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INITIAL SAMPLING USING MULTI-FIDELITY INFORMATION IN SIMULATION OPTIMIZATION OF MANUFACTURING SYSTEMS

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ABSTRACT

High-fidelity models are capable of providing accurate estimates but slow in execution. On the other hand, estimates provided by low-fidelity models are biased but fast. The knowledge embedded in low-fidelity models might be helpful for simulation optimization algorithms. Several multi-fidelity modeling algorithms have been proposed in literature, whereas currently only high-fidelity information is used in the initial sampling phase. This poster provides an algorithm to allocate high-fidelity budgets using multi-fidelity information in order to contain a fixed number of good solutions in the initial design. Results show that the proposed sampling policy can allocate more budgets in promising areas.

1 SURROGATE-BASE SIMULATION OPTIMIZATION

Simulation technique has become more and more popular in manufacturing system performance evaluation, due to the development of computer technology and the increase of complexity of manufacturing systems. High-detailed simulation models are capable of providing highly accurate estimates of system performance under new system configurations. However, they are very expensive to evaluate. This is the reason that surrogate models are frequently used in simulation optimization problems to guide the search and save simulation budget.

Most of studies about surrogate-based simulation optimization focus on problems whose objective function is a black box. In this case, the surrogate model can point out which area has higher probability to contain the optimum so that high-fidelity budgets can be allocated efficiently in next iteration. The surrogate model can be built using several techniques, such as Kriging (Sacks et al. 1989) and Kernel Regression (Wand and Jone 1995) and it can be updated in each iteration when new points are evaluated. More detail can be found in an overview of surrogate-based simulation optimization (Forrester and Keane 2009).

2 MULTI-FIDELITY INFORMATION

In general, besides high-fidelity models (mainly high-detailed simulation models or real data from the field), low-fidelity models (low-detailed simulation model or analytical methods) can be used for performance evaluation and provide approximate estimates fast. More specifically, more than one low-fidelity model might be available for one problem and it is difficult to tell which one is better than others in advance.

Low-fidelity estimates are biased, however, the knowledge embedded could be helpful for analysis. Several techniques have been proposed in literature to use multi-fidelity information in modeling phase to improve the accuracy of surrogate models, such as Co-Kriging (Cressie 1992) and Hierarchical Kriging (Han and Gortz 2012). Extended Kernel Regression, proposed by Lin et al. (2018), combines one high-fidelity model with multiple non-hierarchical low-fidelity models. It can identify the importance of different low-fidelity models in different areas, based on input data, and combines low-fidelity models efficiently.

Most algorithms in computer experiments use space filling designs in the initial sampling phase currently, like Latin Hypercube Sampling (McKay et al. 1979). Only high-fidelity information is used and low-fidelity information is wasted.

3 INITIAL SAMPLING USING MULTI-FIDELITY INFORMATION

In this poster, we propose an algorithm to allocate high-fidelity budgets using multi-fidelity information in the initial sampling phase. The goal is to generate an initial design containing a fixed number of good solutions (denoted as R). The alternative solutions are clustered according to their low-fidelity performances. After clustering, high-fidelity budgets are allocated to each group, based on the information derived from the first step sampling, so that the expected value of the R-th smallest high-fidelity performance estimate among the initial design is minimized: $\min \mathrm{E}\left(y_{h_{(R)}}\right)$, in minimization problem.

Compared to space filling designs, the proposed sampling policy generates an unbalanced initial design in which more points are allocated in more promising positions while less points are allocated in positions having less probability that contain the optimum. This might make the built surrogate model more accurate in the area that could contain the optimum while less accurate in the non-promising area. It could be also helpful for algorithms in which optimum sampling is required, such as Nested Partition (Shi and Olafsson 2009), to obtain good solutions in sampling phases.

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