Imperial College London

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# Uncertainty quantification(UQ) for offshore pile design

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- **Manual** back analysis to reduce the uncertainties is either **time-consuming** or **computationally expensive**
- Current UQ works require considerable resources and expertise to **deploy** and **maintenance**
- There exists a notable absence of **scalable guidelines** for data-driven UQ for offshore piles

# Problems, solutions and goals

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- ✓ Use **PGM**[b] and **control theory**

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[a] Dimensionality reduction

[b] Probabilistic graphical model

Goals: Leverage cutting-edge methodologies in the fields of **surrogate modeling**, **UQ**, **PGM** and **control theory**, to deliver a robust UQ framework in offshore piles

# Choice for the UQ method

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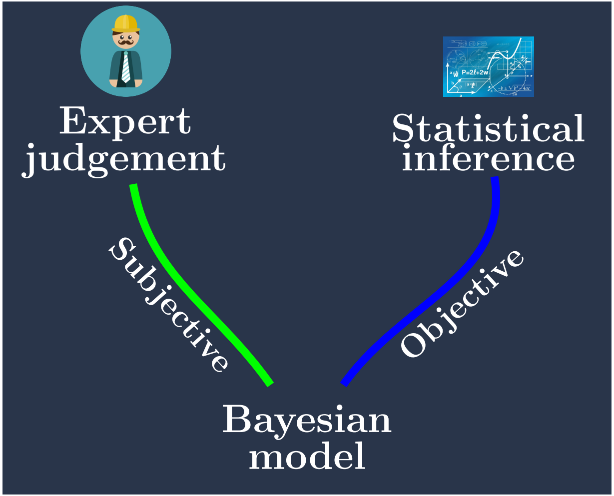
Choice for the UQ method is totally based on the **quantity** of accessible data:

- **Lack** or **no** data available, model can be solely based on expert judgement
- **Substantial** volume data available, model can fully use statistical inference (e.g., the methods of moments[1])
- **Combination** of two above: Bayesian methods

$$\pi(\boldsymbol{x}|\boldsymbol{y}) = \frac{\mathcal{L}(\boldsymbol{x}|\boldsymbol{y}) \cdot \pi(\boldsymbol{x})}{\pi(\boldsymbol{y})}$$



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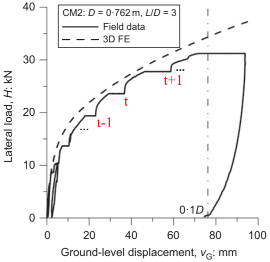
**PISA pile loading**[2]



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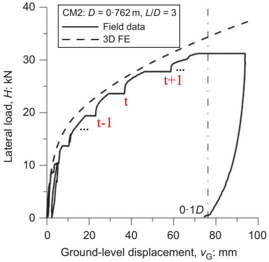
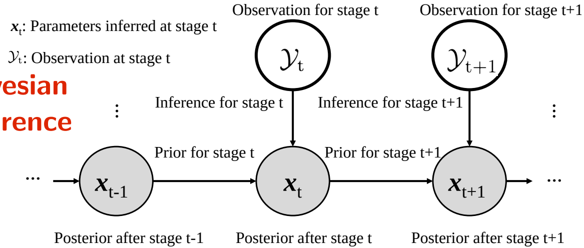



**Bayesian inference**



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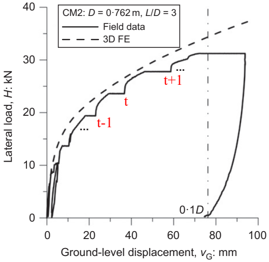


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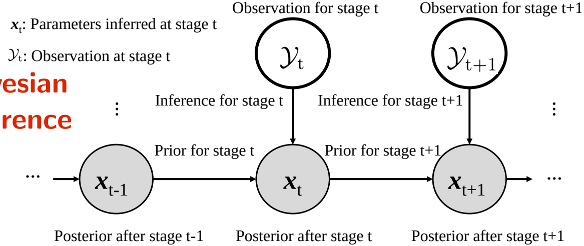


Sequential Bayesian inference setting:

- Adaptive learning to enrich the experimental design
- DR-based surrogate to accelerate inversion
- Advanced MCMC sampler to obtain *QoI*

# Why introduce DR-based surrogate to Bayesian inference

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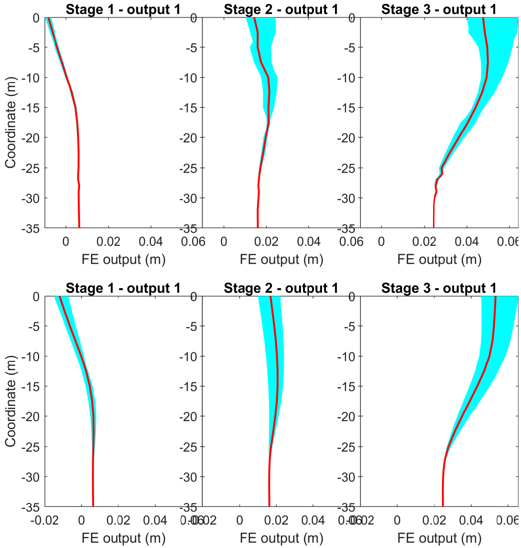
**Surrogate-PCE**

**DR-based Surrogate-(PCA-PCE)**



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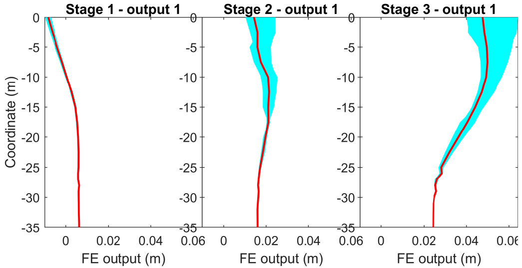


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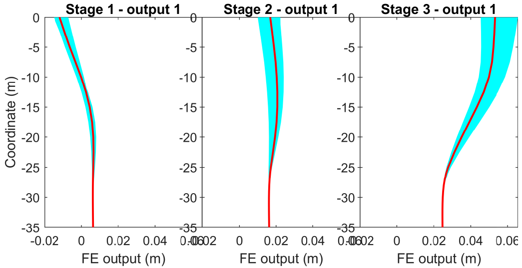

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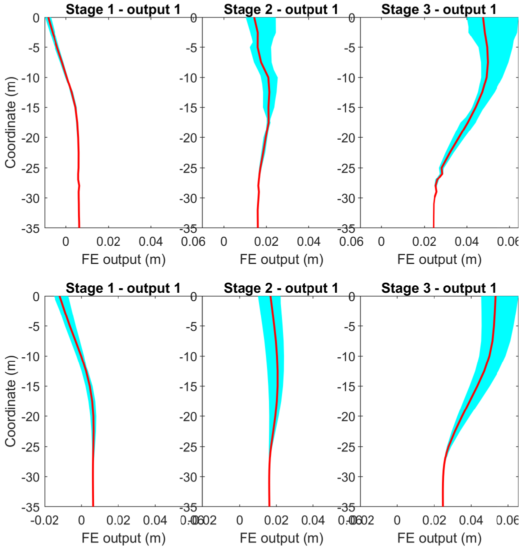


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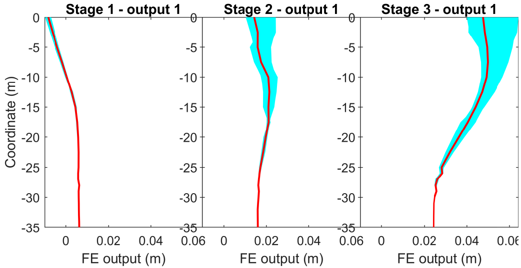
- **Reduce** the output size, and alleviate the burden on the surrogate construction
- Capture the **shape/covariance** matrix of the output
- Compared to scalar models (e.g., PCE, kriging), DR-based surrogate can consider Capture the **multiple output predictions**

**Surrogate-PCE**

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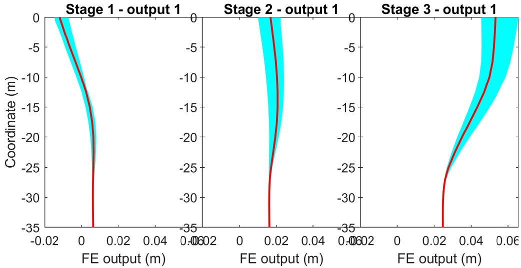

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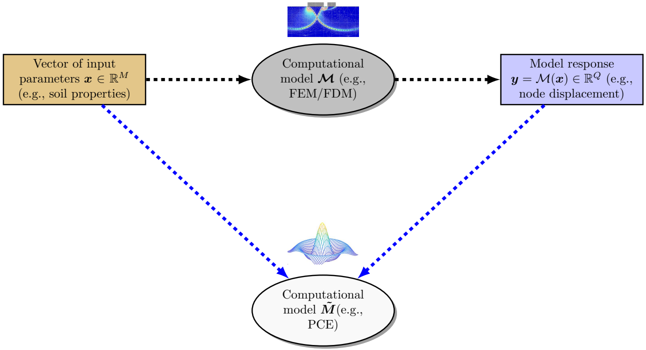

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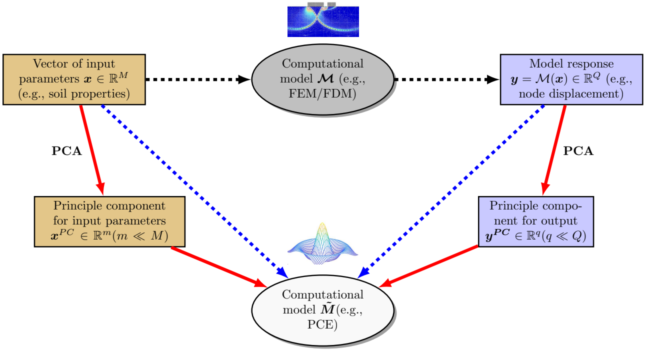

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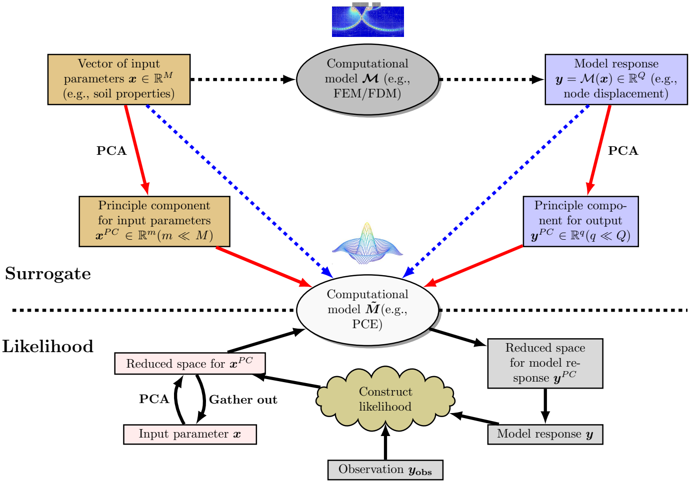


# Next plan
## Active learning for an efficient surrogate

In high dimensions, **experimental design** for a surrogate can be very **expensive**.

Active learning hopes to construct the surrogate in an **adaptive** way

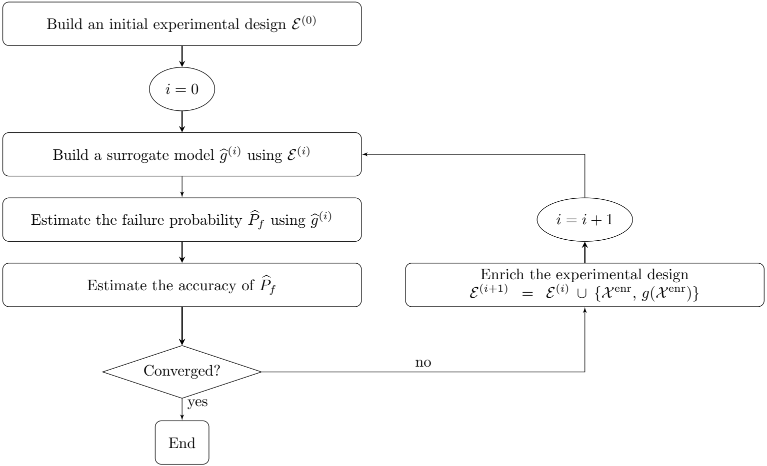
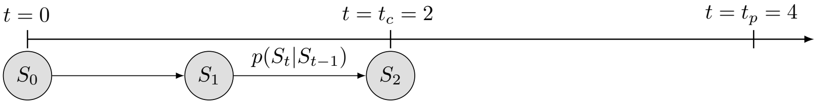



Figure 2: Active learning workflow[3]

# Next plan

## A unified and scalable digital twin for piles

- Visualize the sequential inversion calculation
- Bring in control theory naturally to make prompt actions
- Support the transition from custom defined model towards a unified and scalable digital twin



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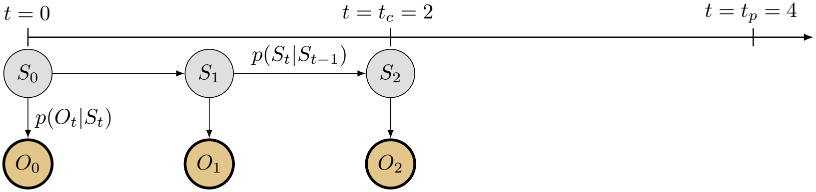

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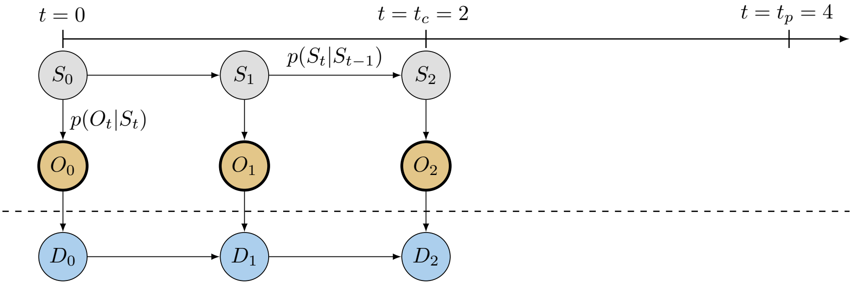

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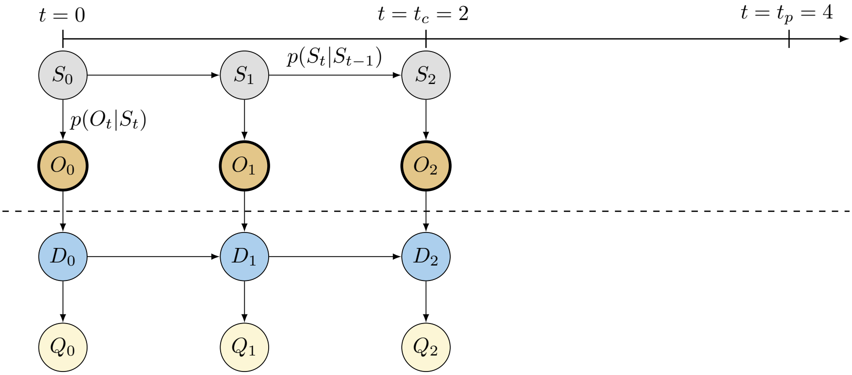

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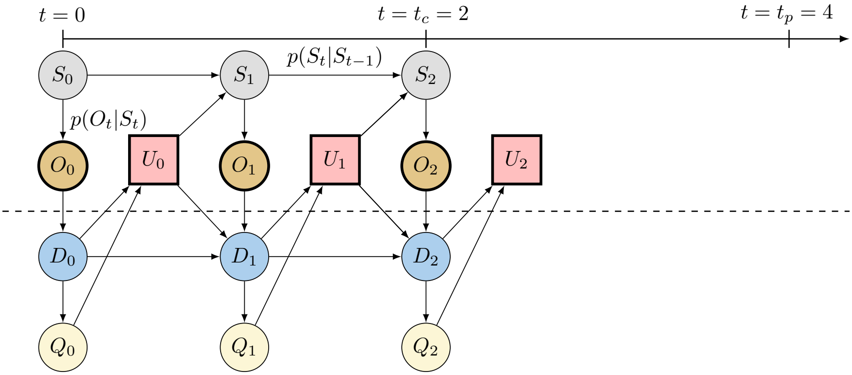

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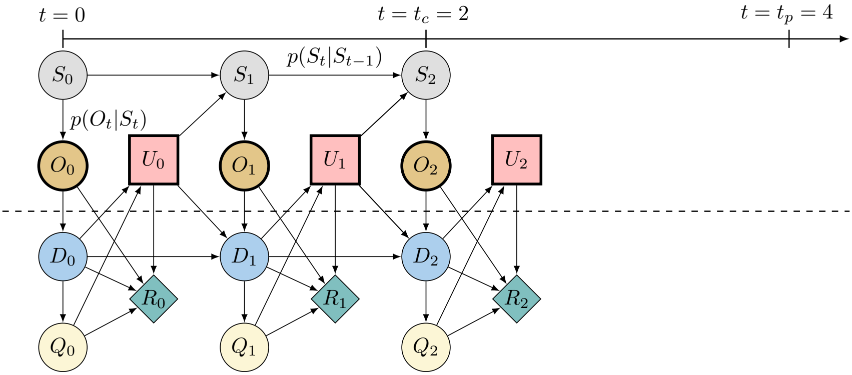

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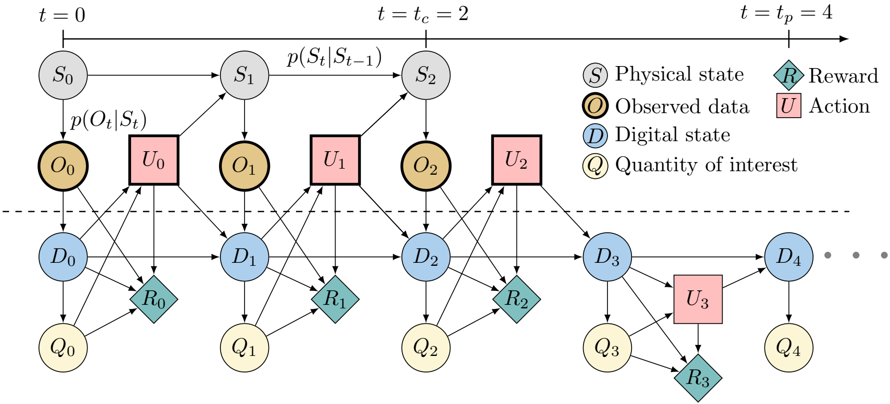

# Time plan

Table 1: PhD timeline

| month | 0 | 3 | 6 | 9 | 12 | 15 | 18 | 21 | 24 | 27 | 30 | 33 | 36 | 39 | 42 | 45 | 48 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Literature review | ✓ | ✓ | ✓ | | | | | | | | | | | | | | |
| Numerical modelling | | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | | | | | | |
| Implementing a data-driven approach (POMDP) | | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | | | |
| Writing PGM in MATLAB or Python | | ✓ | ✓ | ✓ | | | | | | | | | | | | | |
| Constructing the digital twin | | | | | | ✓ | ✓ | ✓ | | | | | | | | | |
| Develop a methodology for calibrating a digital twin prediction | | | | | | | | | ✓ | ✓ | ✓ | ✓ | | | | | |
| Develop an approach for data assimilation based on Bayesian inference framework | | | | | | | | | | | | ✓ | ✓ | ✓ | | | |
| Thesis writing | | | | | | | | | | | | | | | ✓ | ✓ | ✓ |
| Journal/Conference | | | | | | | | ✓ | | | | ✓ | | | | | ✓ |

# Reference


[1] P-R Wagner et al. “Bayesian calibration and sensitivity analysis of heat transfer models for fire insulation panels”. In: *Engineering structures* 205 (2020), p. 110063.

[2] Lidija Zdravković et al. “Ground characterisation for PISA pile testing and analysis”. In: *Géotechnique* 70.11 (2020), pp. 945–960.

[3] Maliki Moustapha, Stefano Marelli and Bruno Sudret. “Active learning for structural reliability: Survey, general framework and benchmark”. In: *Structural Safety* 96 (2022), p. 102174.