SIMULATION EDUCATION AND ITS COLLABORATIONS WITHIN UNIVERSITY CURRICULA

Toni Ruohonen

University of Jyväskylä, Jyväskylä, FINLAND

Edward J. Williams

University of Michigan – Dearborn, Dearborn, UNITED STATES

toni.ruohonen@jyu.fi; *williame@umd.umich.edu*

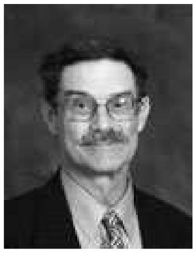
Abstract

Simulation education has been a significant facet of university curricula, both in industrial engineering and in business management, for many years. Indeed, the importance of simulation education to both these curricula approximately coincides with the accessibility of simulation analyses via skillful programming in computer languages on mainframes and significantly precedes the availability of desktop computers and their specialized, largely point-&-click software tools. The simulation educator, whether teaching within a college of engineering (and most likely the sub-discipline of industrial engineering) or within a college of business or management, has various valuable opportunities to emphasize the reliance of simulation upon prerequisite and concurrent course work. Likewise, educators in related disciplines have opportunities to stress the usefulness of material taught in their courses to simulation analyses. When fully exploited, these cross-fertilization opportunities enhance collegiality, student motivation, and retention and integration of important concepts and techniques. In this paper, we explain these opportunities, particularly with respect to statistical concepts, computer analysis and programming skills, industrial engineering and managerial observations, and interpersonal and teamwork skills. Broadly stated, we undertake the examination of both "how the simulation educator can support the educator of related disciplines," and the converse "how the educator of disciplines related to simulation can support the instructor of simulation."

Keywords: simulation, education.

Presenting Author's biography

EDWARD J. WILLIAMS holds bachelor's and master's degrees in mathematics (Michigan State University, 1967; University of Wisconsin, 1968). From 1969 to 1971, he did statistical programming and analysis of biomedical data at Walter Reed Army Hospital, Washington, D.C. He joined Ford Motor Company in 1972, where he worked until retirement (December 2001) as a computer software analyst supporting statistical and simulation software. After retirement from Ford, he joined PMC, Dearborn, Michigan, as a senior simulation analyst. Also, since 1980, he has taught evening classes at the University of Michigan, including both undergraduate and graduate.



1 Introduction

A course in discrete-event process simulation is frequently offered within, and considered an important component of, either or both of the industrial engineering and/or the business management curricula at the university undergraduate level. Such a course almost invariably has as a prerequisite a course in probability and statistics, and this course in turn usually presumes knowledge of calculus. Furthermore, students in a discrete-event simulation class typically have (and even been required to have) computer familiarity and competence including the use of spreadsheets and mild to moderate experience programming in a computer language such as C++ or Java [1]. Sometimes, especially in Europe, the simulation class includes the expectation that the students will program simulation models in one of these computer languages, or even a simulation-specific language such as GPSS. Or, more commonly in the United States, the simulation class will introduce a simulation software package such as Arena®, AutoMod®, ExtendSim®, or WITNESS® and require students to build and analyze models using that package. Irrespective of the tool used to build simulation models, students ideally are expected to work in teams to select a simulation project; gather and analyze pertinent data on the system to be modeled; build, verify, and validate the model; analyze the results; and present these results to the educator and the client – a local company, perhaps the employer of one of the students on the team. As a long-term beneficial effect, if the client company is new to simulation, this project (essentially free from the client company's viewpoint) will become acquainted with the capabilities of simulation. In view of these expectations for the discrete-event simulation course, there are numerous opportunities for the instructor teaching it to reinforce and augment learning undertaken in the prerequisite and co-requisite courses, such as supply-chain analysis, ergonomics, and facility layout analysis, "illustrating the importance of educating engineering students to think across course and discipline lines [2]. In this paper, we will examine these opportunities with respect to statistics, data collection and analysis, behavioral science from the industrial engineering viewpoint, computer software development concepts, and the importance of teamwork, interpersonal collaboration, and both oral and written communication [3]. Likewise, the instructors of prerequisite classes, most particularly the statistics class, have opportunities to motivate students by drawing attention to how concepts taught therein will be useful in discrete-event simulation. Surely every statistics educator has been asked many times in the classroom "Why do we have to study this?" One of many good answers is "These statistical concepts will help you analyze stochastic variation, and one of many good reasons to do so involves the building of simulation models to evaluate proposed improvements to business systems, whether manufacturing or service (such as health care) delivery." When fully exploited, these opportunities enhance and reinforce student learning, promote collegiality within academic departments, and increase coherence of academic program integration within either management or industrial engineering disciplines. Hence this paper undertakes the examination of both "how the simulation educator can support the educator of related disciplines," and the converse "how the educator of disciplines related to simulation can support the instructor of simulation."

2 Simulation Practice Reinforces Statistical Concepts

The instructor teaching a simulation course should seize numerous and important opportunities, listed in this section, to emphasize and reinforce statistical concepts typically taught in a prerequisite course (usually this statistics class, whether for students majoring in industrial engineering or in business, has a calculus prerequisite). In a conference panel discussion devoted to management of simulation technology in large companies [4], all panelists concurred on the importance of this prerequisite. Interestingly, the panelist (Professor Roger Klungle) most accustomed to simulation in *service* industries, recommended *two* such courses as prerequisite.

Most vitally, the importance of variability, and hence statistical techniques to analyze it quantitatively, in the practice of simulation can hardly be overemphasized. In the manufacturing sector, variability is inevitable (e.g., duration of downtimes, quality of incoming raw material, manual cycle times, etc.). In the service sector, variability is often greater still; as [5] stated flatly in a tutorial on simulation in health care, "Variation matters." He gives two vivid examples: (1) the unpredictable length of time a therapist will need to interview a husband and wife on a marital problem, and (2) a hospital emergency room serving five different categories of patients classified by means of arrival and degree of urgency – and there being variation within each group also.

One of these collaborative opportunities consists of warning simulation-analysts-in-training to beware of the seductively convenient probability formula $p(A \cap B) = p(A) \times p(B)$. Since this computation assumes independence of the events A and B, the simulation analysts must beware of perhaps latent dependence. For example, in the first draft of a model of an drive-through oil-change facility, probability distributions for the drainage time of the old (to be replaced) transmission fluid and for the drainage time of the old engine oil were sampled separately and sequentially from the built-in distributions provided by the statistical software package. This model construction tacitly assumed independence of these drainage times. Examination of a scatter plot of the two drainage times for each vehicle showed strong positive correlation, since larger vehicles tend to carry more of each fluid. Correction of the model appropriately lengthened the predicted vehicle queue lengths and time in queue [6]. Opportunities abound to use this lesson in many fields of practical application of simulation. For example, the larger refrigerator may need both more assembly time and more painting time; the sicker patient may need both more doctor-interface time and more laboratory tests. Examples like these represent shining opportunities to repeat the homily "Correlation does *not* necessarily imply causation." For example, the larger transmission-fluid reservoir did not in and of itself increase the size of the oil tank.

Another opportunity the simulation educator should seize is correction of the common misconception that the "normal" distribution is the state of normalcy in almost any stochastic process, and hence other distributions often appropriate for simulation modeling (e.g., Weibull, gamma, lognormal) are rare, exotic exceptions to this expectation. Indeed, it may be an unfortunate accident of history that the misleading name "normal" distribution has almost entirely supplanted (in both North America and Finland) the name "Gaussian" distribution. To correct this common misconception, the simulation educator should provide examples of actual stochastic process data (e.g., cycle times, downtime durations, or times to equipment failure), with emphasis on their descriptive statistics (lack of symmetry in the histogram, impossibility of negative values, and conspicuous positive skewness). Further examples will surely appear, as the students can be assured, when they begin collecting data for an assigned simulation project.

Still another vital point of emphasis to be stressed by the simulation educator is the statistical principle "A sample size of 1 is too small." Particularly among students who have significant experience in computer programming and/or have taken several classes in this field (e.g., classes in Java, C++, and the like), the temptation to think "Excellent! My simulation model (or computer program) has now run to completion and produced sensible output. That part of the study is complete" looms large. These students need vigorous reminding that each run of a validated simulation model is a separate experiment – with different generated random numbers to model stochastic variation within the model – and, as such, produces results representing one data point in a simple random sample. Subsequently, from that simple random sample, a confidence interval will be constructed and/or a hypothesis test will be conducted. At this point in the students' training in simulation, the instructor does well to remind them "If you want a confidence interval only half as wide, you must – other things (e.g. variability) remaining equal, you must make four times as many runs. That number of runs is properly called the 'number of replications.'" [7]. After this foundation is laid and confirmed, the simulation student is ready to comprehend the issues involved in choosing a steady-state versus terminating simulation, and to select the warm-up time appropriate to a steady-state simulation.

Furthermore, the simulation educator will almost surely have opportunities to motivate students to extend their basic prerequisite statistical knowledge to learn and use Design of Experiments (DOE). This opportunity is likely to knock when a team conducting one of the simulation projects remarks "The client is interested in investigating three queuing disciplines, two conveyor capacities, and four potential staffing levels – that's $3 \times 2 \times 4 = 24$ pairwise *t*-tests to run." This moment is the motivational opportunity to mention the power of DOE, and to explain that it can additionally detect interactions: "A larger conveyor might not raise throughput much, and a higher staffing level might not raise throughput much, but implementation of both might raise throughput significantly." The educator may well also remark "Once the simulation is verified and validated, additional data points and multiple replications cost very little. Consider your colleagues in the Mechanical Engineering department, for whom each DOE data point might represent the building and testing of a costly prototype." [8].

3 Simulation Class Introduces Messy (Non-Existent?) Data

Excerpts from an exercise in a textbook frequently adopted by the second author are: "Orders are received for one of four types of parts. The interarrival time between orders is exponentially distributed with a mean of 10 minutes." The exercise then proceeds to specify, for example, that 20% of the parts are type "C," with processing time normally distributed with mean 11.8 minutes and standard deviation 4.1 minutes. [9]. An exercise such as this represents an excellent stage on which the instructor can first guide the students in building a basic simulation model, whether with a programming language or a simulation software package. Before too long, the normal distribution specified will generate a negative processing time – or produce an error message after trying to do so. This moment is a very propitious moment to introduce ideas pertinent not only to simulation, but to many other endeavors pertinent to industrial engineering, such as value stream mapping, time-&-motion studies, supply chain analysis, and ergonomic analysis. The instructor, often abetted by the more eager students, might well raise these questions:

Is this normal distribution, with coefficient of variation 4.1/11.8 > one-third, a plausible model for the cycle time?

Is *any* normal distribution (c.f. above) a plausible model for the cycle time?

When you undertake a real-world simulation study and ask the production line supervisor "How long does this process take for type 'C' parts?", is he or she likely to provide an answer like "It's normally distributed with mean 11.8 and standard deviation 4.1." The student whose viewpoint is "Did I get the answer in the back of the book?" will answer "Yes;" the more educationally mature student will answer "No."

Students are now more steeled against revelations such as "On a 'good day,' the client will have some tabulated data ready for analysis (are those data on scraps of paper or in a spreadsheet file?) On a 'bad day,' we, the industrial engineers, will need to collect the data." They will come to understand that in a simulation study – and many other types of industrial engineering studies – collection and analysis of required input data may require significantly more effort and time than building, verifying, and validating a model.

Data collection activities required to undertake the students' first simulation project often provide another vivid flash of reality – the multimodal distribution. For example, data collection may involve observing the receptionist at a health clinic greeting and providing basic registration services to patients. If the histogram of these cycle times indicates bimodality, as well it may, the educator ought to ask the students "Are there really two data sets here – the generally shorter registration times for arriving patients who have visited this clinic previously, and the generally longer registration times for arriving patients who are new?" This question should motivate the student modelers to observe further and ask pertinent questions of the receptionist. Very possibly, the desired outcome will be documentation of the relative proportions of previous versus new patients, and *two* fitted distributions used in the model – one for each type of patient. Indeed, [10] make reference to this type of deeper investigation of data relative to patient discharge-processing times in an acute-care hospital. Additionally, the exigencies of collecting data, particularly in a service-delivery system, are likely to arise here and should be emphasized by the educator. Most conspicuously, the Hawthorne effect is well-nigh certain to arise, sooner rather than later, when data collection begins [11]. Students should be referred to their ergonomics course (whether previous, concurrent, or impending) relative to the Hawthorne Effect. A similar consideration frequently arises when repair times required by a particular machine or item of production equipment are examined and plotted. A bimodal (or even multimodal) histogram of such repair times implies that the data set of machine downtime durations is really two (or more) data sets, each such set being pertinent to a particular type of failure which has its own frequency of occurrence and characteristic repair time required.

4 Development Of Work Observation And Measurement Skills

Undertaking a simulation project, with its inherent necessity of on-site observation and data collection, hones the work observation and measurement skills industrial engineering students will also need for endeavors such as value stream mapping, workload leveling, and ergonomic analysis. Aside from attention to the Hawthorne Effect just mentioned, the educator should alert students to watch alertly for "hidden behaviors" such as the following – rarely mentioned in textbook exercises:

The cashier chats less with customers and may work faster as the waiting line increases in length, thereby lowering cycle time [12];

When feeling psychologically pressured by conspicuously large backlogs of items to be processed, production workers may take shortcuts – even to the point of dangerously circumventing safety procedures;

When modeling passenger arrivals at a bus stop, it is convenient and reasonable to use an exponential distribution – but very likely the arrival rate, instead of being constant, increases as the scheduled arrival time of the next bus draws near [13].

When workload in a wing of a hospital waxes heavy, the floor nurse of that unit may conveniently "forget" to tell the supervisor of the emergency room that beds in that wing are still vacant, thereby triggering delays and backlogs in the emergency room – a practice known as "bed hiding" [14].

Additionally, simulation models are often directly valuable within the industrial engineering sub-discipline of ergonomics, for improving conditions for the worker at industrial workstations. To this end, the techniques of modeling and simulation are best combined with three-dimensional visualization and integration of ergonomics standards such as (in the United States) those of NIOSH [National Institute for Occupational Safety and Health] [15].

5 Reinforcement Of Computer Science Concepts

Since simulation model building, verification, and validation has much in common with computer software design and implementation, the simulation educator has ample opportunities to reinforce lessons presumably already emphasized in a basic programming course (which may have been taught using C++, Java, or another object-oriented language). This opportunity exists even if the simulation course uses a simulation software package instead of a programming language, since it is a myth that using simulation packages eliminate the need for "coding" [16]. Many simulation educators strongly advocate that even if the students will ultimately use a simulation package, a first small model exercise (e.g., the traditional "barbershop model") should be built in a general-purpose language. Such an exercise forces students to come to grips directly with fundamental concepts such as the current events chain, future events chain, time ties for entity processing, and management of the underlying simulation clock. Having undertaken such an exercise, the student who later models with a package will be strongly motivated to read the dry documentation on *exactly* how the package handles these concepts and issues – and this "how" varies subtly but importantly across simulation software packages [17]. These lessons include the importance of modular design and development of the model, piecewise verification and validation, tracing of the model execution (often from the viewpoint of a single entity), structured walkthroughs, and other techniques [18]. Hence, when students (inevitably) encounter frustrating problems with models functioning incorrectly or illogically, (and, indeed, even before such problems appear), the wise instructor will ask students "When you have written computer programs, what steps did you take to reduce the need for debugging and to make debugging more efficient?" Students who receive this help, plus its implicit message that modeling difficulties are normal and can routinely be overcome, will be much more capable modelers, whether in research or commercial applications.

As an additional reinforcement, especially when student teams begin comparing various user scenarios, the instructor should suggest, for example, "Rather than changing the conveyor speed in the model, enter the speed in a spreadsheet and read it into the model. Users feel much more comfortable handling model input that more convenient way. Remember how your computer programming instructor advised *not* 'baking constants into programs'?"

6 Synergy Between Business And Engineering

As mentioned in the Introduction, at a given university, simulation may be taught in the college of engineering, the college of business, or both. In either case, it is fundamentally incumbent on the simulation educator to consistently and strongly emphasize synergy between the two disciplines – engineering supports business objectives. In service of this duty, the instructor in either venue should heed the advice of Professor Ståhl (a pioneer in recognizing this synergy) [19] by emphasizing the "importance of physical flows and of production economics," and the significance of "the relationship between physical flows and financial flows." Also, the rapidly increasing importance of logistical and supply chain efficiency, which is drawing attention in both industrial engineering curricula and business curricula, enhance the attractiveness of using simulation to attack logistical problems. Several instructive case studies and valuable software components directed toward the goal of integrating simulation education into logistics appear in [20]. In a business curriculum where the constraint of teaching simulation using only spreadsheets (as contrasted to specialized commercial and/or university-developed simulation software tools) prevails, [21] offers very helpful advice.

7 Conclusions

The privilege and challenge of teaching simulation comes with a high responsibility to help train the next generation of industrial engineers in a powerful technology. The educator can best discharge this responsibility by:

1. Devoting attention, both in course development and within the classroom, to the close relationships simulation has with other sub-disciplines of industrial engineering
2. Ensuring that the students' statistical background is adequate, appropriately reviewed, extended as necessary, and properly applied to analysis of both simulation input data and output results
3. Noting that simulation input data in practical and research applications is typically messy, and costly (in money, time, *and* the reservoir of client-engineer goodwill) to obtain
4. Acknowledging that the discipline of simulation owes much of its current maturity to the contributions of computer scientists and computer software developers.

8 Acknowledgement

Comments and criticisms from an anonymous referee significantly improved the presentation of this paper.

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