Postdoctoral position offer : optimization in the presence of uncertainties, application to the energy efficiency of buildings

Mission description

Despite the long-term research efforts put into numerical optimization, many practical applications remain difficult. There are three main reasons: most real problems involve nonlinear models, the objective functions or the constraints are numerically costly to evaluate (e.g., when nonlinear finite elements underlie the optimization criteria), and some of the parameters are uncertain. Including model and environmental uncertainties in decision aiding methods is often seen as becoming increasingly important.

To ease the computing load, Bayesian Optimization (BO) incorporates kriging surrogates to save calls to the objective function, as embodied in the archetypal EGO algorithm [21]. The original optimization problem is translated into a series of other problems, that of the acquisition of new points where the costly function will be calculated. The acquisition criterion is based on the kriging model and it mitigates the optimization of the function and the learning of the kriging model [10]. BO has rapidly been extended to encompass constraints [20, 18][9, 11] or multi-objective functions [5].

In this post-doctoral work, we will focus on costly and general nonlinear constrained multi-objective optimization problems that are affected by uncertainties. We will consider the case where the uncertain parameters can be separated from the optimization variables and can be chosen during the simulations. Because of this separation and providing a probability of occurence of the uncertainties exists, a statistical modeling in the joint *design* $\times$ *uncertain parameters* space is possible. This will be the context of the work.

A key step when optimizing in the presence of uncertainties is the formulation of the problem, i.e., the choice of the robustness criteria. Considering first unconstrained problems, relevant criteria are the expectation of the objective [12] or one of its (super-)quantiles [22, 23]. In Robust Optimization, the uncertainties are handled in terms of specific compromises between the average performance and its dispersion [16, 4]. When there are constraints that depend on the uncertainties, the feasibility of the solutions is typically measured in probability. Probabilistic models of the constraints are called chance constraints [15] or reliability constraints [6]. The optimization problems are formulated in terms of statistical criteria such as probabilities of satisfying the constraints, expectations or (super-)quantiles or conditional quantiles of the objective function [22, 13, 19].

In the last decade, numerous contributions to the optimization of costly functions with uncertainties have relied on the learning of a metamodel of the true functions, in particular Gaussian processes (GP) [8, 14]. In [12] and [2], the GP not only helps for the optimization (or for the inversion) of the design variables, but it also serves to define an optimal sampling scheme.

In [3], the problem of minimizing the mean of a stochastic function under chance constraints is addressed. The objective function and the constraints are costly in the sense that they cannot be calculated more than a hundred times. The uncertainties, which can be described by parameters different from the optimization variables, can be chosen in the calculations. Generalizing [12], an optimization and sampling Bayesian procedure is proposed. It is based on the feasible improvement and the associated Stepwise Uncertainty Reduction (SUR) criterion to choose where to evaluate the uncertain parameters.

The goal of this work is to improve the ideas introduced in [3] by putting them in the context of multi-objective optimization under uncertainties. The expected hyper-volume improvement must be adapted to take into account the uncertainties and a sampling SUR criterion must be devised to choose the value of the random parameter to be evaluated. As it is done in [17] a multi-output Gaussian process can be proposed to take into account the correlation between the objective functions. A wise choice of the correlation kernel should be done. The results wil be compared to others methods [7].

The methods developed will be applied to the design of energy efficient buildings, a major contemporary challenge. The criteria are the energy usage of the building, the thermal comfort and the cost. Important uncertainties affect the cost (through the cost of energy) and the external conditions through the climate change. The building models will be done with the opensource software Energy+ [1].

Practicalities

Dates Renewable 12 months contract. The envisaged start date is flexible between january and june 2024.

Location Institut Camille Jordan (ICJ), Campus of l'Ecole Centrale de Lyon, Ecully

Stays will be expected at Laboratoire d'Informatique, de Modélisation et d'Optimisation des Système (LIMOS), Campus des Cézeaux de l'université de Clermont.

Salary : between 33k euros and 36k euros brut

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Required skills

- doctoral degree or equivalent in mathematics,
- proven strong background in uncertainty quantification or statistical learning theory,
- substantial experience in numerical programming.

References

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