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ABSTRACT

Many people refer to simulation model building as an “intuitive art”. This implies that modeling can only be done by a select group of highly trained creative people and thus isolates many from considering simulation as a usable tool. Model building is a science that is learned through education, training and experience. In this paper, we discuss the role of science in performing a simulation study. We illustrate the teaching of the science of simulation by discussing the simulation curriculum at Arizona State University.

INTRODUCTION

Simulation is one of the most important operations research techniques (Lane, Mansour, and Harpell 1993). It’s many uses range from comparing alternative systems to answering capacity and feasibility questions. Unfortunately, many authors claim that the process of building a simulation model is an “intuitive art”. (Emshoff and Sissin 1970; Shannon 1975; MacNair and Sauer 1985; and Pritsker 1986 are a small subset). This attitude is passed along to students learning simulation. Such a perspective isolates a large segment of the population from considering simulation as a solution technique.

The objective of this paper is to argue that model building is a science learned through experience. We first discuss the roles of art and science in model building. We conclude that experience is the key ingredient. As a role model for building the critical thinking skill of students, we illustrate the structure of the simulation curriculum at Arizona State University. We conclude the debate with a compromise in that possibly modeling is neither an art or a science, but both.

THE ART OF SIMULATION

Shannon (1975) remarks that, “the art of modeling can be mastered by those who possess the necessary skills of ingenuity, insight, and resourcefulness, as well as an extensive exposure to the systems and physical phenomena they are trying to model.” He continues that there are no magic formula on how to formulate a problem. Any formalism that does exist is so specific that its use is limited.

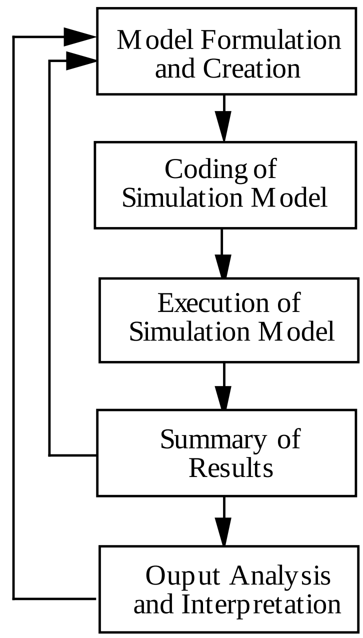

Figure 1: A high level description of the steps in the simulation process.

The most difficult step of the simulation process (Figure 1) is model formulation. In this stage, decisions must be made on which features of the system to include in the simulation model. Modeling is a balancing act (Balci 1989). On one hand, a model should include the essential elements of the system, and on the other hand, it should not include unnecessary detail. Missing an essential element may invalidate the representation provided by the model or make it useless for the intended application. According to Shannon (1975), “Model building requires an ability to analyze a problem, abstract from it its’ essential features, select and modify basic assumptions that characterize the system, and then enrich and elaborate the model until a useful approximation results.” He concludes by stating that the successful approach to model building appears to proceed on the basis of elaboration and enrichment. One starts with a very simple model and elaborates it until it clearly represents the system. Pegden (1990) agrees and summarizes that, “this process of system abstraction and simplification is the essence of modeling art”.

THE SCIENCE OF SIMULATION

With enough commitment, time, training, and patience, can a randomly selected person, with little technical training, be taught how to build a representative simulation model? It would most certainly be a difficult task, but if yes, then simulation modeling cannot be considered an art.

It is true that a successful modeler must possess a certain amount of intuition (a keen and quick insight) in developing models, but this requirement does not constitute an art. For instance, consider a physician who diagnoses a patient with a certain disease or illness. Is not modeling a system similar to diagnosing a sick patient? For both, the doctor and the modeler exercise the same general problem solving steps: (1) define the problem, (2) analyze the problem, (3) synthesize the concept, (4) develop alternatives and select one, (5) implement the solution, and (6) follow-up. Each requires critical thinking skills, but neither facilitates a set of skills or traits that can not be learned through education, training and experience.

A primary problem of simulation modeling is that modelers view models as unique and tend to recreate topologically similar models when only the parameters are different. The System Systems Simulation Laboratory is a major proponent of using pre-existing (generic-specific) models (Mackulak, et al. 1990; Manathkar, et. al 1993; Ozdemirel, et al. 1993; Ozdemirel, et al. 1993). The development of generic-specific models has removed the "art" of modeling.

A generic model is a pre-existing, but empty model (it lacks simulation data) of a typical manufacturing system. A specific model is one in which simulation data about the manufacturing system has been defined. The use of generic-specific models is a process wherein a user selects a pre-existing generic model and fine-tunes it (makes its specific) to solve a specific problem. This means, all equipment (conveyors, storage areas, workstations) are already defined in this "empty" model. Through the process of specifying the simulation data (information about the specific system under study), the modeler "switches on" components of the model (makes it specific). For example, a generic model has both an automatic-guided vehicle (AGV) and conveyor defined for material handling. If the system under study has an AGV but not a conveyor, then through specifying the simulation data, the AGV part of the generic model is "switched on" while the conveyor component remains "switched off".

Generic-specific modeling assumes a model and then collects the simulation data to switch parts "on/off". In comparison, the traditional modeling approach collects the simulation data and then specifies the model. The advantage of this new approach is that it allows the analysis to concentrate on collecting domain knowledge from the industrial setting and answering the design questions at hand and reduces the time spent for model development.

SIMULATION AT ARIZONA STATE

Few will argue with the claim that experience is the best method for developing critical thinking skills. Sadowski (1991) poignantly uses the following example to explain that experience is the essential element in developing a simulation model:

> Teaching the simulation process is somewhat like teaching someone how to ride a bike. You can describe and sometimes demonstrate the process, but the new rider quickly learns there is no substitute for experience. One wrong move or turn of the wheel and the bicycle reacts in a fashion totally different than anticipated; but in hindsight, the bicycle's reaction could have been predicted.

Simulation modeling has its roots in computer science, mathematics, and statistics (Murray and Sheppard 1987). To use simulation correctly and intelligently, the practitioner is required to have training in each of these different fields. Shannon et al. (1985) estimate that a simulation practitioner must have about 720 hours of formal classroom instruction plus another 1440 of outside study to gain this basic knowledge. To provide this essential training, the Industrial and Management Systems Engineering (I&MSE) department at Arizona State University has placed considerable emphasis on developing a strong simulation curriculum. In addition to four courses in simulation (240 hours), students take prerequisite courses in statistics and design of experiments (160 hours), computer programming (100 hours), operations research (80 hours), engineering design (60 hours), systems analysis (60 hours), and economic analysis (60 hours). The total hours spent for these course exceeds Shannon's estimate of 720 hours.

The objective of the simulation program is to develop the necessary critical thinking skills required of a simulation practitioner. Figure 2 outlines the manufacturing engineering graduate curriculum with the specific simulation courses indicated by highlighted blocks.

Two of the prerequisites courses for the simulation curriculum are *Probability and Statistics* (ECE 383) and *Microcomputers in Industrial Engineering* (IEE 205). The statistics course teaches students to applying statistics to engineering problems. Topics include: probability, discrete and continuous distributions, sampling distributions, and descriptive statistics. In addition, there is strong emphasis on the development and application of point estimation, tests of hypothesis, regression, correlation, analysis of variance, design of experiments, and non-parametric statistics. The microcomputer course teaches hardware, software, and networking concepts as they related to industrial engineering problems. These subjects are taught using the C programming language.

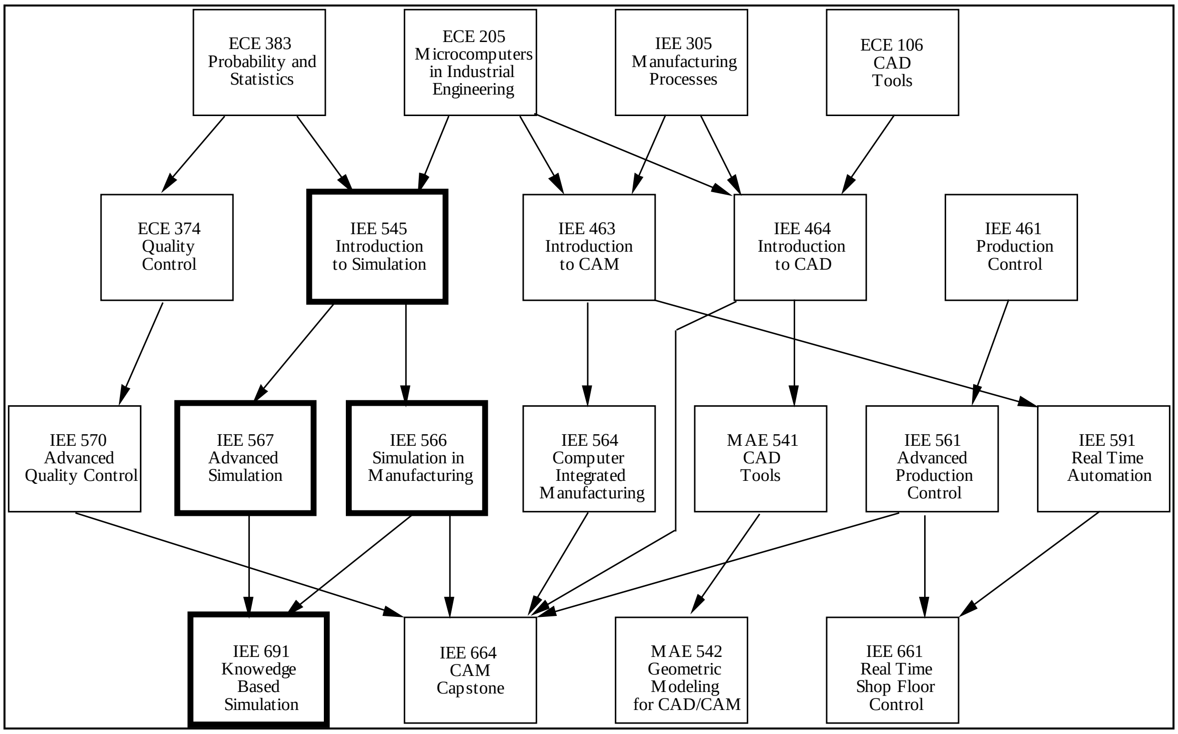

Figure 2: A graphical representation of the Simulation and Manufacturing Engineering graduate curriculum of the I&MSE department at ASU. Simulation courses are highlighted in bold.

Building on the subjects of the prerequisite courses, the first simulation course, *Introduction to Simulation* (IEE-545), introduces the philosophies, principles, and methodologies for discrete-event simulation modeling. The focus is on simulation applications for management and engineering scenarios. The course uses the SLAM II simulation language for model development work.

The advanced simulation course (*Advanced Simulation*, IIE-567), introduces simulation's use in analyzing and designing systems involving continuous and discrete processes. These topics are taught with SLAM II and SIMNET. In addition, statistical issues such as pseudorandom number generation, testing generators, stochastic variate generation, and variance reduction techniques are presented.

Simulation's use in the planning of computer-integrated manufacturing (CIM) systems is a third graduate level (*Simulation in Manufacturing*, IEE-566). Topics include exploring the impact of automated guided vehicles, robots and manufacturing system integration on a system. Additional emphasis is on the use of computer graphics combined with simulation analysis for making CIM decisions. This course uses SIMAN (a simulation language), ProModel (a simulator), and IntelliSIM (a research intelligent simulation environment developed at Arizona State) to illustrate these concepts.

The ASU curriculum is structured such that a student who enrolls in IEE 545 need not have any simulation training. Upon completing this course he possesses a basic understanding of how to develop and analyze a simulation model. Students seeking detailed insight into the specific steps of the simulation process (random number generation, variance reduction techniques, continuous simulation) are encouraged to enroll in the next simulation course, IEE 567. While these two courses teach the skills necessary for performing a simulation study, the third simulation course, IEE 566, explores using simulation as a planning and design tool. Students completing the third course should have the background and practice to successfully apply simulation correctly in a manufacturing setting.

The emphasis of each of these three simulation courses is to provide students a "hands-on" use of simulation. Regular class assignments include modeling small, but moderately complex manufacturing situations. Each assignment requires a complete analysis of the system, including the correct application of all statistical tests and experimental designs. Students document their analysis in reports which are structured for presentation. Each course concludes with a semester project in which each students is required to use simulation to analysis a "real world" system. Past projects have included studying a local manufacturing flow line to modeling the university's parking shuttle transit system.

The format of the final simulation course (*Knowledge-Based Simulation*, IEE-691) is directed readings and research in the knowledge-based aspects of computer simulation.

Topics include expert systems for simulation, qualitative simulation, neural computing for simulation, object oriented simulation, data bases and knowledge bases for simulation, and fuzzy sets. Other advanced topics such as expert systems and intelligent simulation environments for manufacturing systems are studied.

In addition to a diverse simulation curriculum, the Systems Simulation Laboratory (SSL) operates within the I&MSE department. The laboratory was created to concentrate efforts and resources for exploring issues relating to simulation analysis. The goal of the SSL is to establish leadership in the development of simulation techniques and in the conceptualization of the next generation of simulation software tools to solve real problems. A student simulation affiliate program operates in conjunction with the SSL. This program provides a structure in which students with a common interest in simulation may pursue topics in a structured manner by offering a forum which students can compare ideas on research topics.

CONCLUSIONS

The problem of referring to simulation modeling as an "art" is that it isolates many from considering simulation as a useful tool. Such a term implies that modeling can only be done by a select group of highly trained creative people. While it is true that the successful application of simulation requires a certain level of technical expertise and intuition, these qualities can be learned through education, training and experience. The key ingredient to the science of model building is a keen set of critical thinking skills gained through experience.

As a compromise, modeling possibly should be viewed as neither an art nor a science, but both. McHaney (1991) concludes that, "The creativity and instincts used are akin to an art, while the methodology involved in model creation and analysis are based on computer science and mathematical principles." Therefore, elements of both art and science exist in modeling (Figure 3). Generic-specific models are a new approach to model building that typify this perspective.

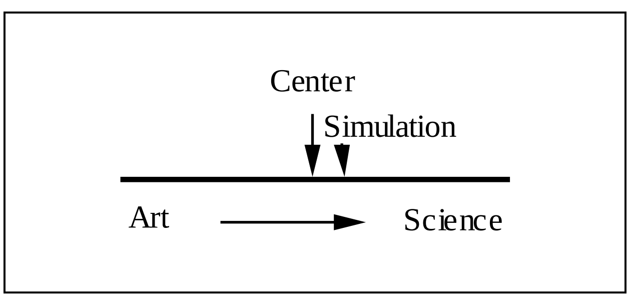

Figure 3: Simulations place on the spectrum extending from art to science (McHaney 1991)

Regardless of the outcome of this debate, few will disagree that experience and education are the keys to successful simulation modeling. Our objective as simulation educators should be to develop courses which challenge and enhance the critical thinking skills of our students. Our approach at Arizona State successfully teaches the science of simulation and we offer it as a role model to be enhanced and improved upon.

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