Meta-modelling techniques for the design of offshore anchor piles

SEAFLOWER
for floating wind energy

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23 September 2021

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Strategies to Exploit Anchors for Floating Offshore Wind Energy Reaping

MARIE CURIE ACTIONS

MSCA-IF-GF

INSTITUTES

BENEFICIARY

PARTNER

THE UNIVERSITY OF WESTERN AUSTRALIA

INRAE

Laura Govoni

Chirstophe Gaudin

Phil Watson

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TEAM

TIMELINE

t = 3 years

15 March 2021	July 2021	**23 Sep 2021**	Jan 2023	March 2023	March 2024

INRAE	THE UNIVERSITY OF WESTERN AUSTRALIA / Alma Mater Studiorum	THE UNIVERSITY OF WESTERN AUSTRALIA	INRAE	Alma Mater Studiorum
3M	18M		3M	12M
SECONDMENT	OUTGOING		SECONDMENT	RETURN

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ALMA MATER STUDIORUM A.D. 1088

THE UNIVERSITY OF WESTERN AUSTRALIA

INRAE

- Support the phase of **pre-commercial** development of floating wind technologies from the **geotechnical standpoint**.
- Aid with a rational **technology transfer** between the **O&G** and **wind market**.
- Develop a procedure to **store previous experience** on anchors and **make it available** for the **new needs of the wind sector**.

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What SEAFLOWER does

STORING

Collect experimental evidence on anchors' behaviour from model tests
plus relevant soil info
built on available data at COFS

PROCESSING

Develop FE models of the experiments → ROBUSTNESS
ADVANCED
SIMPLIFIED
← *optimisation* → COMPLEXITY, COMPUTATIONAL EFFORT

ENCODING

Meta-modelling of FE models
Input and Outputs (as originated by FE) correlation
Built on few FEA yield accurate outputs → LOW COMP EXPENSES, LOW COMPLEXITY, USER-FRIENDLINESS

EXPLOITING

Meta-models for end-users' needs
- Demonstrators, LCOE
- Preliminary design, advanced design

- Predict outputs from a given set of input
- Generate results for probabilistic approaches
- Generate parameters for mechanical models (p-y, macro-element)

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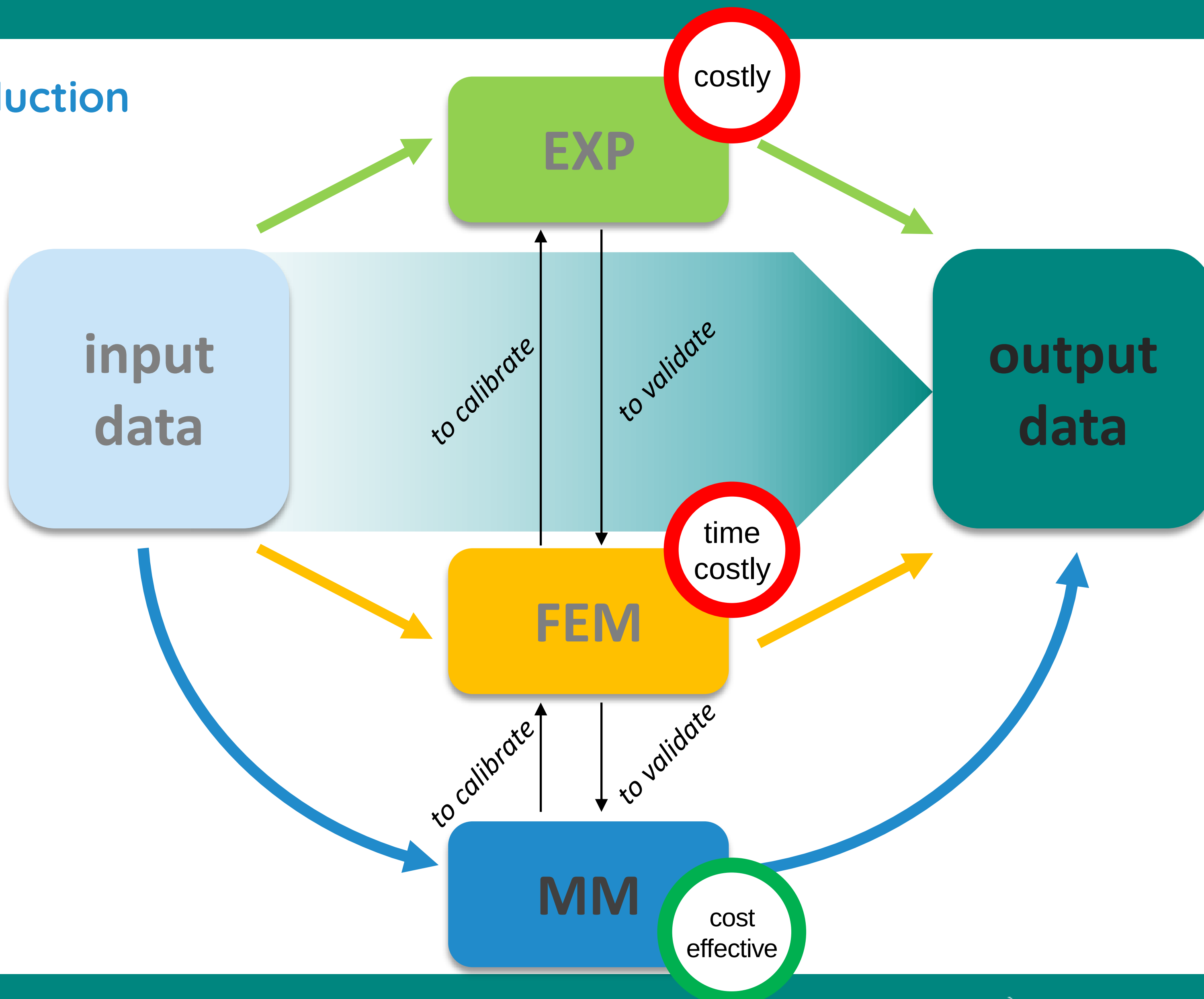
outline

- Introduction
- Finite Element Model
  - Details
  - FE testing programme
  - Sampling with LHS
  - Results
- Metamodelling: the PCE
  - Details
  - Applications and results
- Conclusions

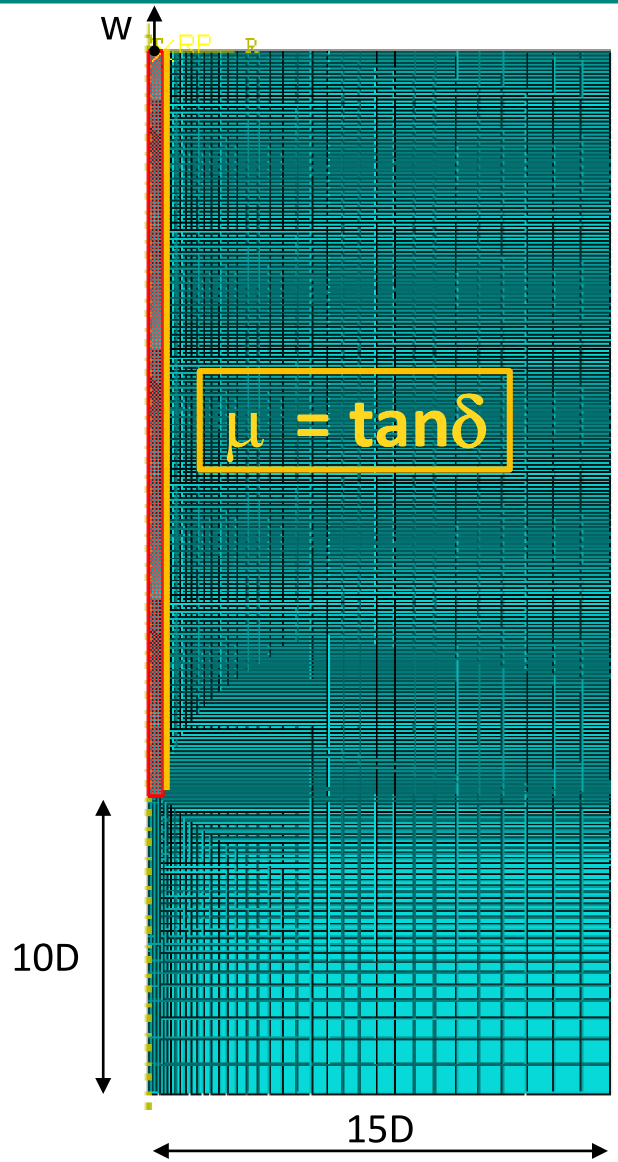
introduction



FEM: details

Proof of concept: anchor pile in sand

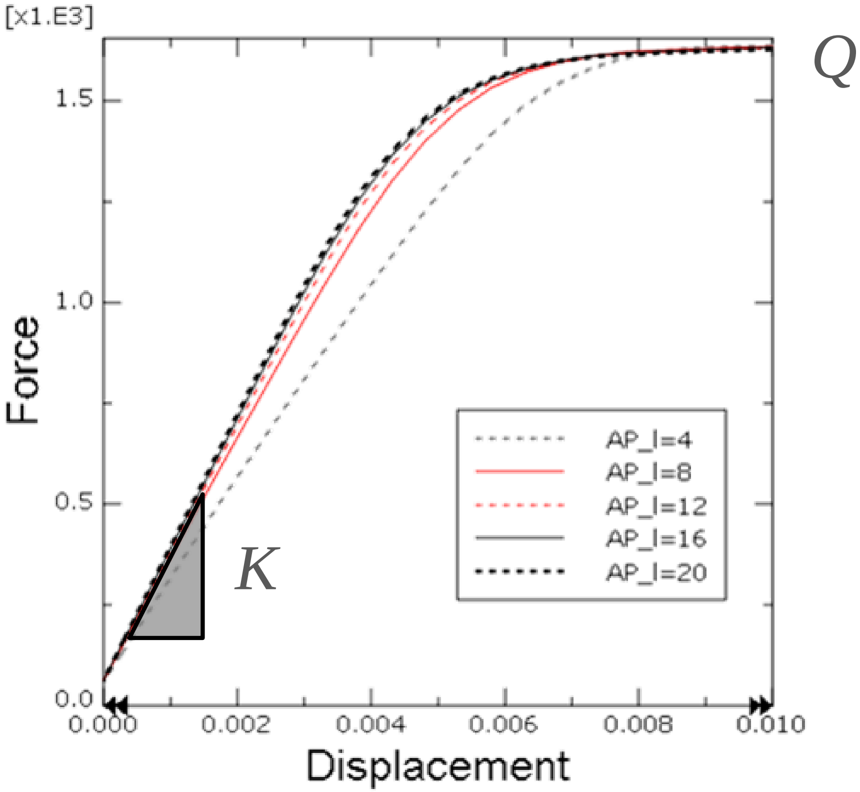
- Axial-symmetric 2D FEM
- Soil:
  - homogeneous, D_r = const
  - linear elastic, $E = f(z)$
  - M-C criterion, $\phi', \psi' = f(z)$
- Pile:
  - linear elastic homogeneous
- Interface: friction law (δ = 29°)
- Soil stress state: Jardine et al. 1998
- Load condition: monotonic tensile (w = 10%D)



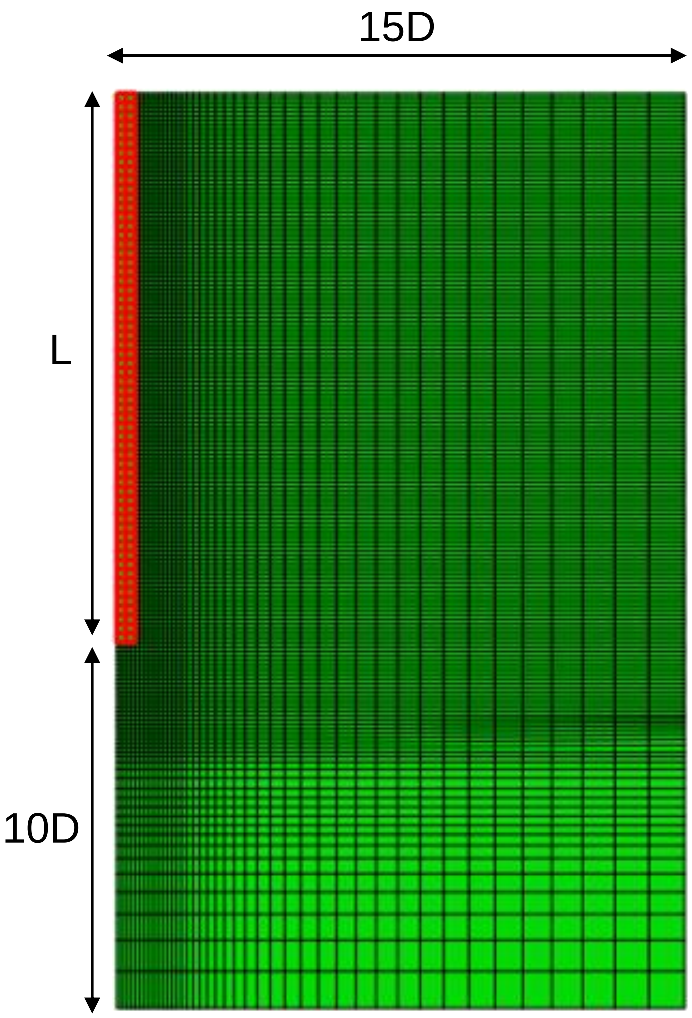
FEM: problem position

FEM input parameters	Symbol [unit]
Pile diameter	D [m]
Pile slenderness	L/D [-]
Wall thickness ratio	D/t [-]
Soil relative density	D_r [%]
Factor for elastic modulus	α [-]

FEM output	Symbol [unit]
Bearing capacity	Q [kN]
Initial stiffness	K [kN/m]



FEM: details



$$q_c = C_o p_a \left(\frac{\sigma'}{p_a}\right)^{C_1} \exp(C_2 D_R)$$

after Schmertmann, 1976

$$C_0 = 24.94; \quad C_1 = 0.46; \quad C_2 = 2.96$$

after Jamiolkowki et al. 2001

$$C = \alpha q_c$$

$$E' = \frac{(1+\nu)(1-2\nu)}{1-\nu} C$$

$$3 \leq \alpha \leq 9$$

after Baldi et al. 1982

$$\sigma'_{rc} = 0.029 \cdot q_c \left(\sigma'_{v0} / p_a\right)^{0.13} \left(h / R^*\right)^{-0.38}$$

after Jardine et al. 1998

$$I_R = D_r \left(10 - \ln p'_0\right)$$

$$3 I_R = 0.8 \psi'$$

$$\phi_p = \phi_{cr} + 0.8 \psi'$$

after Bolton, 1986

input parameters
D [m]
L/D [-]
D/t [-]
D_r [%]
α [-]

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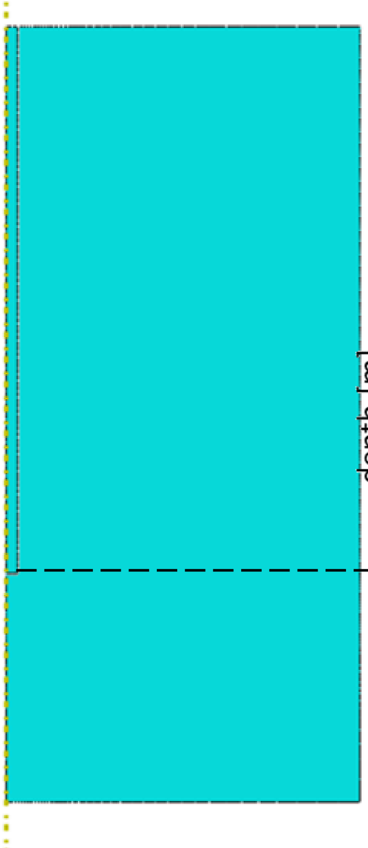
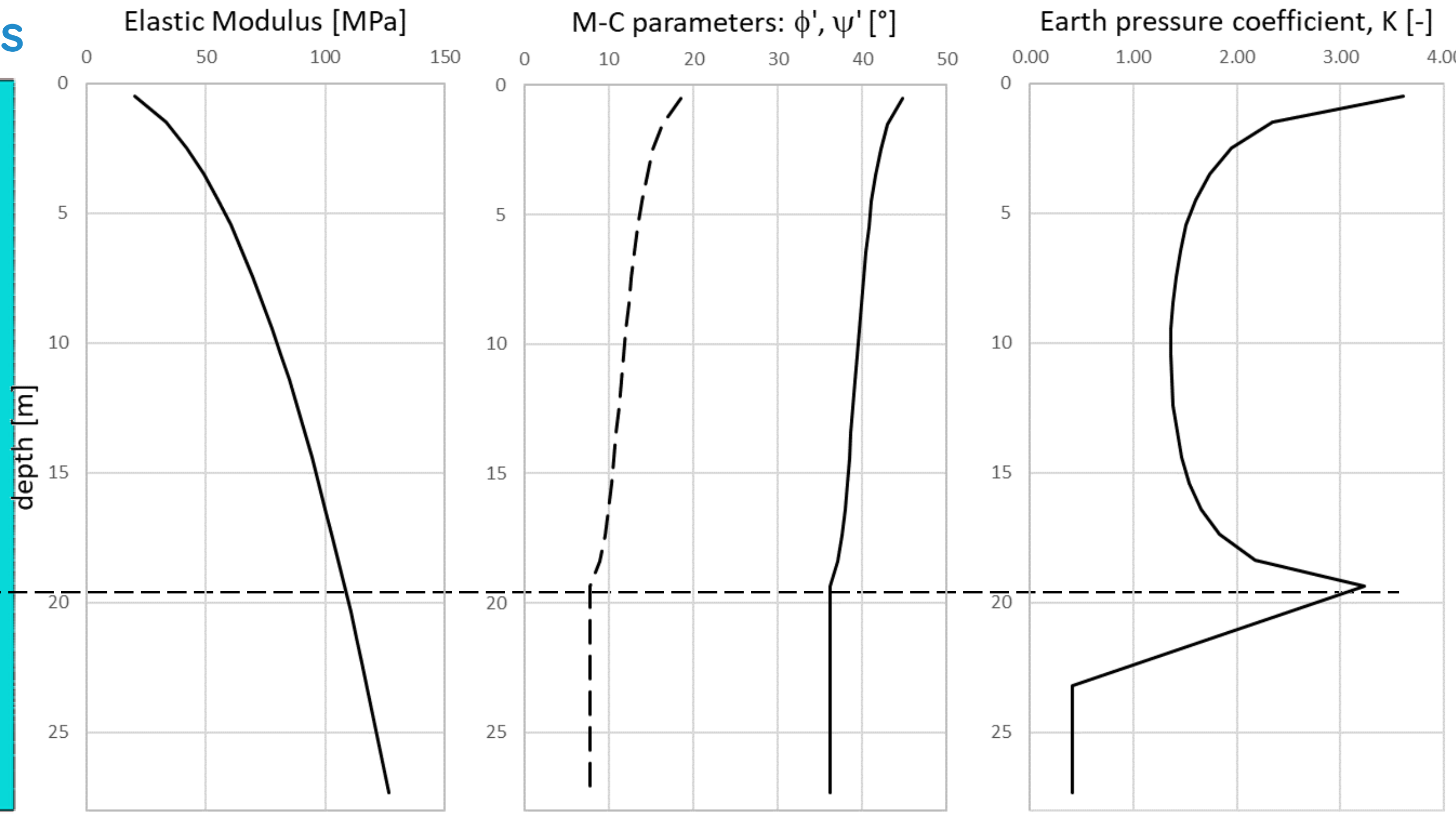
FEM: details





input parameters	D = 0.830m	L/D = 23.925	D/t = 25.372	D_r = 80.44%	α = 4.797

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FEM: FE testing programme

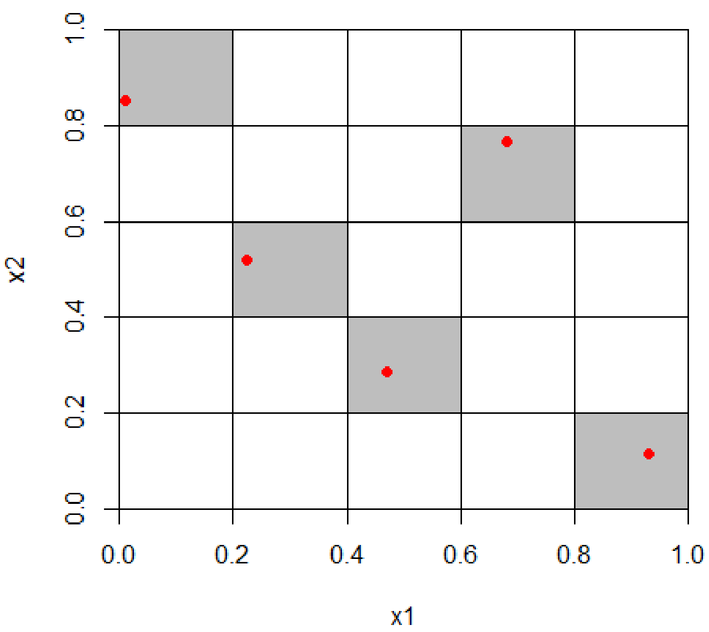
A sample of *N=100* simulations is created by varying the input model parameters within reasonable ranges

FEM input parameters	**Symbol [unit]**	**Range**
Pile diameter	D [m]	0.76 – 2.4
Pile slenderness	L/D [-]	10.0 – 60.0
Wall thickness ratio	D/t [-]	25.0 – 100.0
Soil relative density	D_r [%]	40.0 – 100.0
Dimensionless factor for elastic modulus	α [-]	3.0 – 9.0

Latin Hypercube Sampling - LHS

FEM: sampling with LHS

LHS is a sampling method enabling to better cover the domain of variations of the input variables, thanks to a **stratified sampling strategy**. The sampling procedure is based on dividing the range of each variable into several intervals of equal probability. The number of intervals equals the required sample dimension.



Example

Two linearly independent input variables both ranging from 0 to 1.

Sample size, N = 5

The Latin property of the hypercube requires that each of the 5 equal probability intervals (i.e. 1/5) be filled (**<u>i.e. each row and each column is filled with one point</u>**).

Also notice that the exact location of the design point is randomly sampled within that cell using a uniform distribution for each marginal variable.

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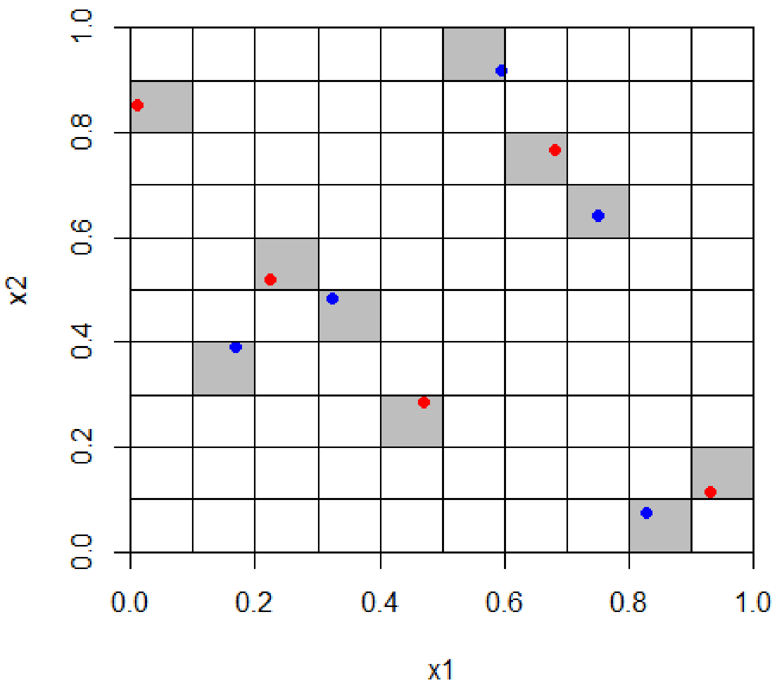
FEM: sampling with LHS

In case the sample size has to be enlarged, it can be done without losing its Latin Hypercube property.



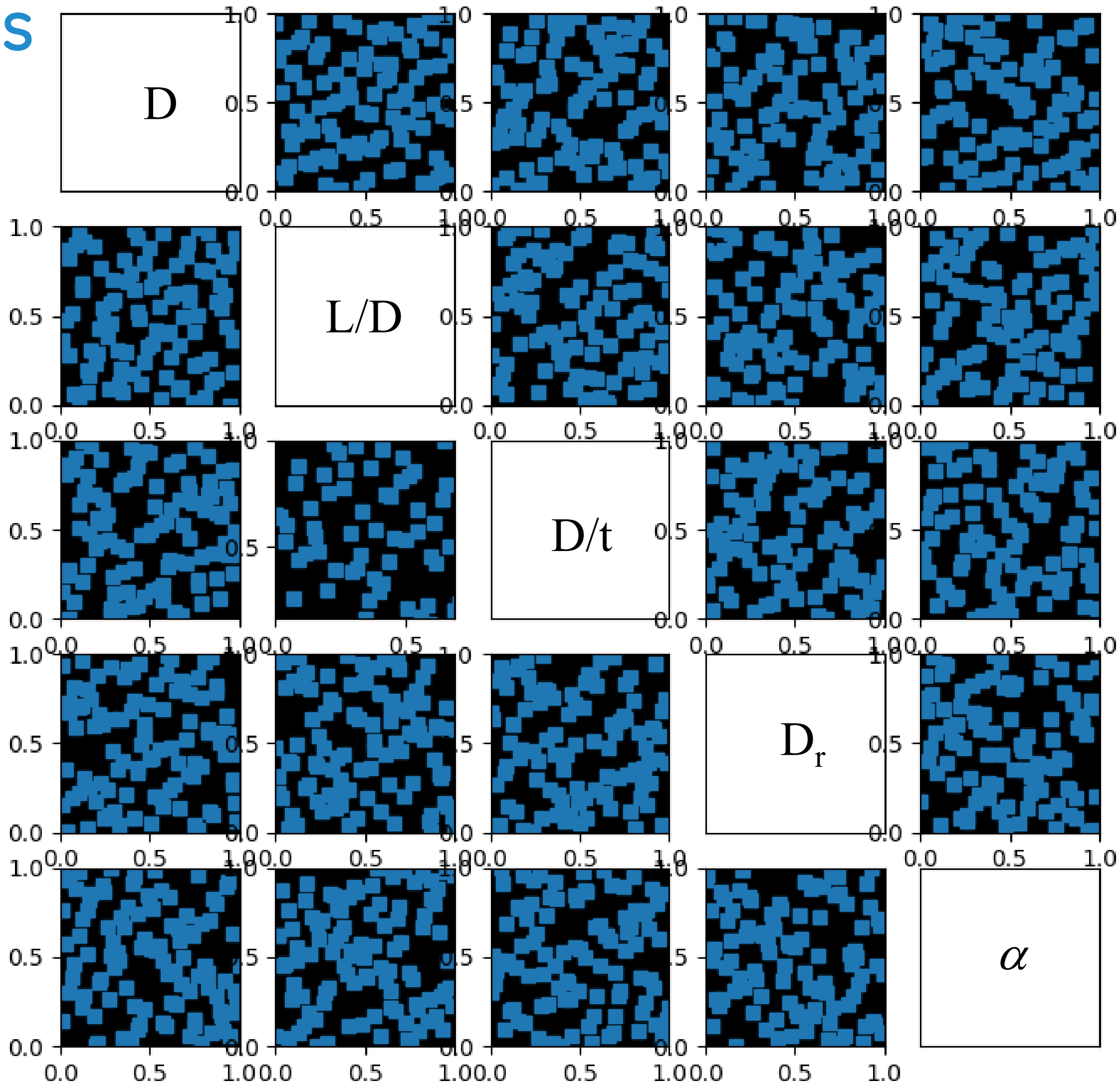
Additional data, N_{add} = 5 → New Sample size, N_{new} = 10

The additional data are added by re-dividing the original design into $N+N_{add}$ intervals (e.g. 5+5=10) keeping the original design points exactly in the same position. It then randomly fills the empty row-column sets.

NOTE: the augmenting points do not necessarily form a Latin Hypercube themselves. The original design and augmenting points may form a Latin Hypercube, or there may be more than one point per row in the augmented design.
If the augmented points are equal to the number of original points, then a strictly uniform Latin hypercube is guaranteed.

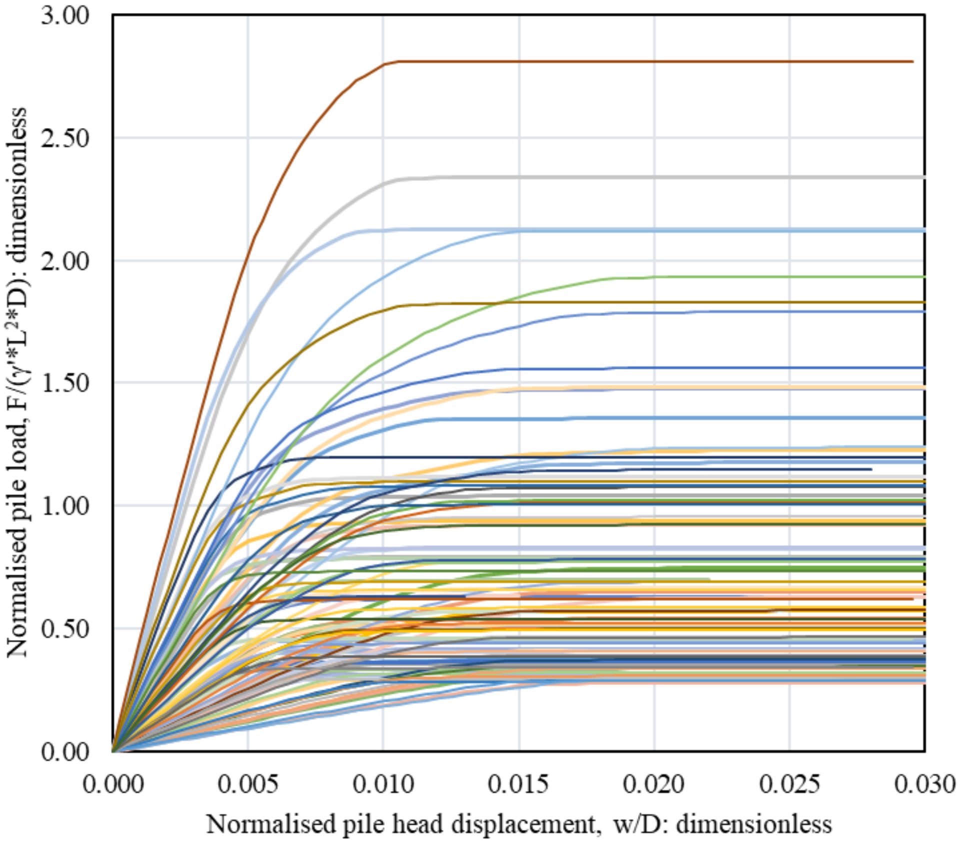
FEM: sampling with LHS

N = 100



FEM: results

python™ → SIMULIA ABAQUS



FEM input parameters	Symbol [unit]
Pile diameter	D [m]
Pile slenderness	L/D [-]
Wall thickness ratio	D/t [-]
Soil relative density	D_r [%]
Factor for elastic modulus	α [-]

FEM output	Symbol [unit]
Bearing capacity	Q [kN]
Initial stiffness	K [kN/m]

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Metamodelling: the PCE

A **metamodel** or **surrogate** model is the model of a model, and **metamodeling** is the process of generating such metamodels. Metamodel are mathematical algorithm representing input and output relations. Metamodelling consists on learning the link between the two datasets.

If the prediction aim of the metamodel is to classify the observations in a set of finite labels, it is said to be a **classification** method. On the other hand, if the goal is to predict a continuous target variable, the metamodel is said to be a **regression** task.

Classification methods	Regression methods
Support Vector Classification **SVC**	Polynomial Chaos Expansion **PCE**

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PCE: details

Input random vector of linearly independent parameters $\boldsymbol{X} = (X_1, \dots, X_n)^T$

Model response vector collecting Experimental or numerical observations $\boldsymbol{Y} = (Y_1, \dots, Y_n)^T$

$$Y = \mathcal{M}(\boldsymbol{X})$$

M may be a physical system or a computer code running a simulation, but **<u>it is a black-box function</u>**. The PCE is an approximation algorithm of this function, which **<u>gathers all type of model response as the projection of the physical model in an orthonormal basis space</u>**.

$$Y \approx \widehat{M}(X) = \sum_{k \in K} \alpha_k \Psi_k(Z)$$

- $\Psi_{\mathbf{k}}(\boldsymbol{Z})$ are multivariate polynomials orthonormal basis with respect to the PDF of Z (f_X)
- α_k are the corresponding coeffients

$\boldsymbol{Z} = T(\boldsymbol{X})$ T is an isoprobabilistic transform applied to the input variables

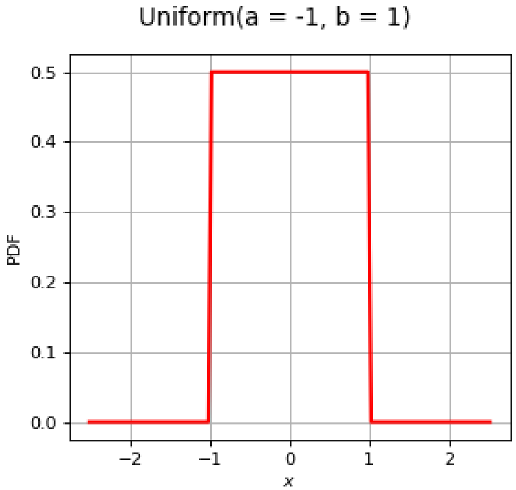
https://openturns.github.io/openturns/latest/index.html

PCE: details

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

Classical families of univariate orthonormal polynomials

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



Orthonormal polynomial basis

Inner product for orthonormality property of the polynomial basis

$$\langle \psi_i, \psi_j \rangle = \int_D \psi_i(x) \psi_j(x) f_X(x) dx = \delta_{i,j}$$

PCE: details - Truncation strategy of the multivariate orthonormal basis

A strategy must be chosen for the selection of the different terms of the multivariate basis in which the response surface by functional chaos is expressed. The selected terms are regrouped in the finite subset K of $\mathbb{N}$.

There are three different strategies available:

- `FixedStrategy`,
- `SequentialStrategy`,
- `CleaningStrategy`.

@ Adaptive Strategy

https://openturns.github.io/openturns/latest/user_manual/response_surface/_generated/openturns.AdaptiveStrategy.html#openturns.AdaptiveStrategy

PCE: details - Evaluation strategy of the coefficients, α_k

@ Projection Strategy

https://openturns.github.io/openturns/latest/user_manual/response_surface/_generated/openturns.ProjectionStrategy.html#openturns.ProjectionStrategy

The vector $\boldsymbol{\alpha} = (\alpha_k)_{k \in K}$ is equivalently defined by:

$$\boldsymbol{\alpha} = \underset{\boldsymbol{\alpha} \in \mathbb{R}^K}{\operatorname{argmin}} \mathbb{E}\left[\left(g \circ T^{-1}(\boldsymbol{Z}) - \sum_{k \in K} \alpha_k \Psi_k(\boldsymbol{Z})\right)^2\right] \quad (1)$$

Least squares strategy

and:

$$\alpha_k = < g \circ T^{-1}(\boldsymbol{Z}), \Psi_k(\boldsymbol{Z}) >_\mu = \mathbb{E}\left[g \circ T^{-1}(\boldsymbol{Z}) \Psi_k(\boldsymbol{Z})\right] \quad (2)$$

Integration strategy

where $\boldsymbol{Z} = T(\boldsymbol{X})$ and the mean $\mathbb{E}[.]$ is evaluated with respect to the measure μ.

PCE: details – looking through the PCE…

isoprobabilistic transform $\boldsymbol{Z} = T(\boldsymbol{X})$

FEM input parameters	Symbol [unit]	Range
Pile diameter	D [m]	0.76 – 2.4

ComposedDistribution(**Uniform(a = 0.76, b = 2.4**), […])

$$T(X) \equiv 2 f_X(x) \cdot (x - \mathrm{E}(X))$$

$$f_X(x) = \frac{1}{b-a}, \quad x \in [a;b]$$

$$\mathbb{E}[X] = \frac{a+b}{2}$$

| y0 = [x0]->[1.2195*(x0-1.58)]

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PCE: details – looking through the PCE…

[1, zero degree

1.73205 * x0,1.73205 * x1,1.73205 * x2,1.73205 * x3,1.73205 * x4, degree one

-1.11803 + 3.3541 * x0^2, […] degree two

[…],1.12741 - 40.5868 * x4^2 + 223.228 * x4^4 - 386.928 * x4^6 + 207.283 * x4^8] degree eight

#87
Legendre orthonormal polynomial basis
Ψ_k

0 : [0.774293 124.217]
1 : [-0.0934781 -23.1485]
2 : [-0.299315 -68.9418]
3 : [-0.0487808 -0.00423974]
[…]
84 : [-0.00532252 -0.895583]
85 : [0.00353601 0.88392]
86 : [0.00243645 0]

#87 (x2)
coefficients
α_k

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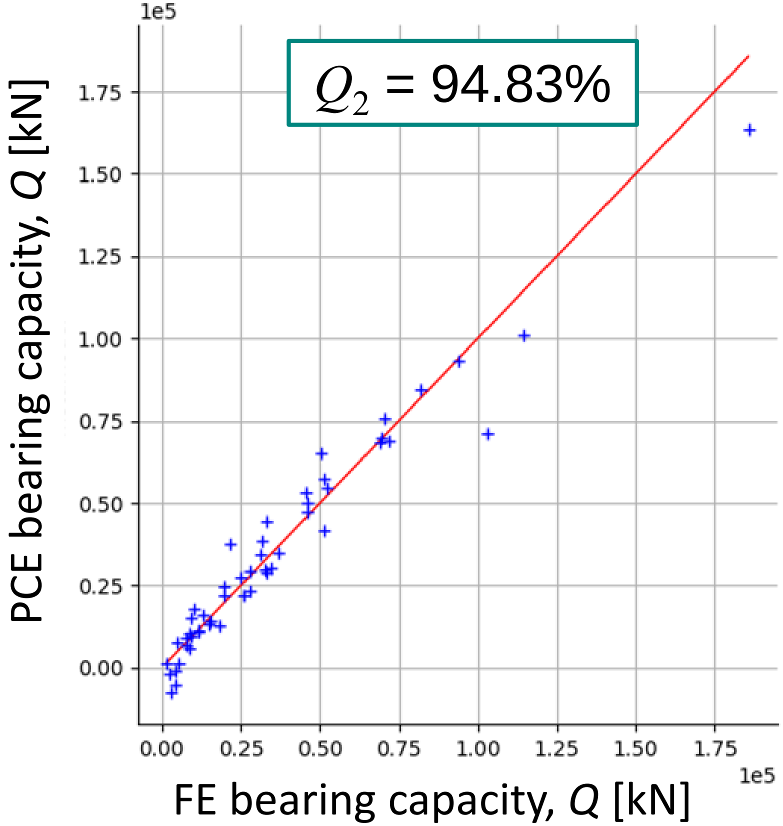
[0.774293,124.217] + [-0.0934781,-23.1485] * (1.73205 * x0) + [-0.299315,-68.9418] * (1.73205 * x1) + [-0.0487808,-0.00423974] * (1.73205 * x2) + [0.334187,44.3097] * (1.73205 * x3) +
[…]
+ [-0.00532252,-0.895583] * (1.12741 - 40.5868 * x2^2 + 223.228 * x2^4 - 386.928 * x2^6 + 207.283 * x2^8) + [0.00353601,0.88392] * (1.12741 - 40.5868 * x3^2 + 223.228 * x3^4 - 386.928 * x3^6 + 207.283 * x3^8) + [0.00243645,0] * (1.12741 - 40.5868 * x4^2 + 223.228 * x4^4 - 386.928 * x4^6 + 207.283 * x4^8)

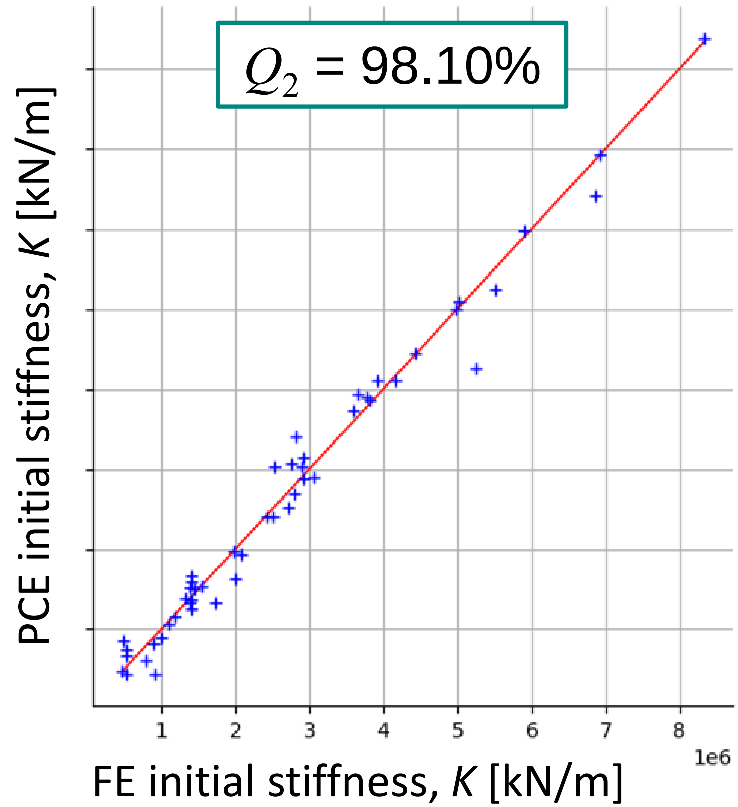
#PCE (x2)

$$Y \approx \widetilde{\mathcal{M}}(X) = \sum_{k \in K} \alpha_k \Psi_k(Z)$$

PCE: results

PCE (N=100) Vs FEM (N=50)





$$Q_2 = 1 - \frac{\sum_{l=1}^{N} (Y_l - \hat{f}(X_l))^2}{Var(Y)}$$

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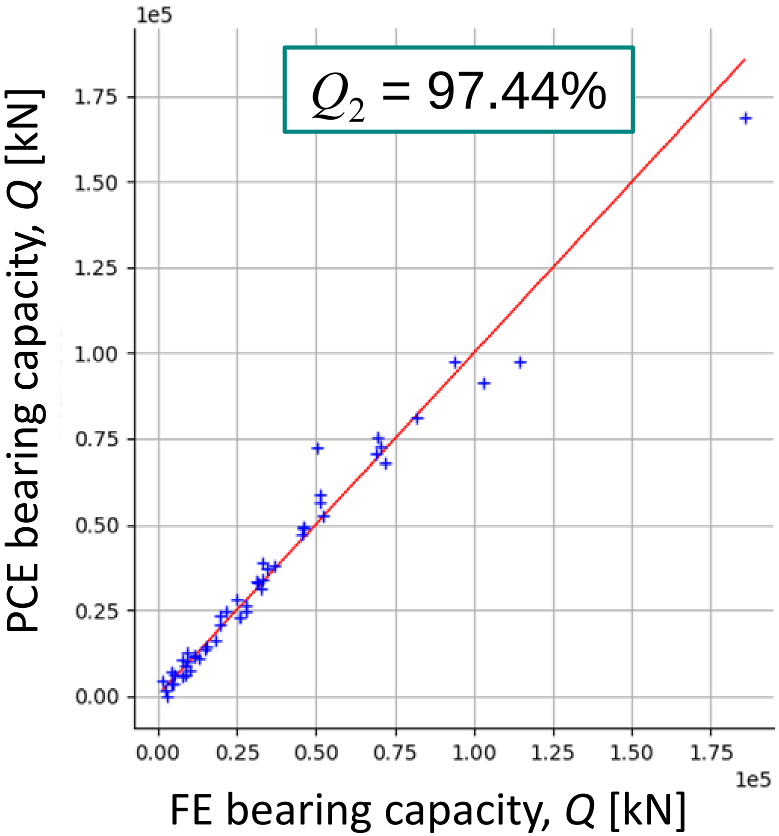
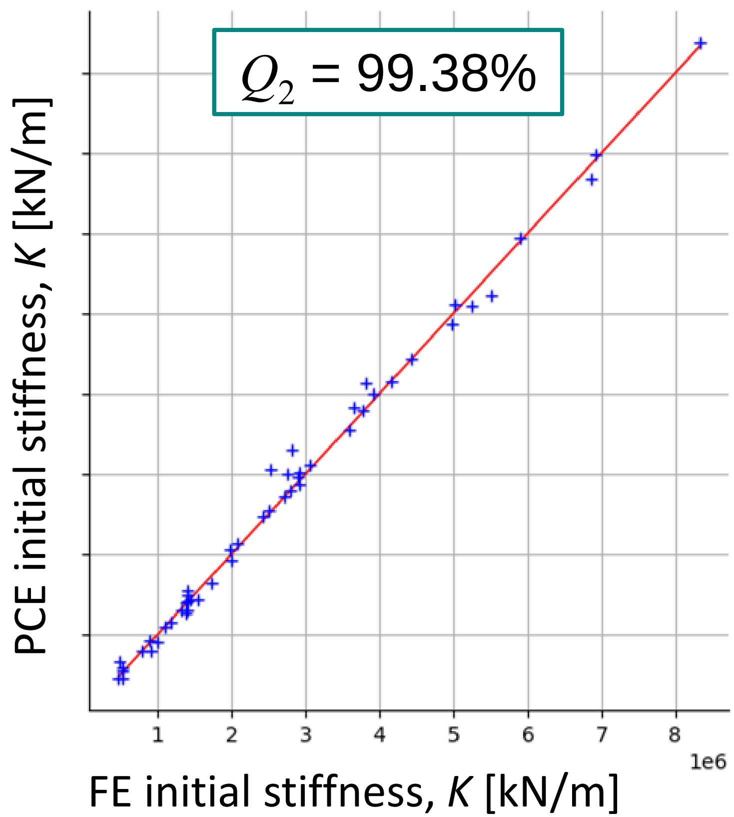
PCE: results

PCE (N=200) Vs FEM (N=50)

Q_2 = 94.83%



Q_2 = 98.10%



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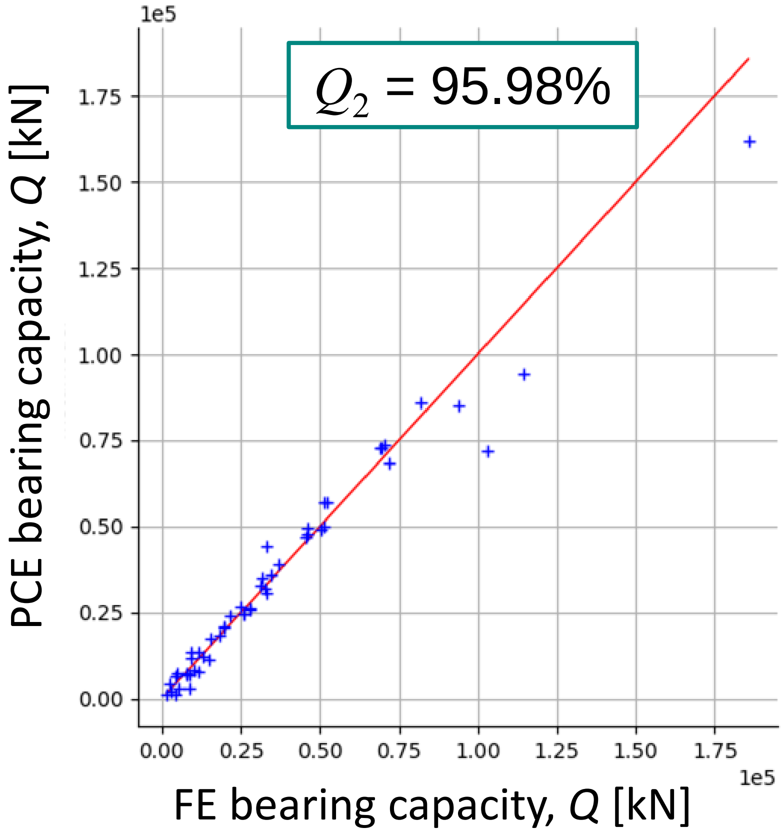
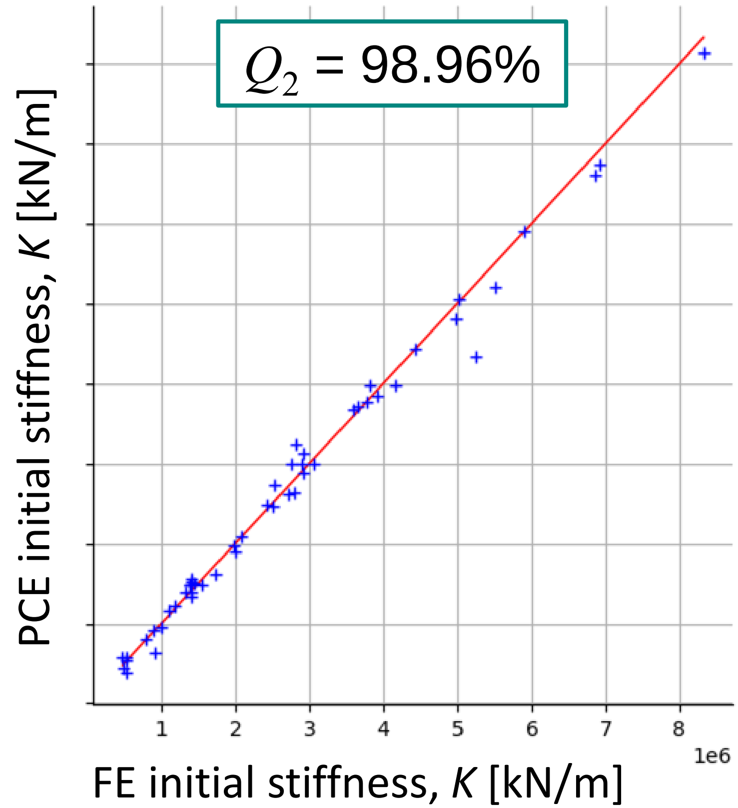
PCE: results

PCE_LOO (N=100) Vs FEM (N=50)

$Q_2 = 94.83\%$

$Q_2 = 98.10\%$





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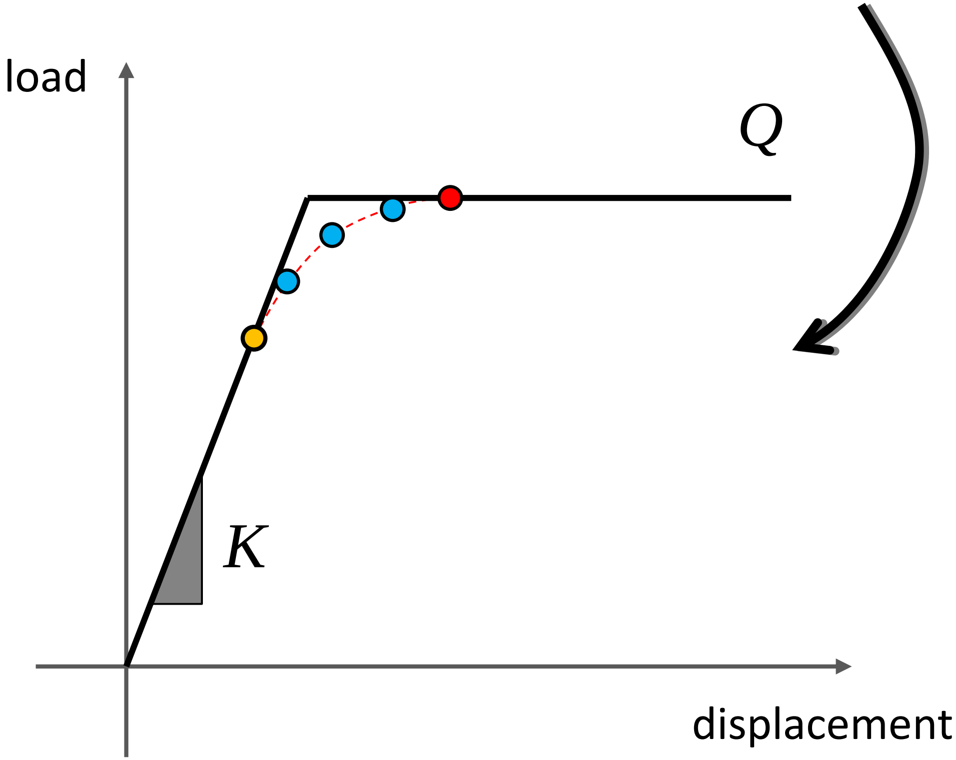
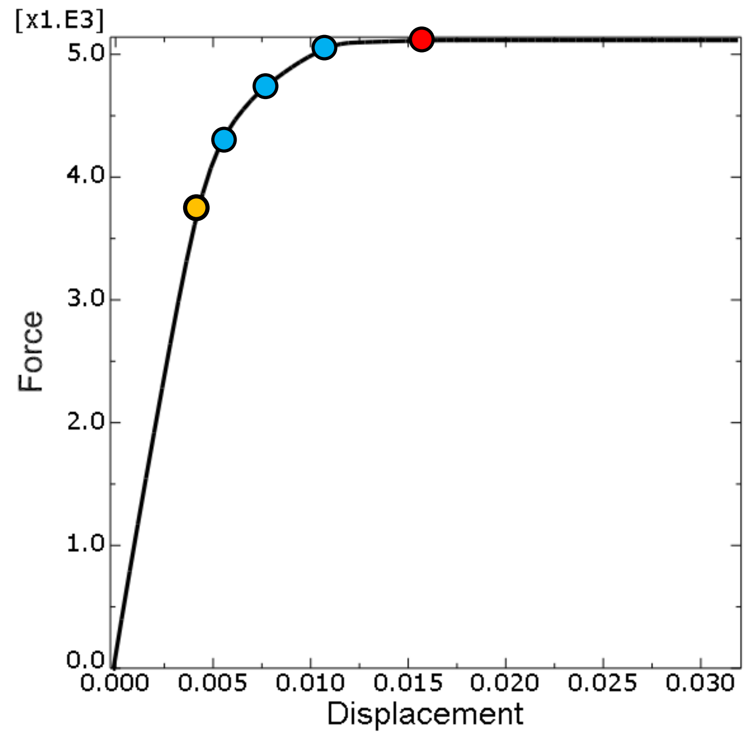
conclusions

input parameters	D [m]	L/D [-]	D/t [-]	D_r [%]	α [-]





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