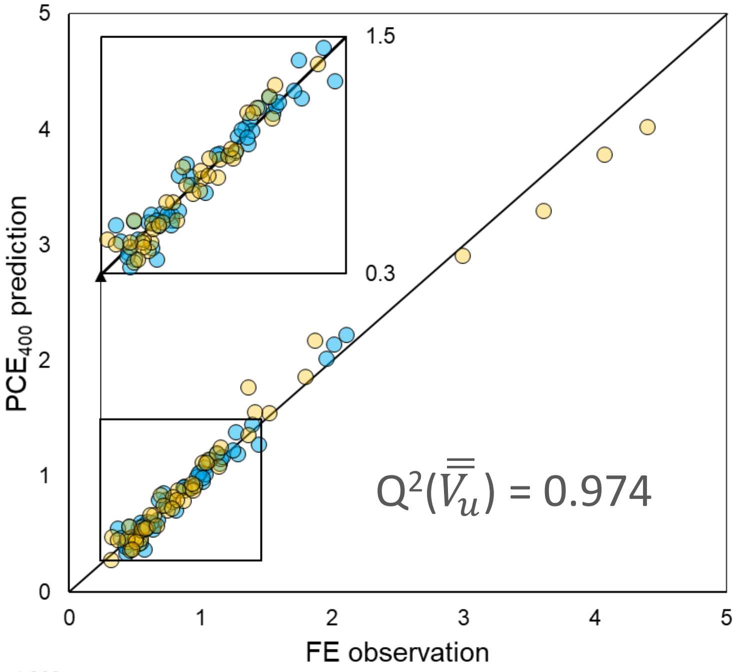
4. MM calibration & validation

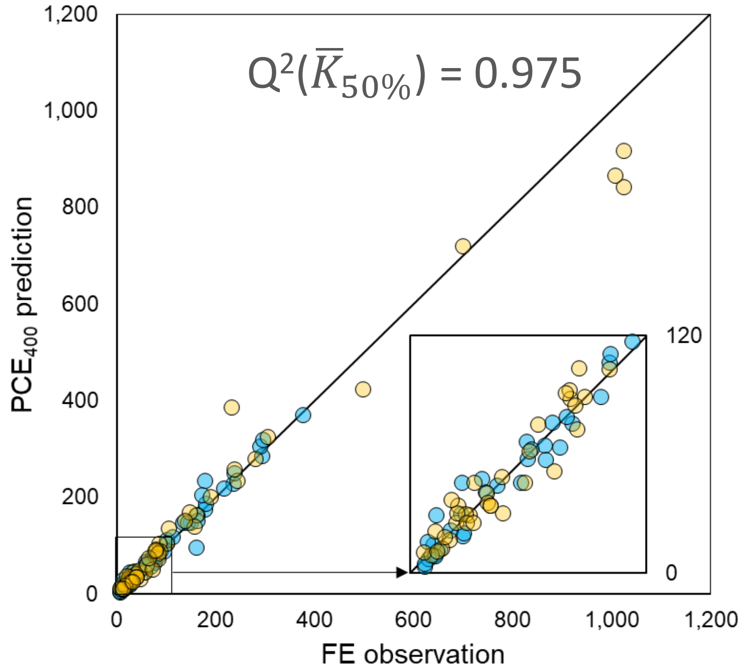
LHS training sample size, N = 400

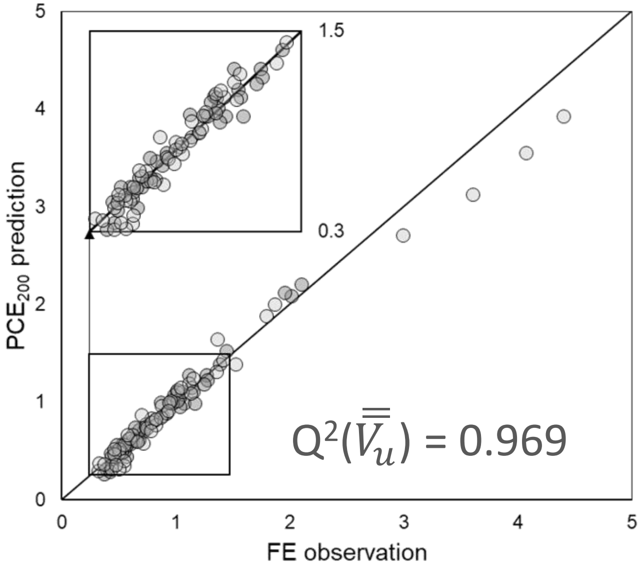
LHS validation sample size, M = 50; 100

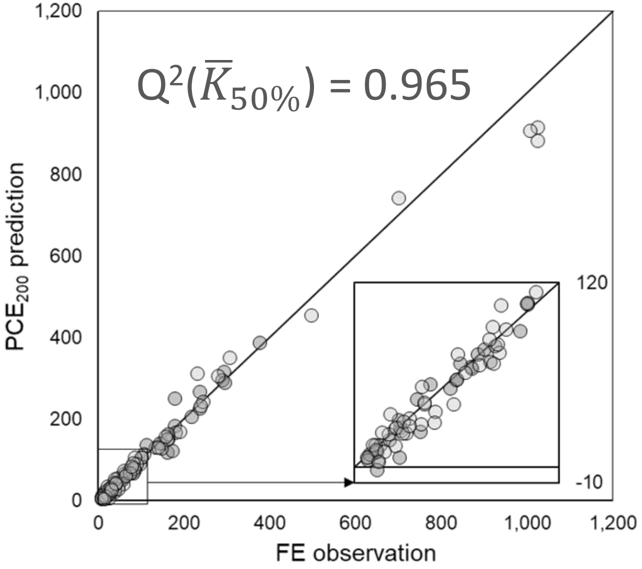
Normalised ultimate capacity, $\bar{V}$



Normalised stiffness at 50%V_u, $\bar{K}_{50\%}$







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case study 2 – pile in sand

5. Input influence: Sobol indices

First-order Sobol' indices

Quantify the portion of the total variance that can be apportioned to the sole input variable X_i

$$S_i = \frac{V_i}{V} = \frac{Var[G_i(X_i)]}{Var[Y]}$$

Second-order Sobol' indices

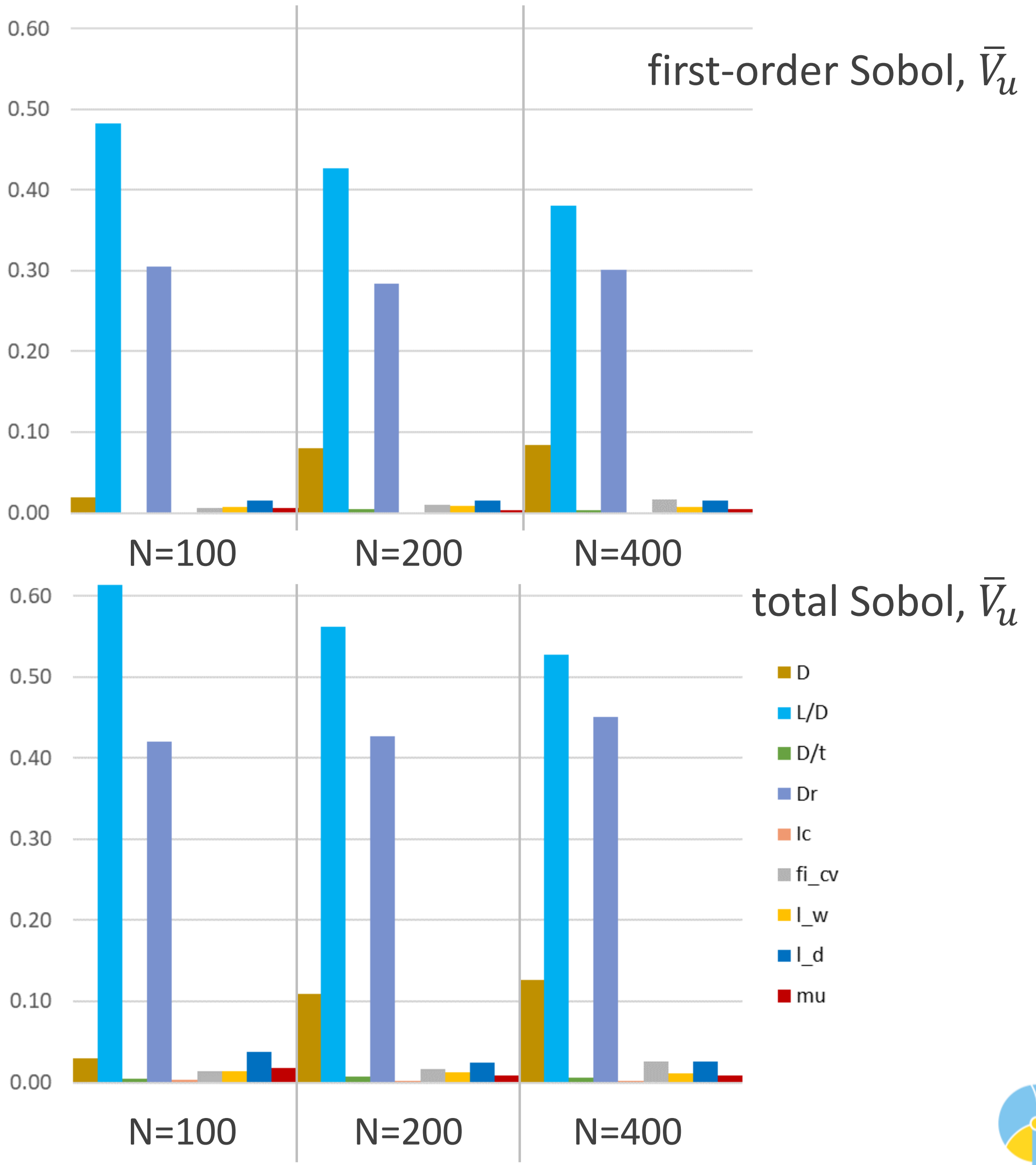
Quantify the joint effect of variables (X_i, X_j)

$$S_{ij} = \frac{V_{ij}}{V} = \frac{Var[G_{ij}(X_i, X_j)]}{Var[Y]}$$

Total Sobol' indices

Quantify the total impact of a given parameter, X_i, including all of its interactions with other variables

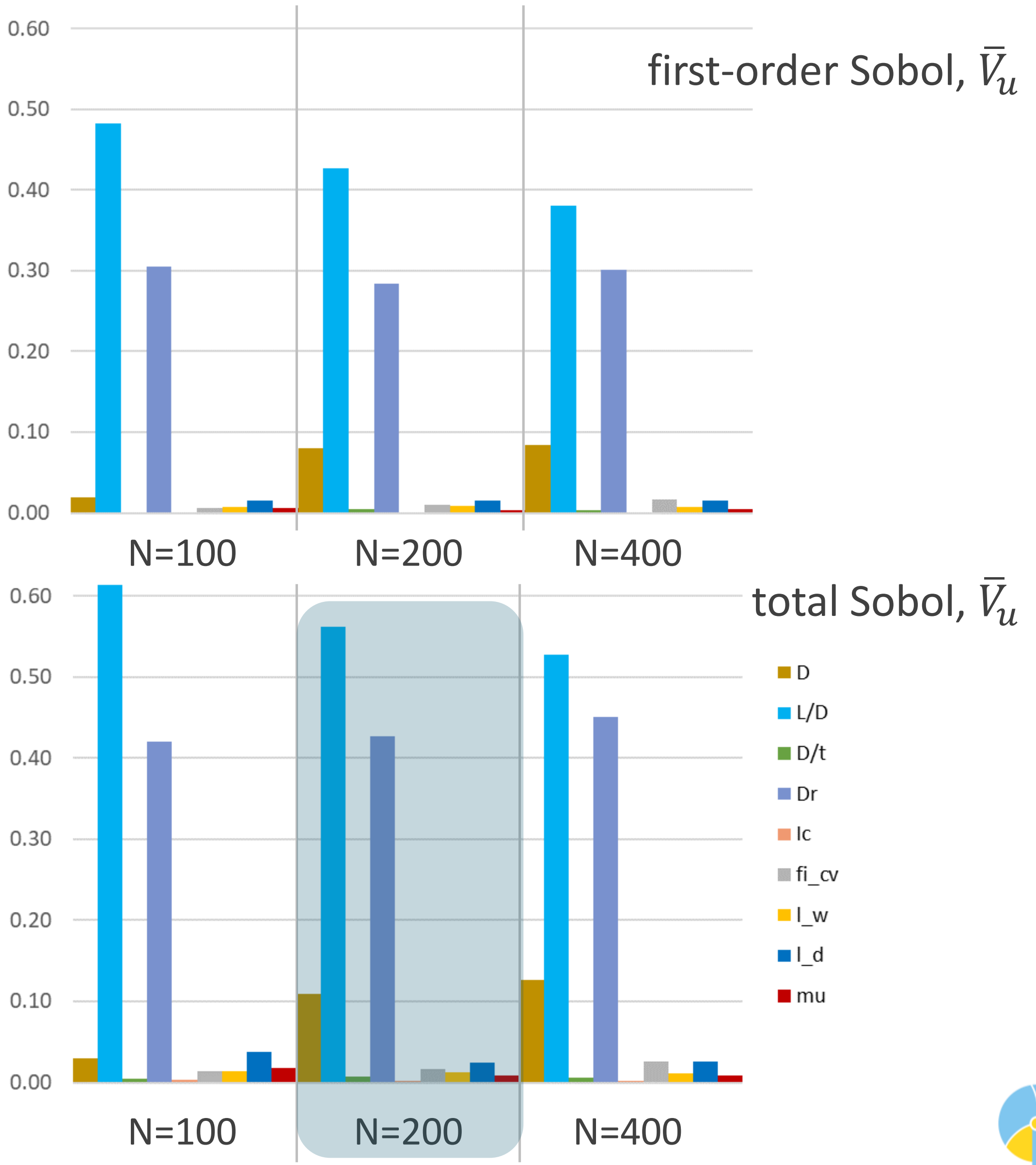
$$S_i^{tot} = \sum_{A \ni i} S_A$$



case study 2 – pile in sand

5. Input influence: Sobol indices

- Most of the prediction capacity is governed by D; L/D and D_r
- With increased (training) sample size the influence of other parameters tends to increase
- There is a very small influence of D/t and I_c
- Rather small influence of ϕ'_{cv}; λ_w and λ_δ, but their second-order indices are high



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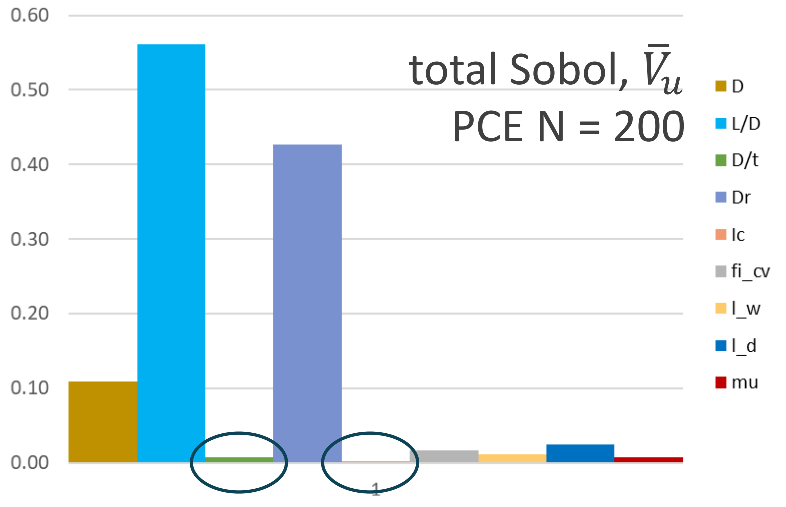
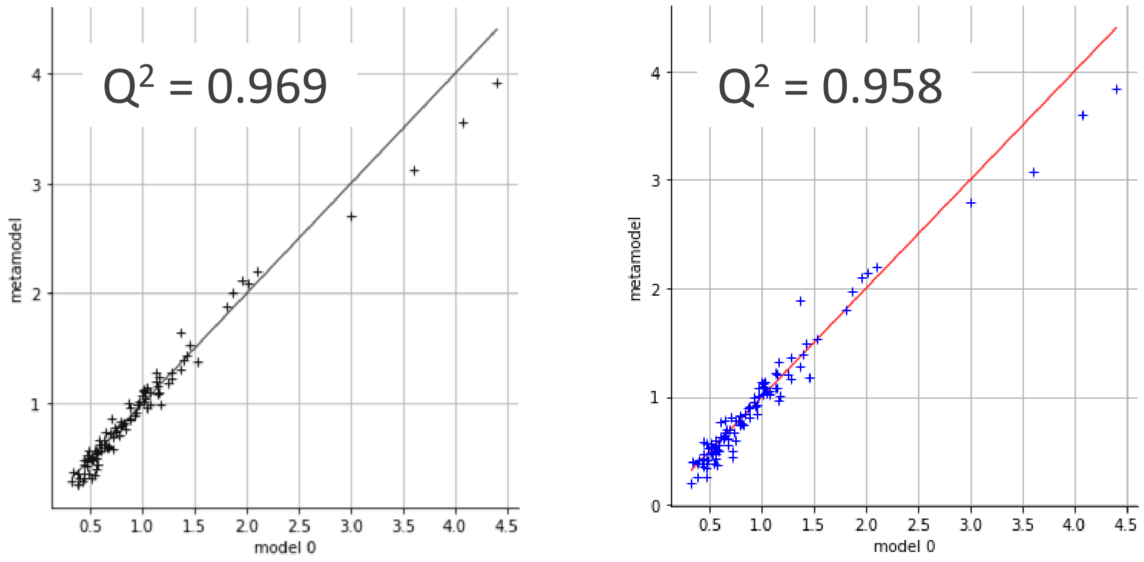
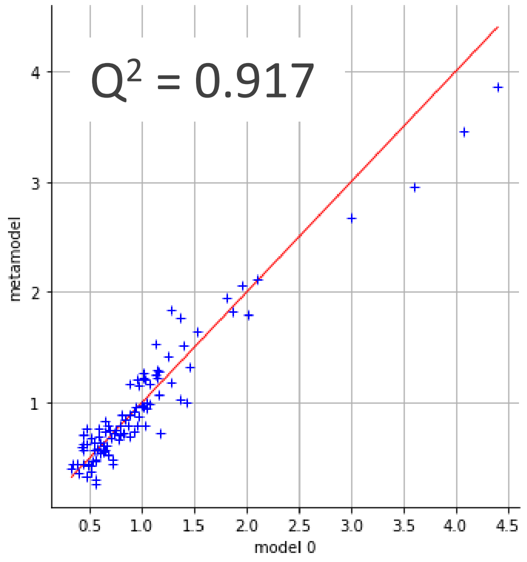
5. Input influence: Sobol indices



PCE is re-built with removing I_c and D/t parameters



PCE is re-built with considering only D; L/D and D_r parameters



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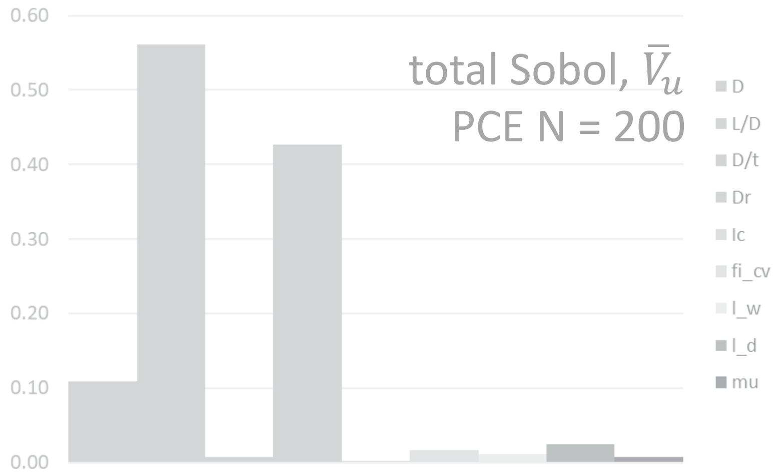
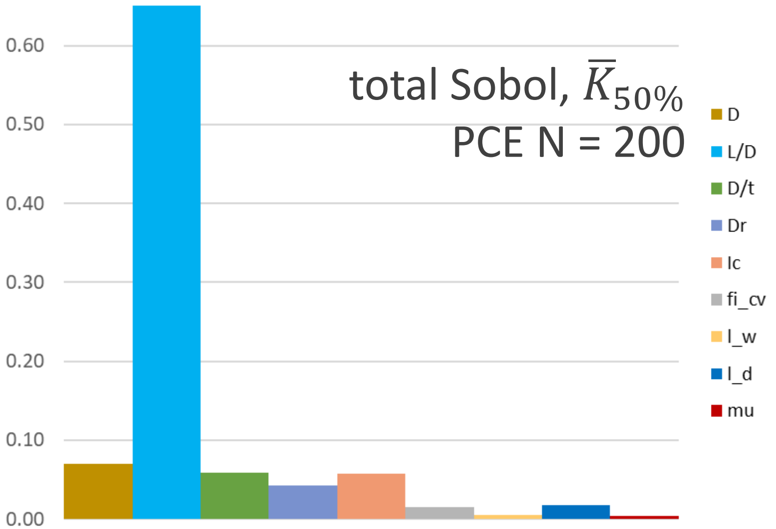
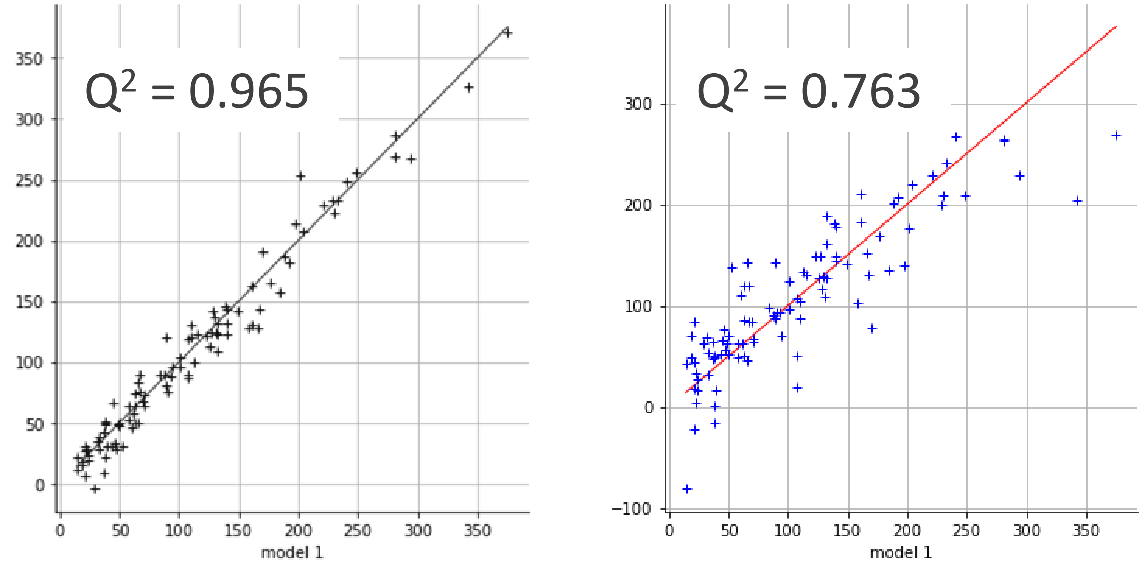
5. Input influence: Sobol indices

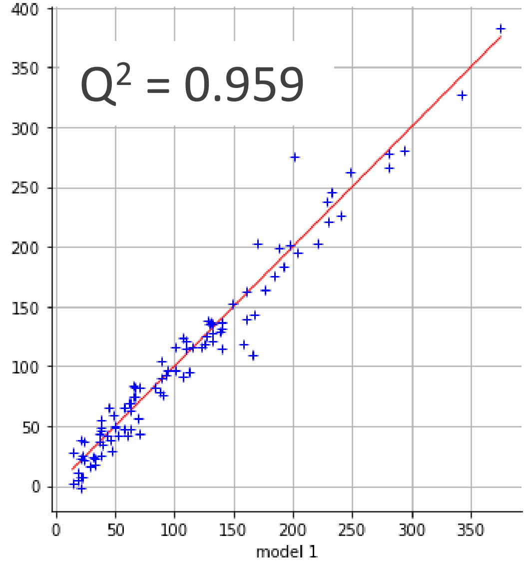




PCE is re-built with removing I_c only



PCE is re-built with removing μ only



case study 2 – pile in sand

→ on-going / planned activities

- Sensitivity and reliability analysis with PCE
- Use of more sophisticated constitutive soil model for the FE model to be emulated
- Centrifuge tests to validate FE model prior/after metamodelling

concluding remarks

The study made use of the following software

Python package for metamodelling

https://openturns.github.io/openturns/latest/index.html

concluding remarks

- The procedure on how to create a metamodel of a FE model has been presented and applied for simplified case studies in the context of offshore geotechnical engineering
- Metamodels proved to be an effective way to store the results of FE simulations and make them available at a low computational cost (carrying out some large size Monte Carlo simulation on the meta-model will be affordable)
- Metamodels can be built using a small number of FE simulations and provide very accurate results over wide domains of input variables
- The procedure, here presented in its essential steps, can be further extended to accommodate modelling features of higher complexity, increasing the number of input variables and can be employed to predict other behavioural aspects, also increasing the numbers of outputs.

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- van den Eijnden, A. P., Schweckendiek, T., Hicks, M.A. 2021. Metamodelling for geotechnical reliability analysis with noisy and incomplete models. Georisk: Assessment and Management of Risk for Engineered Systems and Geohazards
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- Lambert, S., Toe, D., Mentani, A., Bourrier, F., 2021. A meta-model-based procedure for quantifying the on-site efficiency of rockfall barriers. Rock Mech Rock Eng. 54, 487–500
- Wang, Z.Z., Xiao, C., Goh, S.H., Deng, M-X. 2021. Metamodel-Based Reliability Analysis in Spatially Variable Soils Using Convolutional Neural Networks. J. Geotech. Geoenviron. Eng. 147(3), 04021003.

References on metamodelling packages for coding:

- Python: https://openturns.github.io/
- Matlab: https://www.uqlab.com

https://site.unibo.it/seaflower/

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