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SIMULATION OPTIMIZATION FOR A DIGITAL TWIN USING A MULTI-FIDELITY FRAMEWORK

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Abstract

Digital twin technology is increasingly ubiquitous in manufacturing and there is a need to increase the efficiency of optimization methods that use digital twins to answer questions about the real system. These methods typically support short-term operational decisions and, as a result, optimization methods need to return results in real or near-to-real time. This is especially challenging in manufacturing systems as the simulation models are typically large and complex. In this extended abstract, we briefly describe an algorithm for a multi-fidelity model that uses a simpler low-fidelity neural network metamodel in the first stage of the optimization and a high-fidelity simulation model in the second stage. It is designed to find a good solution using a relatively small number of replications of high-fidelity models for the problems having more alternatives than conventional ranking and selection procedures are capable of.

1 Introduction

We consider the use of digital twin technology to optimize a system. Optimization via simulation has traditionally been used to find the best solution using a static simulation model. When optimization is being run with a digital twin simulation, there is a greater need to produce results quickly and efficiently as these models are expected to answer immediate operational questions. The methodology we describe here forms part of a larger project with Ford Motor Company.

Real-time or near real-time simulation optimization lies at the core of Ford's strategy for the use of digital twin or symbiotic simulations. The simulation models that Ford uses to describe their production lines are large, detailed, complex and therefore, computationally expensive. In order to improve the efficiency of the simulation optimization and achieve the near-real-time results required for their operational decision-making, it is important to minimize the number of replications using these computationally expensive models. As a result, we consider *multi-fidelity simulation optimization*, where a simple or low-fidelity model is used in the first stage of the optimization to guide the solutions to test on the detailed or high-fidelity model in the second stage of the optimization. This article complements previous work in the area, which led to the development of MO^{2}TOS (Xu et al. 2014), but uses a different grouping strategy for results from the low-fidelity model. Results on a test case study suggest that it achieves good enough results with a relatively small computing budget.

2 METHODS

We use a multi-fidelity framework with a DES model as the high-fidelity model and a multi-layer feedforward ANN metamodel (Ojha et al. 2017) as the low-fidelity model. The whole procedure could be divided into two stages. The offline process and the online process. In the offline process, we first train the metamodel using the high-fidelity simulation model to the output results of interest for a set of training data. Next, we validate the metamodel by comparing its estimates with output of the simulation model on a validation data set. If the metamodel is a poor fit, we generate more simulated data and refit the metamodel. The validated low-fidelity model is then used in the first step on the right side of the flowchart (i.e. we evaluate solutions via the metamodel).

In the online process, the low and high fidelity models interact with each other. First, we use the validated metamodel to evaluate the solutions. Next, we use the hierarchical agglomerative clustering method (Day and Edelsbrunner 1984) to partition the solutions into N clusters based on their performance, where N is predetermined. Then, the clusters are indexed in the order of their performance, where cluster 1 contains the most-promising solutions and cluster N contains the least-promising solutions. We put the clusters into groups for the next stage of the process, where the number of groups is predetermined. The grouping is designed so that the high-rank groups contain fewer but more-promising clusters and low-rank groups contain more but less-promising clusters. This contrasts with the grouping used in MO^{2}TOS (Xu et al. 2014), where solutions are split evenly between the different groups. By clustering first and then grouping we have more control over the number of solutions in each group. This allows us to have a smaller number of solutions in the high quality group and a larger number in the lower quality group. For example, in the case study on the inventory system (Law 2015), we group 31 clusters into 5 groups with a preset proportion of 1:2:4:8:16. Clusters are arranged into groups as follows.

$$\text{Group } 1 = \{\text{Cluster } 1\}$$
$$\text{Group } 2 = \{\text{Cluster } 2,\ \text{Cluster } 3\}$$
$$\text{Group } 3 = \{\text{Cluster } 4,\ \text{Cluster } 5,\ \ldots, \text{Cluster } 7\}$$
$$\text{Group } 4 = \{\text{Cluster } 8,\ \text{Cluster } 9,\ \ldots\ \text{Cluster } 15\}$$
$$\text{Group } 5 = \{\text{Cluster } 16,\ \text{Cluster } 17,\ \ldots\ \text{Cluster } 31\}$$

In the final stage of the optimization, we use a R&S procedure to allocated sampling budget to each group before sampling a solution from the chosen group and using this as the input to the simulation model. There is no guarantee that all solutions will be sampled at this stage but our method of grouping means that there is a higher chance of the best solutions being sampled and does not preclude any solution from being sampled. At the end of the R&S procedure, the optimization outputs the five solutions with smallest (or largest) estimates by the high-fidelity model.

3 CONCLUSIONS AND FUTURE WORK

We propose a multi-fidelity simulation optimization algorithm that can be used as part of a symbiotic simulation where the digital twin simulation model is complex and computationally expensive to run. We present preliminary results for a simple inventory model comparing its performance with an exhaustive sampling strategy and MO^2TOS, a leading multi-fidelity algorithm. Results suggest that the proposed method has a higher probability of generating optimization outputs that are not significantly different from the optimal solution.

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