Gaussian processes for the management of uncertain functional inputs in computational structural mechanics: Application to automotive brake squeal

Keywords: Computational mechanics, uncertainty propagation, surrogate modelling, Gaussian processes, Bayesian optimisation

1. Global overview of the PhD thesis

1.1. Computational structural mechanics

The competition in industries constantly increases through improving the quality of products and reducing the cost of these products. To achieve these drastic objectives, numerical simulations take a key role in many engineering domains such as automotive, aeronautics and nuclear. Considering for example Finite Element Method (FEM), Smoothed-Particle Hydrodynamics techniques or more recently isogeometric analyses, it is nowadays possible to easily test different materials, different designs, new processes and simulate the related physic mechanisms without systematically performing experimental tests. Numerical simulations have the advantage of being compatible with economic challenges such as reactivity and anticipation and they are becoming cheaper than experiments on 1:1 ratio models. Recent years, evolving computational resources contribute to the increasingly frequent use of more complex numerical models including more components of mechanical systems, more geometrical details and nonlinearities (geometry, material and contact). On the other hand, as the size of some FEM models can currently reach several tens of millions of degrees of freedom, CPU time associated to complex simulations remains constant.

1.2. Uncertainty quantification and propagation

In spite of the advanced tools, the comparison between a deterministic simulation and experimentations are not obvious in many case studies. The resulting gaps can be significant, especially if the studied phenomenon have a fugitive nature. Indeed, during the manufacturing of mechanical structures, it is not uncommon to observe some uncertainties resulting in product variability either on material properties (Young modulus, strain-stress law), on geometric characteristics (gaps, fillets and small geometries) and on interface and boundary conditions. These observed variabilities necessarily affect the dynamic behaviour of structures and more generally the component life and the global efficiency of the system. To significantly characterize experimental behaviour, it is so necessary to consider a family of components rather than only one specimen that can generate significant financial costs. Numerically, to take into account these uncertainties and tend to reliable and robust designs, a current industrial trend involves making multiple numerical simulations by performing sensitivity analyses, designs of experiments, non-deterministic studies [1] or even reliable and robust optimizations [2]. The idea is to simulate the evolution of mechanical responses as a function of input parameter variations and to detect failures and performance reductions of products. Once again, it is obvious to imagine the same computational limitations than in the deterministic case. Currently, several researches are performed in that sense in order to develop efficient, precise and less time consuming numerical advanced methods.

1.3. Surrogate modelling with Gaussian processes

Gaussian processes [3, 4] are stochastic processes that provide a non-parametric Bayesian framework for statistical learning. They form flexible priors over functions where regularity assumptions can be encoded into kernels. One benefit of these processes relies in the tractability of the posterior distribution, i.e. the update of the model with observation data, which is also Gaussian. While the posterior mean is used as a point estimate of the function of interest, the posterior variance is the expected square error of this estimate. This Gaussian processes provide predictions together with confidence intervals that are useful for uncertainty quantification. Moreover, since conditional sample functions can be generated, they are also exploited for simulating results at new input parameters. Due to the versatility and diverse uncertainty quantification tools they provide, Gaussian processes are interesting to tackle mechanical simulations, which are computationally costly. In computer experiments, a code execution corresponds to a function evaluation, where inputs are the simulation conditions (e.g. the geometry, the materials, the boundary conditions) and output values are the quantities of interest of the simulation result (e.g. the frequencies, the displacements, the stresses). These models can allow a better understanding of dynamic patterns and thus better control of subsequent steps.

2. Objectives of the PhD thesis

This thesis is a multidisciplinary work and is focusing on mathematics and computational structural mechanics. **The main objective is to develop a new numerical strategy relying on Gaussian processes to predict transient output data considering uncertain functional inputs (constitutive laws, random topography).** The developments will be applied to automotive brake squeal simulations [5, 6, 7], as described in Figure 1.

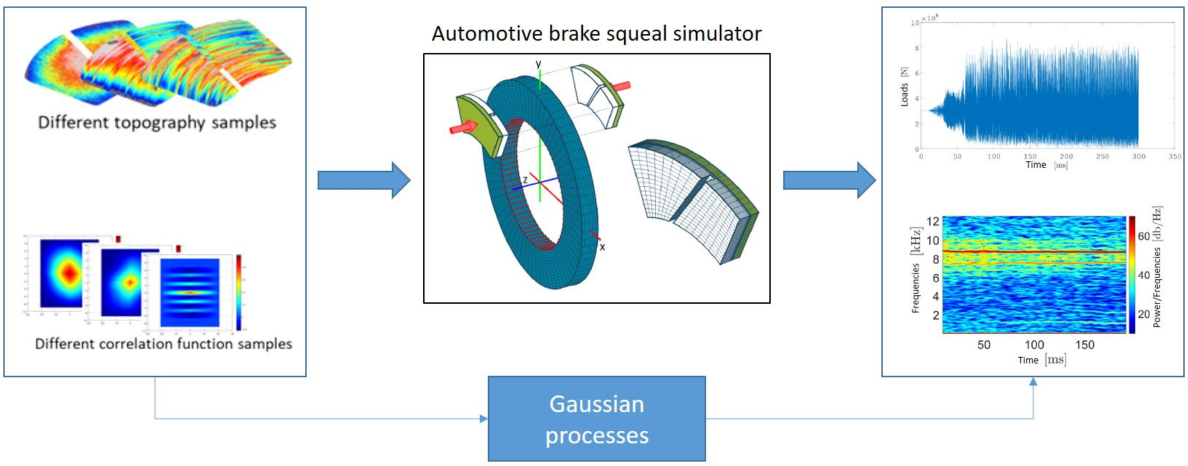

Figure 1: Flowchart of the targeted numerical strategy

3. References

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