Treatment of uncertainties in multi-physics model for wind turbine asset management

PhD first year overview

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Industrial context
Numerical simulation code
Mean damage estimation
Analytical example
Conclusion

Industrial context

- EDF Renewables $\sim$ 10 000 MW of wind turbine (WT) worldwide
- Deterministic design of WT for 25 year lifetime
- In the future:
  - Wind farms reaching end-of-life
  - New technology: offshore floating WT

Needs probabilistic tools to optimize safety margins and asset management

Industrial context

- EDF Renewables $\sim$ 10 000 MW of wind turbine (WT) worldwide
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  - ▷ Wind farms reaching end-of-life
  - ▷ New technology: offshore floating WT

Needs probabilistic tools to optimize safety margins and asset management

Uncertainty quantification (UQ) for:

- Fine power production estimation
- Safe lifetime extension regarding tower damage
- Probabilistic design for floating WT (multiple technologies)

WT offshore technologies

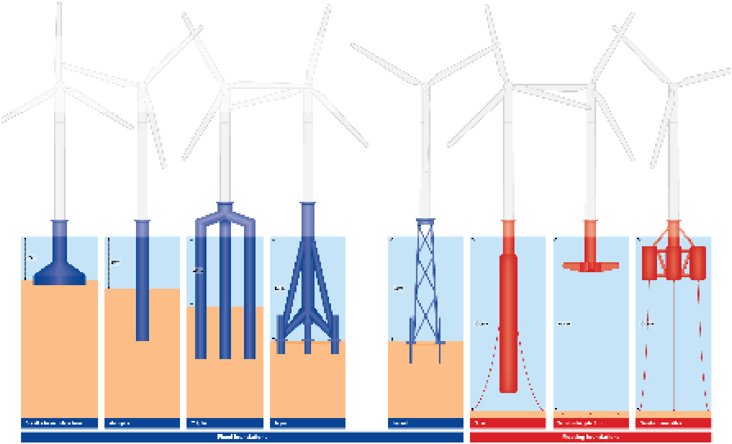

Figure 1: Wind turbine offshore technologies[1]

[1] https://www.windpowermonthly.com/article/1210054

WT studied failure mode

Studied failure mode: mechanical damage in tower welded joints

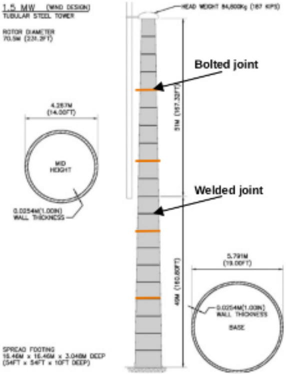

Figure 2: Illustrative tower assembly[1]

[1] M. LaNier. LWST Phase I Project Conceptual Design Study: Evaluation of Design and Construction Approaches for Economical Hybrid Steel/Concrete Wind Turbine Towers. 2005.

TurbSim: turbulent wind field simulation

TurbSim is a stochastic, full-field, turbulence simulator (NREL[1])

- **inputs**: mean wind, wind direction, wind shear, turbulence model, turbulence intensity, hub height, simulation time, etc.
- **outputs**: wind speed field

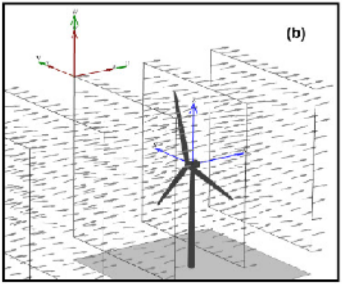

Figure 3: Illustrative wind speed field simulated

[1] B. Jonkman. *Turbsim User's Guide: Version 1.50*. 2009.

DIEGO: Hydro-Aero-Servo-Elasto simulation

Dynamique Intégrée des Eoliennes et Génératrices Offshore, DIEGO is WT multi-physics simulator (EDF R&D[2])

- **inputs**: TurbSim's output, WT geometry, material properties, soil stiffness, controller properties.
- **outputs**: power production, mechanical stress, displacements, etc.

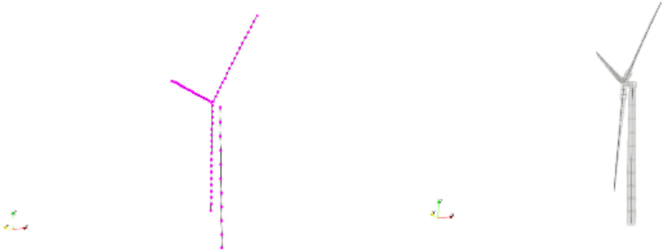

Figure 4: Illustrative structural and aero-dynamic mesh from DIEGO

[2] M. Capaldo et al. "Influence of cracks on the buckling of wind turbine towers". In: *Journal of Physics: Conference Series* (2020).

Mechanical damage assessment

The damage is computed at specific points of the structure

1. Equivalent Von Mises stress time series
2. Fatigue stress cycles identification using Rainflow counting method[3]
3. Damage computation using Miner's rule[4]

CPU time: up to 20 min per simulation of the chain

[3] DNV-GL. *DNVGL-RP-C203: Fatigue design of offshore steel structures*. Tech. rep. 2016.

[4] D. Wilkie and C. Galasso. "Gaussian process regression for fatigue reliability analysis of offshore wind turbines". In: *Structural Safety* (2021).

Mechanical damage assessment

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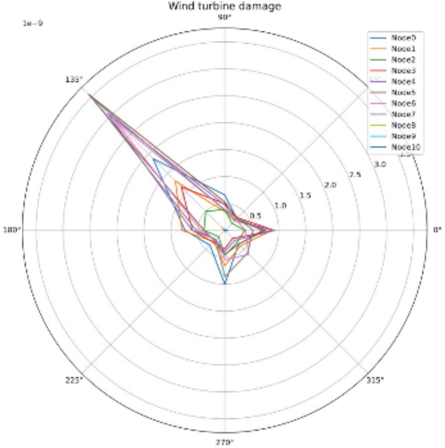


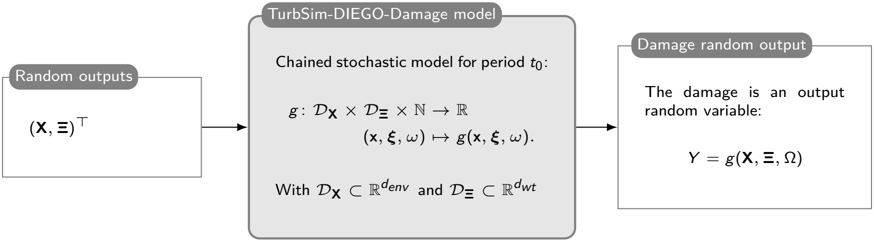
Figure 5: Damage computation of WT tower

Chain simulation codes

Wrap the TurbSim – DIEGO – Damage chain of simulation codes

- Python distributed wrapper (using the `otwrapy` module based on OpenTURNS[5])
- Deployed on EDF R&D High Performance Computers facility

TurbSim is a stochastic model controlled by a pseudo-random seed ω



$\mathbf{X}$ environmental random vector characterized by its joint distribution $f_{\mathbf{X}}(\cdot)$

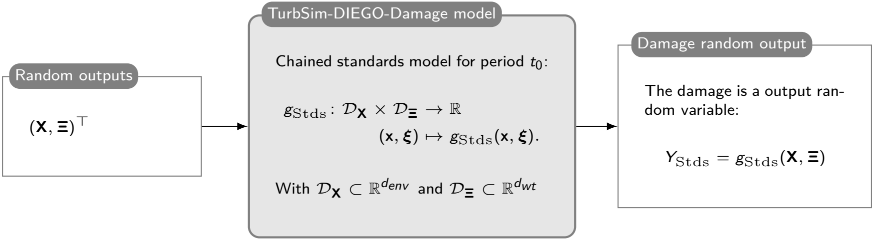
$\mathbf{\Xi}$ wind tubine random vector characterized by its joint distribution $f_{\mathbf{\Xi}}(\cdot)$

[5] `http://openturns.github.io/otwrapy/master/`

Chain simulation codes

Standards[6] recommend to repeat each simulation for $n_{rep} \in \mathbb{N}$ pseudo-random seeds and average the outputs

$$g_{\mathrm{Stds}}(\mathbf{x}, \boldsymbol{\xi}) := \frac{1}{n_{rep}} \sum_{i=1}^{n_{rep}} g(\mathbf{x}, \boldsymbol{\xi}, \omega^{(i)})$$



$\mathbf{X}$ continuous random vector characterized by its joint distribution $f_{\mathbf{X}}(\cdot)$

$\boldsymbol{\Xi}$ wind tubine random vector characterized by its joint distribution $f_{\boldsymbol{\Xi}}(\cdot)$

[6] DNV-GL. *DNVGL-ST-0437: Loads and site conditions for wind turbines*. Tech. rep. 2016.

Output quantity of interest: Damage Equivalent Load

Considering the wind turbine random vector as known $\boldsymbol{\Xi} = \boldsymbol{\xi}$

Standards Damage Equivalent Load (DEL)

Damage Equivalent Load is the expected value of the damage over the environmental conditions (random vector $\mathbf{X}$)

$$\mathbb{E}_{\mathbf{X}}[Y_{\mathrm{Stds}}] = \mathbb{E}_{\mathbf{X}}[g_{\mathrm{Stds}}(\mathbf{X})] = \int_{\mathbf{X}} g_{\mathrm{Stds}}(\mathbf{x}) f_{\mathbf{X}}(\mathbf{x})\, d\mathbf{x}$$

Fully stochastic Damage Equivalent Load (DEL)

Since $(\Omega, \mathbf{X})$ are independent, the previous integral can generalized:

$$\begin{aligned}\mathbb{E}_{\mathbf{X},\Omega}[Y] = \mathbb{E}_{\mathbf{X},\Omega}[g(\mathbf{X},\Omega)] &= \iint_{\mathbf{X},\Omega} g(\mathbf{x},\omega) f_{\mathbf{X},\Omega}(\mathbf{x},\omega)\, d\mathbf{x}\, d\omega \\ &= \iint_{\mathbf{X},\Omega} g(\mathbf{x},\omega) f_{\mathbf{X}}(\mathbf{x}) f_{\Omega}(\omega)\, d\mathbf{x}\, d\omega\end{aligned}$$

Methods for DEL estimation

- Sampling methods for numerical integration
  - Monte Carlo
  - Low discrepancy sequences[7]
  - Latin Hypercube Sampling
- Metamodel + sampling method for numerical integration
  - Space-Filling learning set (one shot)[8]
  - Adaptive learning set, e.g., AKDA (iterative)[9]
- Quadrature methods for numerical integration[10]

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[7] K. Müller and P. Cheng. "Application of a Monte Carlo procedure for probabilistic fatigue design of floating offshore wind turbines". In: *Wind Energy Science* (2018).

[8] R. Slot et al. "Surrogate Model Uncertainty in Wind Turbine Reliability Assessment". In: *Renewable Energy* (2019).

[9] Q. Huchet. "Kriging based methods for the structural damage assessment of offshore wind turbines". PhD thesis. 2019.

[10] L. van den Bos. "Quadrature Methods for Wind Turbine Load Calculations". PhD thesis. 2020.

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Toy case: Branin-Hoo function

Branin-Hoo function

$$r(x_1, x_2) = h \circ t(x_1, x_2)$$
$$t(x_1, x_2) = ((15x_1 - 5), (15x_2))^\top$$
$$h(u_1, u_2) = \frac{\left(u_2 - 5.1\frac{u_1^2}{4\pi^2} + 5\frac{u_1}{\pi} - 6\right)^2 + 10\left(1 - \frac{1}{8\pi}\right)\cos(u_1) + 10 - 54.8104}{51.9496}$$

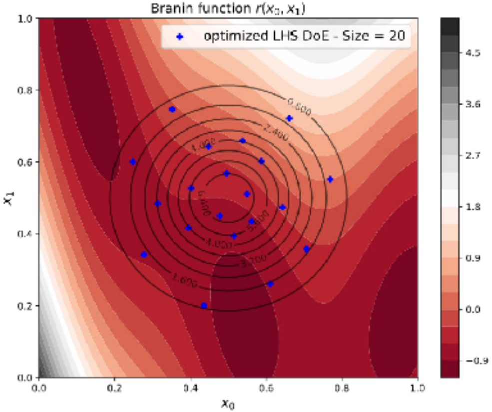
Random inputs:

$$X_1 \sim \mathcal{N}(\mu, \sigma);\ \ X_2 \sim \mathcal{N}(\mu, \sigma)$$
$$\mathbf{X} = (X_1, X_2)^\top$$

We estimate the central tendency of $Y = r(\mathbf{X})$:

$$\mathbb{E}[Y] = \int_{\mathcal{D}_X} r(x) f_{\mathbf{X}}(\mathbf{x})\, d\mathbf{x}$$

Toy case: Branin-Hoo function



- The DoE is not built on a uniform distribution since our objective is not a globally-accurate surrogate modeling
- The LHS DoE is optimized using the Simulated Annealing algorithm with the L^2-centered discrepancy as space-filling criterion

Validation procedure of the mean

Compute a reference mean $m_{ref} = \widehat{Y}$ on a large Monte Carlo ($N_{ref} = 10^9$) using the "true function"

```
Mean = -0.36451364108542894
Standard deviation = 1.5434486434042638e-05
Number of calls to the g function = 1000000000
Coef. of var.= 0.000042
Monte Carlo 95% IC: [-0.3645136420420683, -0.36451364012878956]
```

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```

Compare the performances of mean estimation methods

1. Build a Monte Carlo validation sample $\mathcal{X}_{mc} = (\mathbf{x}^{(1)}, \ldots, \mathbf{x}^{(N)}), N = 10^7$
2. Compute an approximated mean $m_{appx} = \widehat{Y}_{kri}$ on $\mathcal{X}_{mc}$ using a Kriging model
3. Compute number of correct digits between m_{ref} and m_{appx} :

$$N(m_{ref}, m_{appx}) = \log_{10} \left| \frac{m_{ref}}{m_{ref} - m_{appx}} \right| .$$

AK-DA: "Adaptive Kriging Damage Assessment"

Algorithm 1: AK-DA

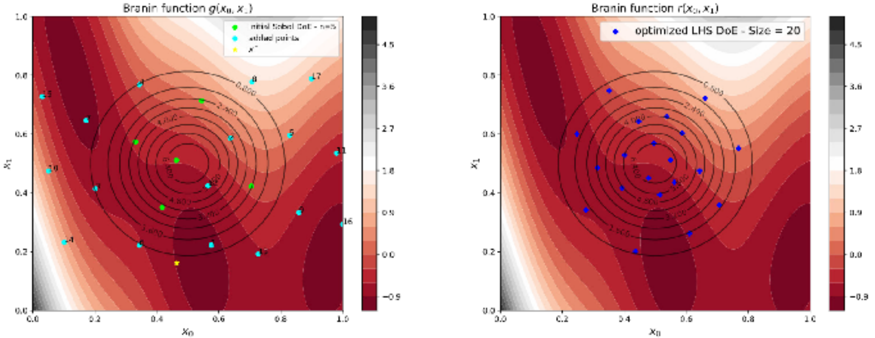
Build a fine regular grid $\mathcal{L}_{grid}$
Compute $f_{\mathbf{X}}(\mathbf{x}^{(k)})$ for $\mathbf{x}^{(k)} \in \mathcal{L}_{grid}$
Build an initial learning set $\mathcal{X}_n = (\mathbf{x}^{(1)}, \dots, \mathbf{x}^{(n)}) \in \mathcal{D}_X$
while *condition* **do**
  Build a Kriging model on the learning set
  Compute Kriging variance $s_n^2(\mathbf{x}^{(k)})$ for $\mathbf{x}^{(k)} \in \mathcal{L}_{grid}$
  Compute acquisition function $\mathcal{A}_n(\mathbf{x}^{(k)}) = s_n^2(\mathbf{x}^{(k)}) \cdot f_{\mathbf{X}}(\mathbf{x}^{(k)})$
  Find

$$\mathbf{x}^*_{n+1} = \underset{\mathbf{x}^{(i)} \in \mathcal{L}_{grid}}{\arg\max}\, \mathcal{A}_n(\mathbf{x}^{(i)})$$

  Add this point to the learning set, $\mathcal{X}_{n+1} = \{\mathcal{X}_n, \mathbf{x}^*_{n+1}\}$
end

Note that the optimization could be done without regular grid. Probably not a big added value in small dimension.

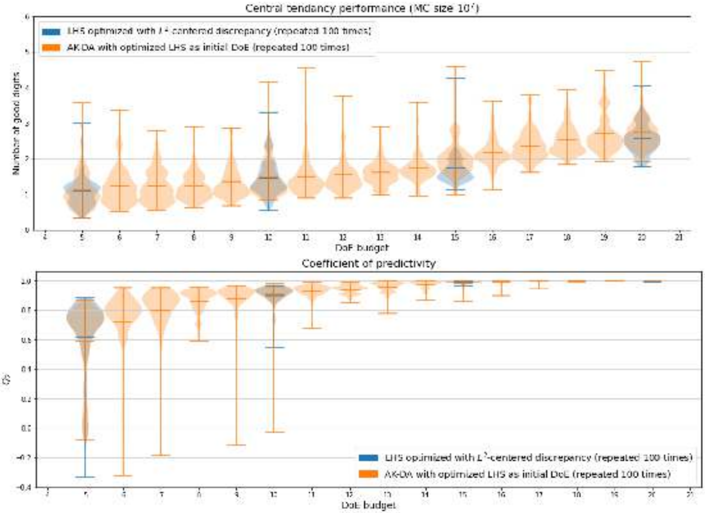
AK-DA vs. Optimized LHS

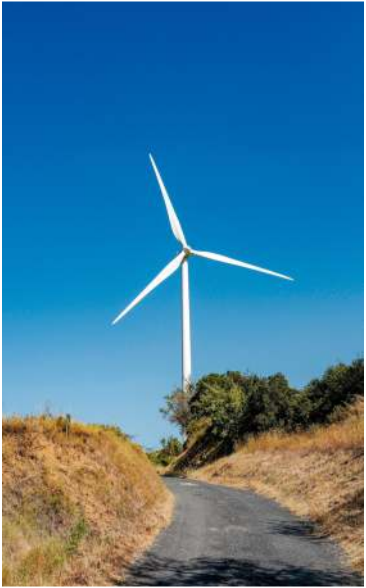


- For this function, AK-DA tends to explore the space more than LHS
- How to build the initial DoE?
  - ▷ dimension and function dependent
  - ▷ Kriging variance needs to be validated for the acquisition function ⇒ initial DoE should be iterative (low disc. sequences, FSSF, Kernel Herding)

AK-DA vs Optimized LHS

LHS optimized on the input random vector (repeated 100 times)





Conclusions

- Toy-function very different from the industrial case (complexity, dimension)
- Here, AKDA performs similarly with Kriging on optimized LHS
- AKDA improved by validating Kriging variance before applying acquisition function
- Need an automated benchmark for central tendency estimation (using `otbenchmark` module[11])

[11] E. Fekhari et al. "otbenchmark: an open source python package for benchmarking and validating uncertainty quantification algorithms". In: *Proc. of the 4th International Conference on Uncertainty Quantification in Computational Sciences and Engineering*. 2021.

Perspectives

Ongoing work

- Contribution to EU-founded project HIPERWIND[12] (DTU, IFPEN, ETH Zürich)
- Iterative design of experiments for metamodel validation

Perspectives

- Industrial use-case of Teesside offshore wind farm
  - ▷ UQ of the environmental random variables (dependent measures available)
  - ▷ Stochastic metamodeling of the damage without replications
  - ▷ Benchmark methods to estimate DEL
  - ▷ Screen non-influential variables among wind turbine variables
  - ▷ Reliability analysis of the DEL over wind turbine variables (e.g., material properties)
- Reliability-based design optimization (RBDO) of floating WT model

[12] https://www.hiperwind.eu/

Bibliography

F. Bachoc. “Estimation paramétrique de la fonction de covariance dans le modèle de Krigeage par processus Gaussiens. Application à la quantifcation des incertitudes en simulation numérique”. PhD thesis. 2013.

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Monte Carlo estimation of Y - Deterministic model

Empirical mean estimator

Let $\left\{\mathbf{X}^{(i)}\right\}_{i=1,\dots,n}$ for $n \in \mathbb{R}$, a i.i.d sample of the random vector $\mathbf{X}$. The empirical mean estimator can be written:

$$\widehat{Y} = \frac{1}{n}\sum_{i=1}^{n} d\left(\mathbf{X}^{(i)}\right).$$

We can demonstrate that $\mathbb{E}[\widehat{Y}] = \mathbb{E}[Y] = \mu_d$ and $Var(\widehat{Y}) = \frac{Var(Y)}{n} = \frac{\sigma_d m^2}{n}$ therefore $\delta_{\widehat{Y}} = \frac{\sqrt{Var(Y)}}{\sqrt{n}\cdot\mu_d}$.

Central limit theorem

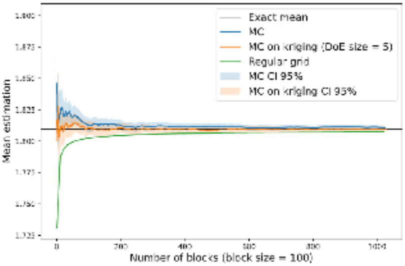
$$\widehat{Y} \xrightarrow{d} \mathcal{N}\left(\mu_d, \frac{\sigma_d^2}{n}\right)$$

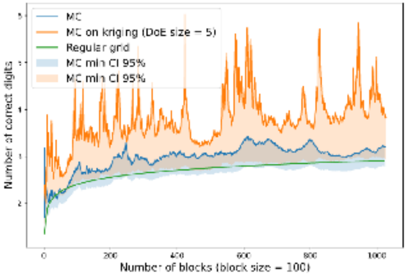
Central tendency estimation: regular grid *vs.* Monte Carlo

Regular grid drawbacks:

- No full control of the central tendency convergence
- Convergence is slower! Note that Quasi-MC was not used yet.

Illustration on a simple function (BBRC RP22[13]) using uniform inputs:





[13] https://rprepo.readthedocs.io/en/latest/

Simple Kriging

1. Assuming that $d(\mathbf{x})$ is a realization of the gaussian process (GP) $D(\mathbf{x}) \sim \mathcal{GP}(m(\mathbf{x}), k(\mathbf{x}, \mathbf{x}'))$.
2. Considering the learning DoE: $\begin{cases} \mathcal{X}_{obs} = (\mathbf{x}^{(1)}, \dots, \mathbf{x}^{(n)}) \\ \mathbf{d_{obs}} = \left[d(\mathbf{x}^{(1)}), \dots, d(\mathbf{x}^{(n)})\right]^\top \end{cases}$
3. Therefore, $\mathbf{D_{obs}} = \left[D(\mathbf{x}^{(1)}), \dots, D(\mathbf{x}^{(n)})\right]^\top$ is a gaussian vector, and one can write the following joint distribution: $\begin{pmatrix} D(\mathbf{x}) \\ \mathbf{D_{obs}} \end{pmatrix}$.
4. The Kriging model $\widetilde{D}(\mathbf{x})$ is the GP $D(\cdot)$ conditioned by the observations $\mathbf{d_{obs}}$

$$\widetilde{D}(\mathbf{x}) = [D(\mathbf{x}) | \mathbf{D_{obs}} = \mathbf{d_{obs}}, \beta, \sigma, \boldsymbol{\theta}] \sim \mathcal{N}(\widetilde{d}(\mathbf{x}), s(\mathbf{x})^2).$$

5. With $\{\beta, \sigma, \boldsymbol{\theta}\}$ called hyper-parameters, usually estimated by MLE.
6. With $\widetilde{d}(\mathbf{x})$ called Kriging predictor and $s(\mathbf{x})^2$ called Mean Squared Error, both defined analytically.

OpenTURNS implementation (1/4)

Problem definition

```
# Import the packages
import openturns as ot
# Define Branin-Hoo function
branin = ot.SymbolicFunction(['x1', 'x2'],
      ['((x2-(5.1/(4*pi_^2))*x1^2+5*x1/pi_-6)^2+10*(1-1/(8*pi_))*cos(x1)+10-54.8104)
     /51.9496'])
transfo = ot.SymbolicFunction(['u1', 'u2'], ['15*u1-5', '15*u2'])
g = ot.ComposedFunction(branin, transfo)
# Create a random joint distribution
trunc_normal = ot.TruncatedDistribution(ot.Normal(0.5, 0.15), 0., 1.)
distribution = ot.ComposedDistribution([trunc_normal, trunc_normal])
```

Learning and validation set

```
# Build a LHS Experiment: learning set
experiment = ot.LHSExperiment(distribution, 10)
in_learn_sample = experiment.generate()
out_learn_sample = g(in_learn_sample)
# Build a Sobol Sequence: test set
sequence = ot.SobolSequence(2)
experiment = ot.LowDiscrepancyExperiment(sequence, distribution, 128)
in_test_sample = experiment.generate()
out_test_sample = g(in_test_sample)
```

OpenTURNS implementation (3/4)

Build a Kriging model (Default MLE solver failed -> multi-start method applied)

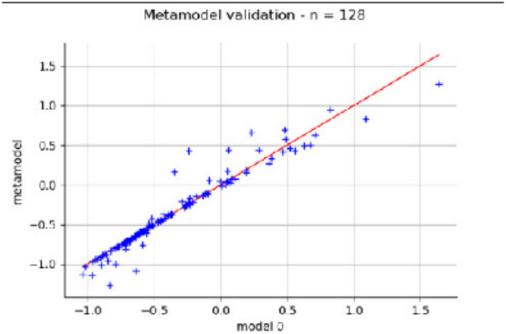
```
# Define a Squared Exponential kernel (Scale=[1, 1], amplitude=1)
covarianceModel = ot.SquaredExponential([1., 1.], [1.])
# Build a constant function basis
basis = ot.ConstantBasisFactory(dim).build()
# Build default Kirging model
kriging = ot.KrigingAlgorithm(in_learn_sample, out_learn_sample, covarianceModel, basis)
kriging.run()
```

Results and validation

```
# Get kringing results and metamodel
krigingResult = kriging.getResult()
kriging_mean = krigingResult.getMetaModel()
# Compute Q2 on the Sobol test set
val = ot.MetaModelValidation(in_test_sample, out_test_sample, kriging_mean)
q2 = val.computePredictivityFactor()
# Prints
print("Optimal scale = ", krigingResult.getCovarianceModel().getScale())
print("Optimal amplitude = ", krigingResult.getCovarianceModel().getAmplitude())
print("Optimal trend coefficients = ", krigingResult.getTrendCoefficients())
print("Q2 = ",q2)
```

```
Optimal scale= [0.218602,0.474411]
Optimal amplitude = [1.0884]
Optimal trend coefficients = [[-0.0938758]]
Q2 =  0.928937137828958
```

OpenTURNS implementation (4/4)

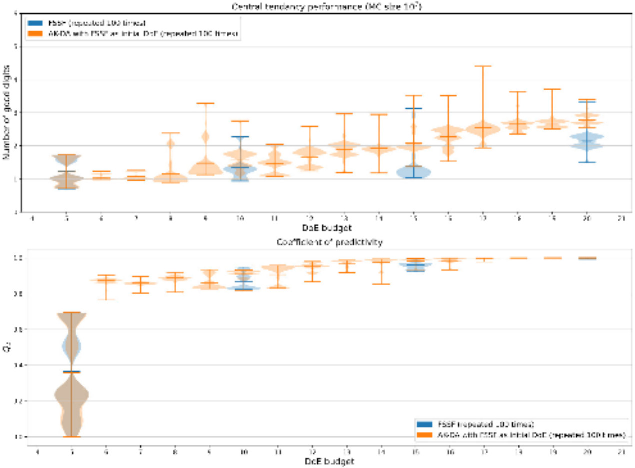


OK but how good is the mean estimation?

⇒Metamodel for a QoI

FSSF

Fully Sequential Space Filling (FSSF[14]) input DoE (repeated 100 times)



[14] B. Shang and D. Apley. "Fully-sequential space-filling design algorithms for computer experiments". In: *Journal of Quality Technology* (2020).

Improved AK-DA

Idea inspired by Bayesian optimization:

- Iteratively validate the Kriging variance using the Predictive Variance Adequation[15]
- Then start the adaptive enrichment strategy (AKDA)

Let be the test set $\mathcal{X}_p = (\mathbf{x}^{(1)}, \dots, \mathbf{x}^{(p)}) \subset \mathcal{D}_X$, disjoint from the learning set $\mathcal{X}_n$,

$$PVA := \left| \log_{10} \left(\frac{1}{p} \sum_{i=1}^{p} \frac{(d(\mathbf{x}^{(i)}) - \widetilde{d}(\mathbf{x}^{(i)}))^2}{s(\mathbf{x}^{(i)})^2} \right) \right| .$$

In practice: Start AK-DA once $Q_2 > 0.7$ and $PVA < 2$

[15] F. Bachoc. "Estimation paramétrique de la fonction de covariance dans le modèle de Krigeage par processus Gaussiens. Application à la quantifcation des incertitudes en simulation numérique". PhD thesis. 2013.