Preface

"Simulation" and "optimization" are two very powerful tools in systems engineering and operations research. With the advance of new computing technology, simulation-based optimization is growing in popularity. However, computational efficiency is still a big concern because (i) in the optimization process, many alternative designs must be simulated; (ii) to obtain a sound statistical estimate, a large number of simulation runs (replications) is required for each design alternative. A user may be forced to compromise on simulation accuracy, modeling accuracy, and the optimality of the selected design. There have been several approaches developed to address such an efficiency issue. This book is intended to offer a different but ambitious approach by trying to answer the question "what is an optimal (or the most efficient) way to conduct all the simulations in order to find a good or optimal solution (design)?" The ultimate goal is to minimize the total simulation budget while achieving a desired optimality level, or to maximize the probability of finding the best design using a fixed computing budget. The primary idea is called Optimal Computing Budget Allocation (OCBA).

This book aims at providing academic researchers and industrial practitioners a comprehensive coverage of the OCBA approach for stochastic simulation optimization. Chapter 1 introduces stochas-

tic simulation optimization and the associated issue of simulation efficiency. Chapter 2 gives an intuitive explanation of computing budget allocation and discusses its impact on optimization performance. Then a series of OCBA approaches developed for various problems are presented, from selecting the best design (Chapter 3), selecting a set of good enough designs (Chapter 5), to optimization with multiple objectives (Chapter 6). Chapter 4 provides numerical illustrations, showing that the computation time can be reduced significantly. Chapter 4 also offers guidelines for practical implementation of OCBA. Chapter 7 extends OCBA to large-scale simulation optimization problems. The OCBA technique is generic enough that it can be integrated with many optimization search algorithms to enhance simulation optimization efficiency. Several potential search techniques are explored. Finally, Chapter 8 gives a generalized view of the OCBA framework, and shows several examples of how the notion of OCBA can be extended to problems beyond simulation and/or optimization such as data envelopment analysis, experiments of design, and rare-event simulation. To help those readers without much simulation background, in the appendix, we offer a short but comprehensive presentation of stochastic simulation basics. We also include a basic version of OCBA source code in the appendix.

OCBA has several strengths: it is effective, easy to understand, simple to implement, and can be easily generalized or integrated with other methods to extend its applicability. We believe that this book is highly useful for different purposes.

1. For researchers, this book offers a series of promising approaches for efficiency enhancement in computer simulation, stochastic optimization, statistical sampling, and ranking and selection. The generalized framework may lead to numerous new lines of researches.
2. For courses, this book could serve as a textbook for advanced stochastic simulation or simulation optimization courses. They can cover Appendix A, Chapters 1 and 2 for introductions; Chapters 3 through 4, and parts of Chapters 5 through 8 for advanced materials.

3. For practioners, this book offers a simple but effective approach to enhance the computational efficiency of simulation optimization. Simulation practioners from industries, governments, and the military should find this book useful and relatively easy to read and apply because it gives numerous intuitive illustrations, well-structured algorithms, and practical implementation guidelines.