Bayesian methods for multi-objective simulation-based optimization

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Abstract:

Interest in multi-objective simulation-based optimization, or in other words, multi-criteria optimization based on stochastic simulators, can be traced back to at least the mid-70s. But it is only quite recently that algorithms aiming at providing an estimate of the entire Pareto set, and/or Pareto front, started to appear [1, 5].

We consider the problem of multi-objective optimization in the case where each objective is a stochastic black box that provides noisy evaluation results. More precisely, let $f_1, \dots f_q$ be q real-valued objective functions defined on a search domain $\mathbb{X} \subset \mathbb{R}^d$, and assume that, for each $x \in \mathbb{X}$, we can observe a noisy version of the objectives: $Z_1 = f_1(x) + \varepsilon_1, \dots, Z_q = f_q(x) + \varepsilon_q$, where the ε_is are zero-mean random variables. Our objective is to estimate the Pareto-optimal solutions of the problem:

$$\min f_1, \dots, f_q \,. \tag{1}$$

In situations where individual simulations have a non-negligible run time (or cost), one cannot hope to obtain an arbitrarily accurate estimation of these sets given a limited budget of time (or money). Bayesian optimization, where stochastic (often Gaussian) process models are used to quantify the optimizer's uncertainty about the properties of the simulator, is a natural candidate for such situations—see, e.g., [3], in the context of multi-objective optimization. In essence, Bayesian optimization consists in choosing a probabilistic model for the outputs Z_i and defining a sampling criterion to select evaluation points in the search domain $\mathbb{X}$.

In this communication we extend the scalarisation approach proposed by Knowles [2] for solving the stochastic multi-objective problem (1). The existing algorithm aggregates several objectives through the iterative use of an augmented Tchebycheff scalarisation function with weights selected randomly. Evaluation points are sequentially chosen based on the Expected Improvement (EI) infill criterion.

We present several contributions. First, we select a suitable infill criterion to be used with noisy observations—see, e.g., [4] for a review of infill criteria adapted to the noisy case. Second, a weight selection technique that takes advantage of the stochastic process models generated at each iteration is proposed. Third, we account for the fact that the observation noise of the objective functions introduces a bias when a nonlinear scalarisation function is used. Additionally, we

study the use of an optimal batch size to provide a trade-off between short-run and long-run performances.

Differences in terms of performance will be illustrated over several academic test problems.

References

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Short biography – With a background in Industrial Engineering and Management (University of Lisbon), and a Master Degree in Renewable Energies (Ecole Polytechnique), Bruno began his PhD in November 2018 with CentraleSupéelec and EDF R&D.
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