

Objectives

1. Estimation of the structure's **failure probability** using **surrogate models**.
2. Development of numerical methods for the automatic selection for surrogate that best fits the limit state function by using an **evolutionary algorithm**.
3. Determination of the surrogate associated weights when ensemble of surrogates are selected to approach the limit state function.

Introduction

- ▶ **Structural reliability analysis** is a challenging task as it is a very time-consuming computation. It consists of evaluating the **failure probability**, which requires a very complex and multi-variable integration based on the limit state function. In engineering problems, the limit state function estimation involves complex and time-consuming finite element analyses. Consequently, **surrogate models** are usually used instead since they can reduce the computational cost. Various surrogate models exist, such as the polynomial chaos expansion (PC), response surface method, Kriging model etc. exists with different tuning. The choice of the most suitable one for a given problem is not obvious. In this work, we are interested in developing an automatic selection procedure based on an **evolutionary algorithm**. It should determine the optimal surrogate to any problem. Furthermore, there are situations where none of the meta-models is the best choice and distinguishing between those surrogates is not an evidence. Using **ensembles of surrogates**, in this case, should be a reasonable solution.

Definitions

- ▶ **Surrogate models**
 - ▷ Surrogate models are mathematical models used to approach computationally expensive simulations. They have to be as accurate as possible.

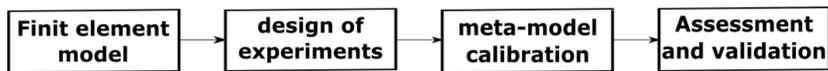


Figure 1: Process of calibrating a meta-model

- ▶ **Evolutionary Algorithms**
 - ▷ Evolutionary algorithms are population based heuristic optimization algorithms inspired by biological evolution.

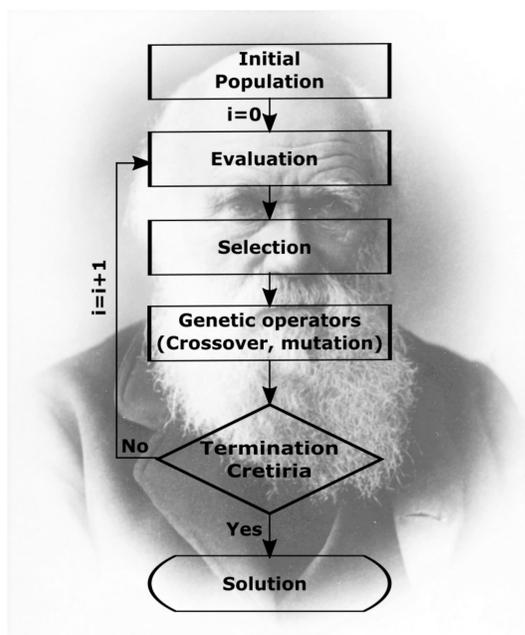


Figure 2: Flowchart of Evolutionary Algorithms

State of the art

- In the literature, this problem is generally studied using different approaches:
- ▶ Gorissen and al (2009) proposed in [1] an evolutionary algorithm to perform surrogate model selection. But they emphasize the existence of so much parameters to tune and the dependence on the genetic operators.
 - ▶ Shi and al (2012) introduced in [2] a selection method under data uncertainty in the context of large scale optimization.

State of the art: Continuation

- ▶ Zhou and Jiang, 2016 tackled the meta-model selection in [3] by using a stepwise regression.
- ▶ Ben Salem and Tomaso (2017) developed in [4] a new selection criteria used in a genetic aggregation method.

Methods

- ▶ Structural Reliability Analysis based on surrogates
 - ▷ The failure probability of the structure is $P_f = \int_{g(\mathbf{x}) \leq 0} f_X(\mathbf{x}) d\mathbf{x}$.

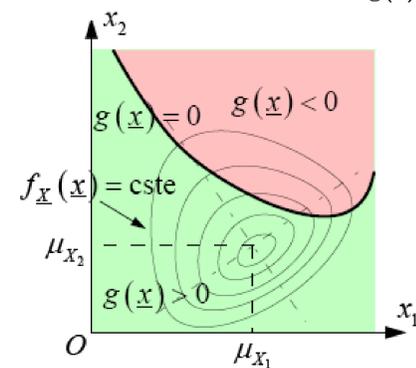


Figure 3: Performance Function $g(\mathbf{x})$

- ▶ The estimation of P_f is done either by approximation (FORM/SORM) or simulation (MCS, IS, etc.).

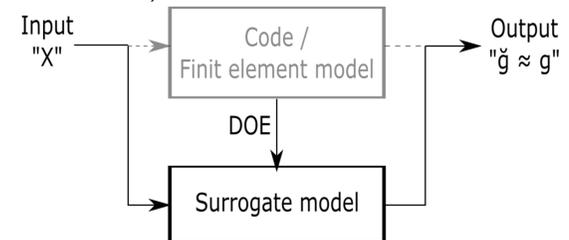


Figure 4: Using a surrogate model

- ▶ **Meta-models automatic selection using an Evolutionary Algorithm**
 - ▷ The individuals are the different optimized surrogate models.
 - ▷ The fitness function is the selection criteria.
 - ▷ The optimized meta-model settings are the genetic informations of the individuals.
 - ▷ The aggregation of meta-models occurs if the genetic operators are applied to the settings of two different types.

$$\hat{G}(\mathbf{x}) = \sum_{i=1}^P w_i \hat{g}_i(\mathbf{x})$$

Challenges and perspectives

- ▶ Proposing a **new relevant surrogate model selection algorithm** using an **evolutionary algorithm**.
- ▶ Tuning the evolutionary algorithm parameters.
- ▶ Choosing an appropriate **criteria of selection**.
- ▶ Optimizing the surrogate associated **weights** in case ensembles are created.
- ▶ Assessing the **level of confidence** of the selected surrogate prediction.

References

- [1] Dirk Gorissen, Tom Dhaene, and Filip De Turck. Evolutionary model type selection for global surrogate modeling. *Journal of Machine Learning Research*, 10(Sep):2039–2078, 2009.
- [2] Lei Shi, RJ Yang, and Ping Zhu. A method for selecting surrogate models in crashworthiness optimization. *Structural and Multidisciplinary Optimization*, 46(2):159–170, 2012.
- [3] XiaoJian Zhou and Ting Jiang. Metamodel selection based on stepwise regression. *Structural and Multidisciplinary Optimization*, 54(3):641–657, 2016.
- [4] Malek Ben Salem and Lionel Tomaso. Automatic selection for general surrogate models. In *12th World Congress of Structural and Multidisciplinary Optimisation*, 2017.