

SIMULATION-BASED OPTIMIZATION FRAMEWORK FOR THIRD LEVEL OF DIGITAL TWIN

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ABSTRACT

This paper proposes a simulation-based optimization (SBO) framework for a third level of digital twin (DT3). Efficient SBO is necessary for DT3 which optimally controls the corresponding physical system based on the synchronized simulation model in real-time. To this end, this framework consists of three parts: a preprocessor to reduce the search space, an SBO algorithm to decrease the number of simulation replications, and a distributed/parallel simulation environment to shorten the execution time of replications. The framework suggests appropriate SBO algorithms in consideration of the characteristics of a simulation model, search space, and optimization objective so that practitioners can easily apply DT3 to various fields.

1 INTRODUCTION

A digital twin is a cyber model to describe the structural or operational characteristics of a physical system. The implementation level of digital twin can be divided into three stages: 1) building a model to analyze a physical system, 2) synchronizing the model with the physical system to monitor it in real-time, and 3) optimal control of the physical system through simulation of the model (Velosa et al. 2016). For applying the third level of digital twin (DT3) which optimally controls the physical system with the synchronized simulation model in real time, an efficient simulation-based optimization (SBO) is necessary.

So far, various SBO algorithms have been proposed. Due to the nature of simulation models that inverse models cannot be derived, SBO inevitably requires many iterative simulations. The common goal of these algorithms is to reduce the number of simulations. These algorithms can be classified into two categories: metaheuristics represented by genetic algorithm and ranking and selection (R&S) represented by optimal computing budget allocation (OCBA). Each algorithm has different characteristics and situations where it can be applied, however, typically it is not easy for DT3 practitioners to understand this fact and use an appropriate algorithm. Therefore, this paper proposes an SBO framework to allow practitioners to apply DT3 effectively. This framework not only suggests suitable SBO algorithms but also includes a preprocessor to reduce the search space and a distributed/ parallel simulation environment to shorten the simulation execution time, thereby enhancing the efficiency of SBO.

2 PROPOSED FRAMEWORK

The proposed SBO framework consists of three parts: ①preprocessor, ②SBO algorithm, and ③distributed/parallel simulation environment, as shown in Figure 1. First, considering the given search space and optimization objective, the preprocessor reduces the search space by eliminating regions where optimal solutions are unlikely to exist based on the design of experiments and meta-modeling. Then,

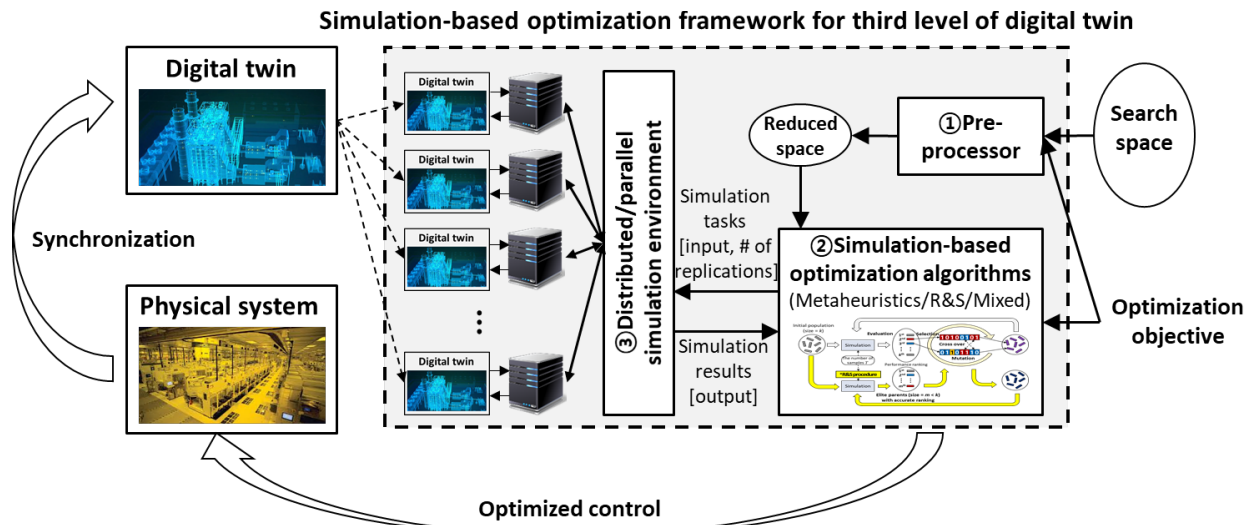


Figure 1: Simulation-based optimization framework for third level of digital twin.

appropriate SBO algorithms are suggested to decrease the number of simulation replications, according to the characteristics of the model, the reduced search space, and the optimization objective. If the model is deterministic and the search space is continuous or has many input combinations from discrete values, the framework suggests metaheuristics-based algorithms suitable for achieving the optimization objective. On the other hand, if the model is stochastic and the search space consists of a small number of input combinations, R&S-based algorithms are suggested. Here, if the search space has many combinations, hybrid algorithms that combine metaheuristics and R&S can be effective (Xu et al. 2015).

Any SBO algorithm performs an iterative process to find optimal solutions. If an appropriate algorithm is selected, then in each iteration, the selected algorithm produces a set of model inputs and the number of required simulation replications per input. For example, metaheuristics for deterministic model update the input set at every iteration, however, the number of replications for all inputs is just one. On the other hand, R&S for stochastic model updates the number of replications for each input without changing the input set. To increase the efficiency of SBO, this framework runs the given simulation task through a distributed/parallel simulation environment. Based on DEXSim (Choi et al. 2014), this environment dynamically estimates the simulation execution time for each input in a heterogeneous computing environment and distributes the task so that it can be conducted in the shortest time. Then, the simulation results are collected and sent back to the SBO algorithm. In summary, the proposed framework maximizes the efficiency of SBO based on these three parts, so that practitioners can effectively implement DT3 in various fields.

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REFERENCES

- Choi, C., K. M. Seo, and T. G. Kim. 2014. "DEXSim: an experimental environment for distributed execution of replicated simulators using a concept of single simulation multiple scenarios". *Simulation* 90(4):355–376.
- Velosa, A., Y. Natis, and B. Lheureux. 2016. "Use the IoT Platform Reference Model to Plan Your IoT Business Solutions". Gartner Research, Stamford.
- Xu, J., E. Huang, C. H. Chen, and L. H. Lee. 2015. "Simulation optimization: A review and exploration in the new era of cloud computing and big data". *Asia-Pacific Journal of Operational Research* 32(3):1550019.