

## Bayesian calibration of nested computer models

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**Ph.D. expected duration:** 2015-2018

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### Abstract:

Thanks to computing power increase, risk quantification relies increasingly on computer modeling. Methods of risk quantification based on a fixed computational budget exist, but in these methods, even in the case of serial computer models, computer models are almost always considered as a single black box.

In this paper, we are interested in analyzing the behavior of a complex phenomenon, which evolution can be modeled by two nested parametrized computer models. By two nested computer models, we mean that some inputs of the second model are outputs of the first model. Based on a set of observations of the considered phenomenon, the idea is, first, to calibrate the parameters of each model, and then, to construct a predictor for the output of the second model, which takes into account the fact that, on the first hand, the two models are not perfect, and on the other hand, there exist uncertainties in the parameters' calibration.

Concerning the calibration of the models parameters we distinguish between parallel calibration and grouped calibration. In case of a parallel calibration, each model is calibrated separately whereas in case of a grouped calibration, the parameters of the two models are calibrated all together. In both cases, it is shown to what extent the proposed predictor for the output of the second model integrates all the uncertainties of the nested system.

The choice of the observations is decisive for the prediction quality, therefore methods to choose observations are studied. In particular the way to use partial information for grouped calibration is shown (the number of observations is not the same for the two computer models). Sequential strategies to choose new observations in order to improve predictions are proposed.

The proposed methods are then applied to examples.

### References

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**Short biography** – Graduate from Ecole Centrale de Lyon in 2010, I have worked for 5 years as engineer in building energy performance (internships in EDF R&D and CSTB for one year and six months and 4 years in a SME specialized in building energy certification)  
In 2014-2015 I have studied in M2 ISIFAR at Université Paris Diderot Paris 7 and I have done an internship in applied mathematics at CEA. Then I have pursued with a PhD in bayesian calibration of nested computer models, which I have started in November 2015.