Preface

As is often the case, this book grew out of a course. The interesting part is that the course grew out of this story: I was helping one of our graduate students, Viji Krishnamurthy, whose research involved developing rules for the use of flexible workers in a repair and maintenance environment (Iravani and Krishnamurthy 2007). Using Markov chain analysis, Viji had derived some optimal strategies for simple systems and now wanted to test their robustness for more realistic problems. This is where simulation came in. Viji had taken the typical first simulation modeling course that used a commercial simulation product and an advanced course that focused only on design and analysis, but not model building. She (and I) spent hours trying to trick a commercial product into simulating the complex worker allocation rules that she wanted to test. Commercial simulation environments make modeling easy by including the sort of system features that users typically want. Unfortunately, making it easy to model typical features can make it difficult to represent something different, and research is always about something different.

Finally, in frustration, I handwrote three pages of pseudocode to simulate exactly what Viji wanted, handed her the notes, and told her to code it up in C (which fortunately she could do). She came back the next day excited: “Now I can test anything I want, and it runs in seconds!” From this experience, IEMS 435 Introduction to Stochastic Simulation—a required course for all of our Ph.D. students—was born. IEMS 435 is not just about modeling and programming, however. Viji also needed to run well-designed experiments on her model, experiments that could provide compelling evidence for or against her analytically derived rules. So, experiment design and analysis are also a part of the IEMS 435 course, which this book was written to support.

The objectives of the book are as follows:

- To prepare students who have never had a discrete-event, stochastic simulation course to build simulations in a lower-level programming language. I am convinced that if they can do this, they can easily pick up higher-level simulation modeling environments when they need them (maybe for teaching a course as faculty).
• To prepare students to use simulation in their non-simulation research. This is why I emphasize actually programming simulations—which provides the greatest flexibility, control, and understanding—and experiment design and analysis.

• To prepare students to go into an advanced course on simulation methodology, including independent studies directed by their advisers. The usual first course in simulation emphasizes modeling and commercial software and is poor preparation for a research-oriented advanced course which may treat the simulation almost entirely as a mathematical object, breaking the critical connection between modeling and analysis.

• To provide a solid mathematical/statistical grounding in simulation and some (but not all) tools to solve actual problems.

The philosophy of the book is similar to Law (2007) in covering both simulation modeling and analysis, but is different in that there is no attempt to be comprehensive or survey the field. The goal is to be concise, precise, and integrated, leaving a lot of room for the instructor to expand on areas of interest or importance to them. The hope is that an instructor will want students to read all of the book to get a complete, coherent picture before jumping off into other reference texts or journal papers. To that end, I provide pointers to relevant literature. However, while not comprehensive, the book is complete; so, it is appropriate for students or researchers who need to learn the basics of simulation on their own without the benefit of a course. The book by Asmussen and Glynn (2007) shares some of the same objectives as this book; it is an excellent introduction to advanced simulation analysis and covers more of the topic than I do, but it does not address modeling or programming to the same extent.

The material on simulation modeling and programming, which is isolated to two chapters, uses Visual Basic for Applications (VBA) in Excel. This choice was driven by the reality that fewer and fewer graduate students come to me with programming experience. VBA/Excel is readily available, is easy to pick up quickly, and prepares students to learn Java, C++, or any other programming language later. This part of the book can be skipped for students who already know how to program simulations without compromising the remainder. Both Java and Matlab versions of Chap. 4, all of the software described in the book, and any data sets needed for exercises are available for download at the book website:

users.iems.northwestern.edu/~nelsonb/IEMS435/

The book should serve advanced undergraduates and graduate students. A prerequisite is a solid course in probability and statistics; statistics alone is not adequate. Although the book uses tractable stochastic process models (e.g., Markovian queues) as examples, the reader is not expected to have any background in these topics (in fact, students may find the stochastic processes course more intuitive and meaningful after having worked through this book). If students have had no experience with programming computer algorithms—for instance, in Matlab or some other programming language—then the instructor will have to supplement the book with more programming practice. Being an accomplished, or even good, programmer is not required, however.
Chapter 1 provides a concise summary of the book—except for programming—through a simple reliability problem. Chapter 2 then fills that gap by giving a quick start on simulation programming, using VBA. Chapter 3 introduces a number of tractable examples that illustrate the key issues that arise in analyzing stochastic systems via simulation; these examples recur throughout the book and so it is a must-read chapter. VBASim, a collection of VBA subs and class modules developed to support the book, is covered in Chap. 4 and is skippable if some other programming language or package will be used. Chapter 5 strengthens the connection between simulation and mathematical/numerical analysis of stochastic processes; it has the dual mission of setting up the design and analysis chapters that follow and preparing the student for more advanced courses on simulation methodology. Chapters 6–8 cover input modeling, output analysis, and experiment design, respectively, and are largely independent of the programming approach actually used to construct the simulation. The book concludes with Chap. 9, a guide to using simulation in research as opposed to using simulation to solve systems analysis problems.

What is missing? The book does not touch on the computing environment, and there are things you might want to do differently if you have, say, 500 CPUs available in a cloud computing cluster. I anticipate that by the time there is a need for a second edition, it will be easier to leverage such an environment for discrete-event, stochastic simulation, and I will add some general guidelines and recommendations. And while there is a lot of material on simulation optimization, the text is light on specific algorithms, reflecting the fact that there is no current agreement on baseline methods for all types of problems. That too will change. Finally, beyond discussing what it means, I did not do justice to the topic of validation of simulation models.

A number of students and colleagues contributed to the development of the programming approach used in this book. IEMS 435 initially used Law and Kelton (2000) as the text, and Dingxi Qiu spent a summer converting all of the C code in that book into VBA. Christine Nguyen helped in the development of VBASim, the simulation support library described in this book. Feng Yang worked on a research project with me where we used VBA for simulation analysis. Lu Yu assisted with the development of the solutions manual. The Java and Matlab versions of VBASim were translated by Luis de la Torre and Weitao Duan, respectively.

I have gotten a lot of feedback. Students in IEMS 435 suffered through incomplete versions of the text, spotting errors and typos with glee. Larry Leemis provided a thorough mark-up of an early draft, and Jason Merrick taught from it. It is good to have friends, and a number of mine read and marked up sections of the nearly complete book, including Christos Alexopoulos, Bahar Biller, John Carson, Xi Chen, Ira Gerhardt, Jeff Hong, Sheldon Jacobson, Seong-Hee Kim, Jack Kleijnen, Jeremy Staum, Laurel Travis, Feng Yang, Wei Xie, Jie Xu, and Enlu Zhou. Michael Fu guided my thinking about how to develop the section on gradient estimation, and Bruce Schmeiser did the same for error estimation. Seyed Iravani, Chuck Reilly, and Ward Whitt made sure I did not mangle the message of their papers in Chap. 9. In addition to those listed above, other people whose work influenced my think-
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