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Issues in Developing an Undergraduate Simulation Course

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ISSUES IN DEVELOPING AN UNDERGRADUATE SIMULATION COURSE

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ABSTRACT

Experience in developing an undergraduate simulation course is described. The course introduces the philosophies, principles, and methodologies for discrete-event simulation modeling. Strategy in choosing the course simulation software is discussed, plus important areas of teaching emphasis are highlighted.

INTRODUCTION

Simulation is one of the most important operations research techniques [Lane et al., 1993]. Cochran et al. [1995] indicates that more than half (58%) of simulation practitioners learn simulation at a university. Given this high percentage, what does one teach in a introductory (university) simulation course? To answer this question, the first step is to understand how simulation is applied. There are many papers that describe the simulation process, diagnose the common problems and pitfalls that can occur during a simulation study, or offer advise on how to perform a study [Dietz, 1992; Annino and Russell, 1979; Gogg and Mott, 1993; Law, 1986; Law and McComas, 1986; Musselman, 1993; Sadowski, 1991; Thesen and Travis, 1991; and Ulgen, 1991 are a small sampling].

After a review of these papers, an undergraduate simulation courses was developed to introduce students to the concepts of model building and simulation. Specific objectives of the course include:

- Understanding what a model is and identifying important general modeling principles.
- Understanding how simulation modeling can improve the performance of an existing systems.
- Knowing which problems are best studied with discrete-event simulation.
- Understanding what aspects of a real system to include in the model.
- Understanding how to develop a model in a specific language.
- Understanding how to analyze simulation output.

To cover these important objectives, the course is divided into several components (Table 1). The course is in progress as this paper is being written. Therefore, the course outline is tentative and modifications that occur will be presented at the conference. The remainder of this paper offers insight into selecting the simulation software for the course and highlighting important issues to be taught.

SELECTING THE SIMULATION SOFTWARE

In developing a simulation course, a key question is selecting what simulation software the students will learn and on what hardware platform will they learn it.

Simulation Hardware Platform

Cochran et al. [1995] report that simulation practitioners (in industry and universities) perform simulation studies with personal computers 42% of the time, workstations 29%, mainframes 20%, and minicomputers 9%. As part of their study, they found that industry’s use of mainframes for simulation studies is nearly zero.

Table 1: Outline of the Undergraduate Simulation Course.

Topic	Objective
What is a Model?	Provide an understanding of how models describe a system, how different types of models exist and compare with one another, and introduce principles for developing a model.
What is Computer Simulation?	Provide an overview of computer simulation, a discussion on the goals/objectives of simulation, simulation uses and disadvantages, simulation components.
The Simulation Process	Provide an understanding of the steps involved in developing a simulation model in a specific language and validating the model.

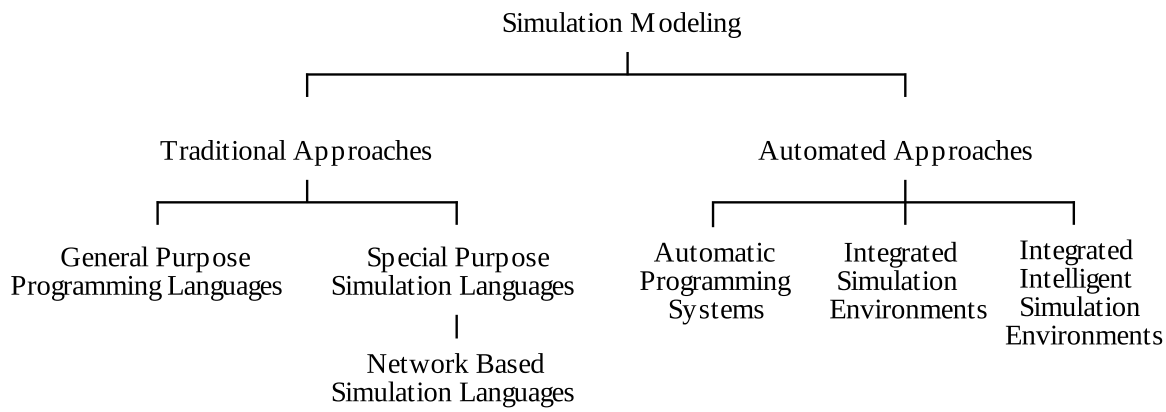

Figure 1: Classes of Simulation Software.

Simulation Software

In choosing simulation software there are two major classes to select from (Figure 1). The *traditional* or *manual* approaches to simulation model development involves creating a simulation model in a general purpose programming language or a special purpose simulation language. The second branch of the tree represents different methods to *automate* the process of developing and running models. Each category represents an increase in system sophistication and a decrease in the effort and simulation expertise required of the user. These different types of software can also be rated in terms of their ease of use and level of instruction required (Table 2).

The use of a general programming language (Table 3) for model development is decreasing [Cochran et al. 1995]. SIMAN and SLAM are the most common general purpose simulation languages in use. Of those who use a simulator, ProModel is the most common choice.

Software that was Selected

From the above criteria, it was decided that the simulation course should use SIMAN (a network based simulation language) in conjunction with ARENA (an integrated simulation environment) as the simulation software. Due to several factors such as availability, execution speed, and high industry use, a cluster of IBM RS/6000 workstations was selected as the hardware platform.

Table 2: Spectrum of Simulation Software (0 is the most time consuming and 7 is the least).

6 = intelligent simulation environments
5 = integrated simulation environments (ARENA, ProModel)
4 = automated programming systems
3 = network based languages (SIMAN, SLAM, GPSS, SIMSCRIPT)
2 = general purpose simulation languages (GASPS IV, Dynamo, Simula)
1 = higher level languages (Fortran, BASIC, C)
0 = assembly language

Table 3: Distribution of Languages and Environments used in a Simulation Study [from Cochran et al. 1995].

General Purpose Languages		General Purpose Simulation Languages		Special Purpose Simulators	
C	28%	SLAM II	28%	PROMODEL	14%
FORTRAN	27%	SIMAN	28%	SIMFACTORY	8%
PASCAL	7%	GPSS	11%	FACTOR	4%
BASIC	6%	SIMSCRIPT	6%	Other	12%
LISP	4%	Other	11%	None	60%
Other	10%	None	16%		
None	18%				

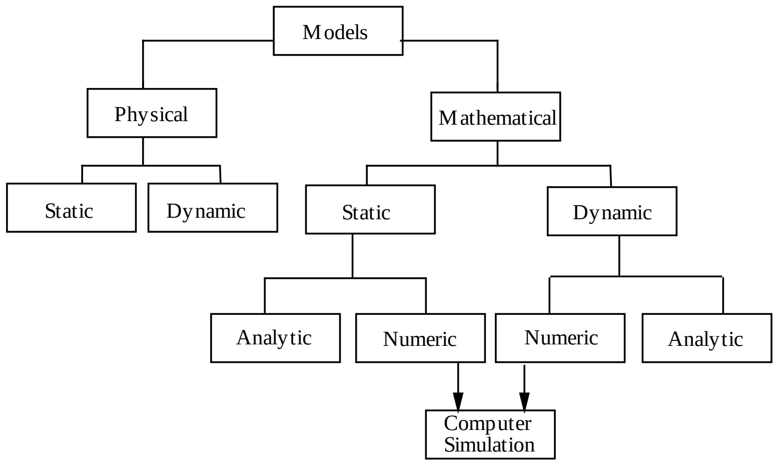

Figure 2: Classification of Models [modified from Gordon, 1969].

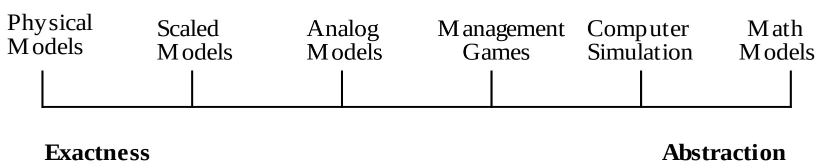

Figure 3: Spectrum Classification of Models [from Shannon, 1975].

IMPORTANT ISSUES TO BE TAUGHT

Deciding what to teach and emphasize in a course is one of toughest part of teaching. The following discussion highlights several of the key concepts that should be reviewed.

Classification of Models

Before a student can understand the concept of a simulation model, he should be aware of the different types of models that exist (Figure 2).

Models can also be compared to one another using a continuous spectrum (Figure 3). The spectrum goes from exact physical models or prototypes which are expensive and time consuming to build and need exact conditions to model the real system and proceeds to completely abstract mathematical models (analytical or heuristic).

Model Building Principles

Ravindran et al. [1987] presents the following list of model development principles (I use this list in both my simulation and operations research course):

(1) *Do not build a complicated model when a simple one will suffice.* Table 4 summarizes that a proper perspective must be maintained when developing a model.
(2) *Beware of molding the problem to fit the technique.* Not all real-world problems need to be modeled with simulation, there may be a better (i.e., analytical) technique.
(3) *The deduction phase of modeling must be conducted rigorously.* For the model conclusions to be accurate, the model assumptions must be correct.
(4) *Models should be validated prior to implementation.* Models should be checked to see that they accurately represent the system.
(5) *A model should never be taken too literally.* Just because a model is large and complex does not guarantee that it is accurate.
(6) *A model should neither be pressed to do, nor criticized for failing to do, that for which it was never intended.* A model is only as good as the data/assumptions used to build it.
(7) *Beware of overselling the model.* Do not sell your model as "factual" when it is in fact an "integrated set of plausible assumptions that lead to useful conclusions" [Ravindran et al., 1987].
(8) *Some of the primary benefits of modeling are associated with the process of developing the model.* By exploring and describing the system, many improvements to the system can easily be seen.
(9) *A model cannot be any better than the information that goes into it.* Simulation is performed on a computer and a general rule of thumb with computers is: "Garbage In, Garbage Out".
(10) *Models cannot replace decision makers.* Models aid decision makers by offering insight into a system, but decision makers still have to interpret the results and make conclusions.

Table 4: Considerations Between a Complex and Simple Model [from Lee 1988].

Consideration	Modeling Approach Complex Model (Accurate Solutions)	Simple Model (Approximate Solutions)
Resources Required		
Cost	High	Low
Time	High	Low
Manpower	High	Low
Organizational Acceptance		
Involving People	Low	High
Understanding the Effort	Low	High
Implementation of Results	Low	High
Solution to the real problem	Good	Approximate

What is Computer Simulation?

In defining simulation, an emphasis should be on when to and not to use it. One approach to studying a system is to use analytical techniques (*i.e.,* operations research techniques - linear programming, queueing theory, Markov chains, etc.) which seeks to get some unique and/or optimal solution of the variables. Unfortunately, many times a system has multiple attributes of interest, is highly complex, has processing times modeled by probability distributions, has different routings of parts, has limited queue capacity, and has multiple competition for limited resources. In such a case, mathematical modeling of the system may have no practical analytical or numeric solutions. In fact, analytical tools may be too complex or unavailable for modeling the system. Another approach to studying the system is to use a heuristic model. With such an approach, one:

(1) constructs a model of the system
(2) observes the behavior of the variables over time
(3) based on the observation, hypothesizes how the system is/will behave

These three tasks exactly describe what **SIMULATION** does!

Goals of Simulation Modeling

Simulation can be used for prediction, scheduling, and optimization. Specific goals for (manufacturing) simulation are summarized in Table 5.

Table 5: Goals for a Simulation Study [Ozdemirel and Mackulak, 1993].

Model	**Type**	**Use**
Predictive Models		job volume, effect of hot jobs, bottleneck resources, breakdown effects, product quality, and absenteeism effect
Scheduling Alternative		product mix, sequencing alternatives and push versus pull inventory systems
Optimization	Fixed Shop Structure	lot size verses setup time, utilization verse cycle time, minimization of buffer stocks, minimization of work-in-process, and input data accuracy and sensitivity for fine tuning of the model
	Optimize Structure	optimizing work station layout, optimizing use of material handling equipment, optimizing physical work-in-process areas, optimizing the use of secondary resources and the general layout of the facility

Table 6: Comparison of Experimental Design for Simulation and Other Areas [from Thesen and Travis, 1991].

	Other Areas	**Simulation**
Data Collection	May produce errors	Perfect
Outliers in data	Present	None
Randomness of data	Assumed	User control
Replications	No always possible	Under user control
"Noise" in data	Often unknown origin	Fully explained
Scenarios	Often uncontrollable	Under user control
Underlying Model	Unknown	Fully specified

Experimental Design

There are important differences (Table 6) in how experimental design operates in simulation versus other areas.

Simulation Time Frame

The typical time from for a student simulation project is one to two weeks. This unfortunately leads some students to assume that most real-world systems can be modeled in a similar time frame. Cochran et al. [1995] indicates that the typical time frame to complete a simulation project is 1 to 3 months (Table 7). The minimum time for most projects is one week or less, while the maximum time for projects is over six months.

CONCLUSIONS

A students cannot learn all of simulation in one course. Shannon et al. [1985] estimate that a simulation practitioner must have about 720 hours of formal classroom instruction (240 hours of which is in simulation) plus another 1440 of outside study to gain this basic knowledge. To provide this essential training requires a sequence of simulation courses to develop the necessary critical thinking skills required of a simulation practitioner [Savory and Mackulak, 1994].

The first simulation course introduces the philosophies, principles, and methodologies for discrete-event simulation modeling. The focus is on simulation applications and the development of a model in a specific language. Upon completing this course a student possesses a basic understanding of how to develop and analyze a simulation model.

Topics for advanced courses include using simulation in analyzing and designing systems involving continuous and discrete processes, statistical issues such as pseudorandom number generation, testing generators, stochastic variate generation, and variance reduction techniques. Simulation's use in manufacturing is an additional advanced course [Medeiros, 1994; Banks, 1994; Sadowski, 1994]. Such a course focuses on successfully apply simulation in a manufacturing setting.

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Table 7: The Time Frame of a Simulation Project [from Cochran et al., 1995].

	1 Week or Less	1 Week to 1 Month	1 to 3 Months	3 to 6 Months	More than 6 Months
Minimum time for a project	49%	25%	13%	6%	7%
Average Time for a project	4%	20%	31%	16%	29%
Maximum Time for a project	0%	4%	15%	16%	65%
Man-effort to complete a project	6%	36%	29%	13%	16%

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