MultiObjective Optimization assisted by Gaussian Process model for distributed computing

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Abstract:

The aim of this presentation is to compute the whole Pareto Front (PF) of a multiobjective optimization problem in the case where the evaluation of the objectives is numerically expensive. To provide results in a reasonable time, distributed computing must be privileged and the number of function evaluations is limited.

To control this computational budget, the use of surrogate modeling for fitness function evaluations is a widespread approach. Surrogate-models are low-cost analytic functions that are fitted by minimizing the error committed on a set of input-output couples coming from the reference model. Among these, Kriging is a probabilistic surrogate model: it considers that the output is a realization of a Gaussian process, conditioned by the Design of Experiments (DOE). This characteristic is useful since it allows computing analytically an estimation of its uncertainty.

For single-objective optimization, the EGO algorithm (developed by Jones [4]), based on Kriging, has proven its efficiency. This approach relies on an iterative enrichment of the DOE. To choose the point to add at each iteration, the expectation of improvement of the model, the so-called Expected Improvement (EI), has to be maximized. This criterion has been generalized in the multiobjective case by adapting the definition of the EI to the Pareto dominance. There are different measures existing to define an improvement depending on this dominance. For instance, the Euclidean distance to the PF as in Forrester and Keane [2] or the Hypervolume as in Emmerich [1] are commonly used.

The maximization of EI for multiobjective optimization has two drawbacks. Firstly, it is by definition optimal only for one-step-ahead methods so the use of this criterion is not suited to distributed computations. Secondly, the exploration of the design space can be insufficient for high dimensional design spaces. To overcome those restrictions, two methods to enrich sequentially the DOE with distributed computations will then be proposed: the first one is built around multiple constrained maximizations of the multiobjective EI at each step. Those constraints are applied on the objective space, which is decomposed in subspaces to force the optimizer to improve the PF simultaneously in different areas. The second one consists in associating NSGA-II algorithm (Emmerich 2006) with this EI criterion: the Kriging predictions of the fitness functions are minimized using the genetic algorithm and, thanks to the EI criterion, only the most interesting individuals of the population are selected and evaluated to augment the DOE at each generation. Once again and for the same reason, those points are chosen in different subspaces of the objective space. These strategies aim to decrease the uncertainty of the surrogate model and thus to improve the accuracy of the PF.

Those two methods will be compared on analytic models (MOP2 and ZDT3 cf Huband [3]) and on an industrial problem with two objectives, one of them being a worst-case computation from a costly thermal model of an equipment. This thermal use case comes from the TOICA European project (Thermal Overall Integrated Conception of Aircraft).

References

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Short biography – I was graduated from a master degree on Partial Differential Equations, modeling and scientific computing and from a school of engineering with a specialization in aerodynamics and numerical simulation. My PhD is now focusing on optimization under uncertainty of transient thermal phenomena.