*Proceedings of the 2012 Winter Simulation Conference*
*C. Laroque, J. Himmelspach, R. Pasupathy, O. Rose, and A.M. Uhrmacher, eds.*

# THE EXPONENTIAL EXPANSION OF SIMULATION IN RESEARCH

Matthew J. Powers
Susan M. Sanchez
Thomas W. Lucas

Operations Research Department
Naval Postgraduate School
Monterey, CA 93943, USA

## ABSTRACT

Simulation has overcome critical obstacles to become a valuable method for obtaining insights about the behavior of complex systems. George Box's famous assessment that "all models are wrong, some are useful" referred to statistical models, but should now be reimagined to reflect that many simulation models are "right enough" to aid in decision making for important practical problems. Over the past fifty years, simulation has transformed from its beginnings as a brute-force numerical integration method into an attractive and sophisticated option for decision makers. This is due, in part, to the exponential growth of computing power. Although other analytic approaches also benefit from this trend, keyword searches of several scholarly search engines reveal that the reliance on simulation is increasing more rapidly. A descriptive analysis paints a compelling picture: simulation is frequently a researcher's preferred method for supporting decision makers and may often be the "first resort" for complex real world issues.

## 1 INTRODUCTION

The 1958 article, "Simulation Techniques in Operations Research" by John Harling, described simulation as a tool of "last resort." Harling considered simulation to be analogous to waving the white flag and settling for an approximate solution when it becomes too difficult to break a system down into a "simple" model. However, three sentences after Harling called simulation a method of last resort, he went on to mention that that the cost of simulation often outweighs the benefits because "large machines are so often involved." This criticism seems laughable today, because Harling had yet to realize the phenomenon that Gordon Moore would formalize in 1965, when he predicted the exponential growth of computing power. While simulation was once an expensive and cumbersome brute-force means of estimating an answer, today's analysts have more than 10 billion times more processing power (according to Moore's Law) than Harling did. With this expanded processing power, as well as advances in the practice of simulation, it makes sense that simulation should be an increasingly valuable technique.

Astonishingly, the argument that simulation should be a last resort is, unfortunately, alive and well fifty years later. In their 2008 article, "Dynamic Allocation of Airline Check-In Counters: A Queueing Optimization Approach," Parlar and Sharafali (2008) constructed a complex queuing model to "optimize" the number of employees that should man the counters for a modern airline. Aside from a number of oversimplified, unrealistic assumptions (such as exponential service times, independence, and a known number of only one customer at a time arrivals) that allowed for tidy math, the article claimed that the problem should be tackled via "analytical treatment" rather than "resorting" to simulation because that approach is "more realistic" and the "results are on firmer ground."

In this paper, we present the results of keyword analysis involving several large search engines. This assessment of simulation publications provides one measure of how the field has developed. We find that the usage of simulation has grown exponentially, much like the computing power that supports such models. A comparison of search engine searches for analytical keywords "linear programming" and "optimization" shows that the growth of these particular topics has not kept pace with that of simulation. A more detailed look at influential years, and historical developments leading up to these years, provides more context about the way simulation has developed as a field. We feel that understanding this context is an interesting and useful topic for both undergraduate and graduate courses, as we prepare the next generation of simulation modelers, analysts, and researchers. Moreover, teachers can use these findings to motivate their students, as they show the value of the material being taught.

## 2 EARLY ROOTS

Simulation proved useful as an analytic technique long before the astonishing growth in computing power. In order to fully understand and appreciate the impressive rise in the use of simulation, one must pay respect to the genesis of its expansion. In the early computer days of the 1950s and 1960s, simulation was by no means a new concept. The use of simulation predates computers, with perhaps the most famous example being Buffon's "needle experiment" to estimate the value of $\pi$ in 1777 (Nance and Sargent 2002). Another well-known simulation took place in 1908, when William Gosset used manual simulation to empirically derive an estimate of the probability density function for his "Student's 't' distribution (Student 1908). Over the years researchers were beginning to adopt the opinion that simulation could be used as a means of putting years of research and data to work. Similarly, the use of simulation motivated further research and stimulated advancement across all operational fields as well as the business and military worlds.

In the business world, the dollar is the bottom line. With that philosophy in mind, it makes sense that simulation began to gain popularity in the business world as the cost of sophisticated computers began falling. In 1954, Cuthbert C. Hurd wrote of a machine-shop scheduling problem that was addressed using simulation after other methods failed. Researchers from the 1953 Operations Research Society of America meeting attempted to solve the scheduling problem through analytical means. Specifically, they tried to apply "the theory of game and of linear programming," but found those methods to be of little help. What *was* of great help was the IBM 701, a machine that "calculated directly" the solution to the machine-scheduling problem through simulation (Hurd 1954).

Some of Hurd's words were unique in that he complemented mathematicians and their deep exploration of complex systems and the formulations that motivate them. He credited their studies for benefitting the physical world and for igniting the desire for further research. Hurd's tip of the hat to theoretical mathematicians is in stark contrast to the common simulation versus analytical solution arguments that exist among some scholars. Hurd suggested that "simulation by computation" was the key to unearthing deeper mysteries. He went on to mention that simulation was continuing to gain popularity thanks to the falling "unit cost of carrying out computation." In other words, computers were getting cheaper. Thinking back to the "bottom line" mentality, a cheap machine that computed the most cost-effective decision rules made perfect sense as the weapon of choice for high-level decision makers (Hurd 1954).

Speaking of weapons, let us recognize the early uses of simulation as a tool in tactical decision making. That tool is known as the "war game." In a 1955 paper titled "Simulation as an Aid in Model Building," R. P. Rich discussed a model that was based on a fleet air defense system. He stressed that the fact that a military example was being used was purely "coincidental," because almost any complex scenario could have been used to demonstrate the utility of simulation. Rich's paper is valuable in that it illustrates many benefits that arise from simulation, but his words on war gaming are particularly relevant in the way they highlight how simulation has been used to model battlefield operations. In a peculiar way, Rich (1955) used the word "machine" to describe simulation before he or the world had fully come to realize the impact that machines would have on the subject. When he wrote that, "a war game is just a special type of simulator, with the opposing teams so many parts of the machine," he was not referring to a computer that ran the model, but rather the individuals whose actions provided the decisions within the scenario and added stochastic variability. The people playing the game were key moving parts. Rich did, however, mention a "simple device" that played a role in "emulation" for the fleet air defense scenario. It was the combination of the device and the opposing team "parts" that provided the basis for this very special type of simulator. The war game would prove to be a type of model that would play an important role in strategic and tactical development across all branches of the military.

Today, the United States Department of Defense (DoD) regularly utilizes hundreds of large simulations (M&SCO 2012) to help in deciding how forces should be equipped, organized, trained, employed, deployed, and maintained. To capture the complexities of the real world, these simulations sometimes involve many thousands of input variables and can take several hours to run a single Monte Carlo experiment. One such simulation environment in widespread use is the Extended Air Defense Simulation (Teledyne Brown Engineering 2009). First deployed in 1989, EADSIM was used to analyze air operations in advance of and during operation Desert Storm. EADSIM is currently being used by nearly 400 agencies around the world. Its success derives in large part from its object oriented design and pre and post processing graphical interfaces. As with most DoD models, EADSIM has followed one of this paper's author's "Lucas's Law," that is: "The detail within a model grows in proportion to the processing power available, leaving runtimes relatively constant."

## 3 SEARCH ENGINE KEYWORD ANALYSIS

To investigate the behavior of the growth of simulation, and compare it to a few other fields, we use keyword searches for several scholarly search engines. Through data collection via varying search engines, exploration of the increase in use of simulation was not limited to the scope of specific journals. The year-by-year keyword, title, and abstract searches by journal display increases in the frequency and proportion of simulation-inspired articles. Each search engine allows for an "advanced search" that permits the filtering of articles, year-by-year, in such a way that only those articles with the central topic of simulation appear on the results page. The search engines provided by the Naval Postgraduate School library online database used for this research are JSTOR (Journal Storage), INFORMS, EBSCOhost (Elton B. Stephens Co.), and ACM DL (Association for Computing Machinery Digital Library). These search engines also display the relevant article counts per year, so data collection became a simple (yet painstaking) matter of recording the results in a form amenable for analysis.

We begin with simple graphic displays of the data, but our analysis goes further by fitting regression models. In these models, the first year of the collected data (1960) is "Year 1," 1961 is "Year 2" and so on, through "Year 51" (2010). The purpose of these fits is not to predict the future, but rather to quantify past trends and help identify years that were particularly influential in the development and acceptance of simulation as a research tool. Those years that have been identified as influential will enrich the narrative and understanding of the sorts of advancements—both technological and theoretical—that have had the greatest impact on the simulation world. Years that reflect particularly important leaps (and drops) in the frequency of simulation publication are also of interest. Due to the lag between article submission and publication, an influential year actually represents a window of time around which to investigate.

For comparison purposes, the "simulation" curves appear alongside "linear programming" and "optimization" curves that, while incomplete, were collected in the exact same matter as the simulation searches. Our intent is not to minimize the impact of these important operations research methods, but rather to examine whether the increase in simulation-based articles is mirrored across other fields that benefit from increased computational power. It is important to note that "simulation" keyword searches were excluded from "optimization" keyword searches to avoid overlap in results that included articles with both keywords. This allowed for articles that dealt with "simulation optimization"—a vibrant topic in the simulation community over the past decade—to default as "simulation" articles. For additional details and discussion, see Powers (2012).

### 3.1 JSTOR Results

In Figure 1, a simple display of the frequency of simulation articles over a fifty-year time frame paints a compelling picture. Overall, the growth during the first thirty years is less than half that of the last twenty years. The changes in JSTOR_LP and JSTOR_Opt are not nearly so dramatic. JSTOR_LP rises slightly but then falls to near its original levels, while JSTOR_Opt increases at a slow, but steady, rate.

The variability of JSTOR_Sim increases over time. So, we transform the keyword search results (JSTOR_Sim) to reduce the impact of heteroscedasticity. After fitting several regression models to the JSTOR search engine data, we settle on a final parsimonious model of the form:

$$\text{JSTOR\_Sim}^{0.5} = 5.1870 + 0.4437 * (\text{Year}).$$

This model has a p-value < 0.0001 and an $R^2$ value of 0.976. Cook's Distance measures the influence of points on this model form as a combination of their leverage and their residuals. For our final model, the most influential years are 1960, 1961, 1972, and 1973. The first two (1960 and 1961) will appear several times and will be discussed later in this analysis. The remaining unusual years are 1972 and 1973. Upon inspection of the data, one can see that there was a particularly high jump in simulation articles between 1971 and 1972 (120 articles in 1971 and 171 articles in 1972). One would expect to find some interesting happenings that would pertain to simulation on or about the year 1971. A simple internet search reveals a few possibilities (Computerhope 2012):

- 1970: Intel announced the first RAM chip, the Intel 1103, with more than 1,000 bits of memory.
- 1971: Intel developed the first microprocessor, the Intel 4004, capable of 60,000 instructions per second and a clock speed of 740 kHz.
- 1972: The C programming language was developed. It introduced structured programming and was a prelude to object-oriented programming.

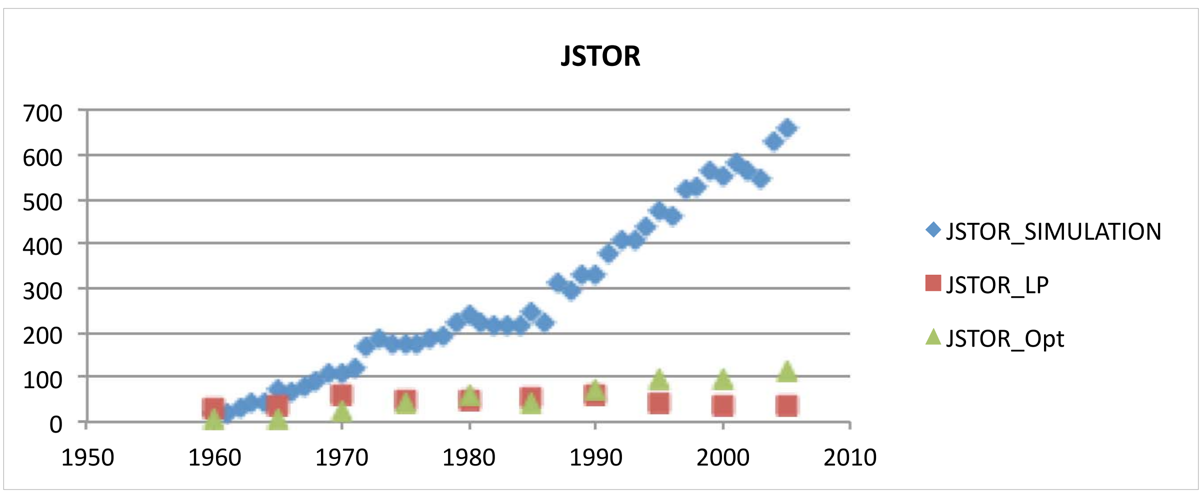


Figure 1: JSTOR data scatter plot. The growth of the simulation data is impressive when compared to the slight decline of linear programming (LP), and the slow linear growth of optimization (Opt) articles.

Further scholarly research suggests some other landmarks that very well may have contributed to a surge in simulation use.

- 1969: Alan Pritsker of Purdue University produced GASP II, which is software that aided in making simulation programming languages portable across operating systems (Hollocks 2006). At the time, this FORTRAN-based language was praised for being flexible and well document-ed—and it was already being taught at Arizona State University (Petersen 1969).

- 1970: B. W. Hollocks implemented GSP-III's features with FORTRAN as a platform to create FORSS (FORTRAN-based Simulation System). Its portability resulted in wide use (Hollocks 2006).
- 1970: Jeffrey R. Raskin's "A Tutorial on Random Number Generation" recognizes the benefits of computer-generated pseudorandom numbers, particularly their ease of generation and the ability to reproduce results (Raskin 1970). Raskin's paper represents one of many at the time that dealt with the idea of improving on existing methods of random number generation because of its necessity in the field of simulation.

The analysis of the JSTOR data identified an influential window of time from the late 1960s through the early 1970s. Computational developments have almost certainly played a role in the apparent jump of simulation-inspired articles.

### 3.2 INFORMS Results

Figure 2 displays the results from the INFORMS search engine. Once again, we see that the growth of simulation-related articles is more dramatic than the growth of articles related to linear programming. The final model for the INFORMS search engine data is

$$\text{INFORMS\_Sim}^{0.4} = 3.8179 + (5.2906 * \text{Year}) - (0.8676 * \text{Year}^2).$$

This model has a p-value $< 0.0004$ for the first-order term for Year, a p-value $< 0.05$ for the second-order term, and an $R^2$ value of 0.822. The naming convention remains the same as the JSTOR model. The influential years are 1960, 1963, and 2008 through 2010. This could simply because these are a set of "bookend" years, or because they were truly unusual. By the year 2008, advances in computing technology are so dense that it is nearly impossible to pinpoint several events that could have inspired a leap.

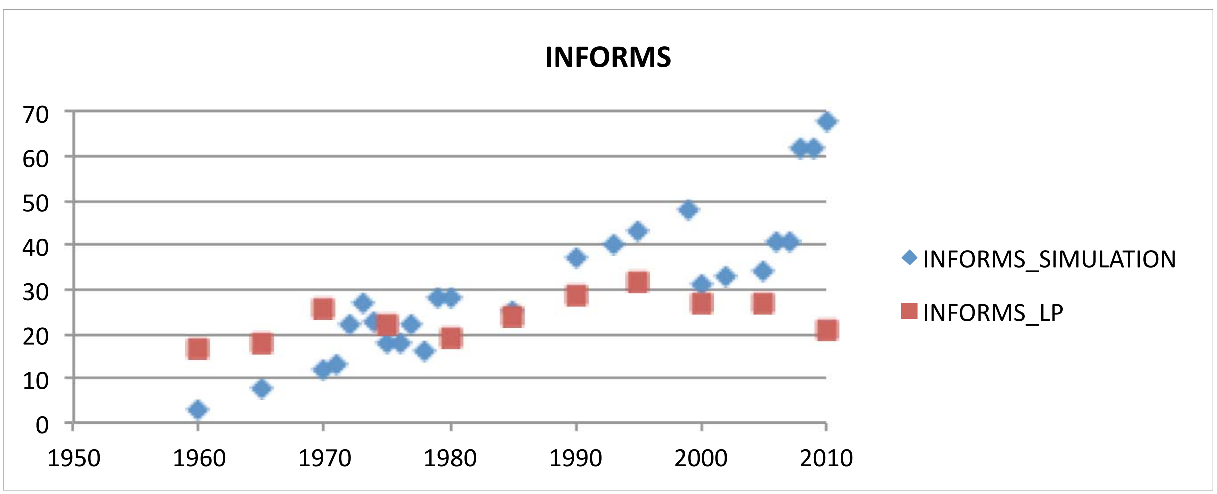


Figure 2: INFORMS data scatter plot. Once again, the simulation results grow faster than linearly while the LP results display a linear trend. The search engine did not allow for exclusion of "simulation" from "optimization," so no trend line for "optimization" exists. One of the most interesting aspects of the simulation curve is how the data points drop below the trend line for the years 2002 – 2007.

While the numerical results of the INFORMS search engine may appear to be less impressive, the fact that the search results spawn from a smaller sample of publications allows for a more intimate analysis. A look at the data, as represented on a scatterplot, reveal an interesting story. An exploration into the INFORMS society itself may explain the drop in simulation articles from 2002 to 2007. The following are summaries of key events obtained from the minutes of the INFORMS Simulation Society Business Meetings from 1999 through 2008.

- May 1999: At this time, the organization was known as the INFORMS College on Simulation. The College was acting like a Society in that, among other things, it was running the PhD colloquium at the Winter Simulation Conference and actively inviting interested students to attend the conference. The minutes reveal a decline in College representation at the annual meetings and a need to encourage more simulation-related article submissions.
- November 1999: More concern over the dropping number of simulation submissions was noted. It is mentioned that the College would have more influence if it were a society.
- October 2004: The College had over 500 members, which was large enough to be considered a Society. The members at the meeting unanimously voted to petition for Society status.
- November 2005: The organization held its first meeting as a Society. It is mentioned that simulation submissions are on the rise.
- November 2007. As a sign of great success, it is mentioned that 742 authors are contributing to the Winter Simulation Conference, and that all the hotel blocks reserved for the conference have been booked.

By 2008, the number of simulation-related articles had risen above the trend line.

### 3.3 ACM DL Results

While the earlier results show polynomial growth in the number of simulation-related articles, the results for the ACM DL search engine data are fit well by an exponential curve (p-value < 0.0001, $R^2 = 0.945$). Figure 3 shows the results from the ACM DL search engine. The final model is

$$\log(\text{ACM\_Sim}) = 3.4251 + (0.1051 * \text{Year}).$$

The influential years (in terms of Cook's Distance) are 1960, 1964, 1966, and 1967. This set of years shall be discussed in the results of the next search engine.

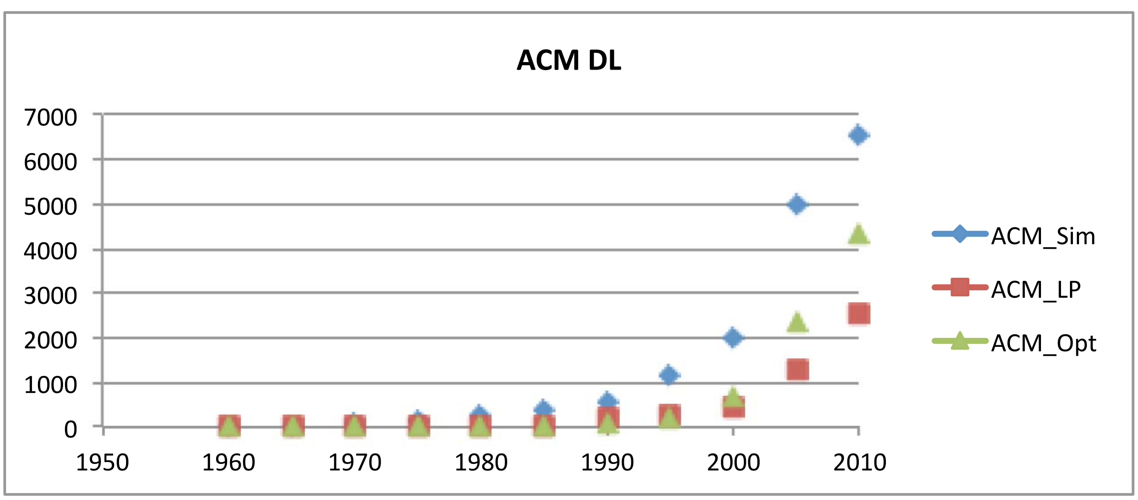


Figure 3: ACM DL data scatter plot. The ACM DL search engine allowed for separation of "simulation" from "optimization" searches. The "optimization" (Opt) and "linear programming" (LP) curves, while exponential, are dwarfed by the "simulation" (Sim) curve.

A look at the exponential curve and the data point corresponding to the year 2005 reveals some interesting characteristics. The change from 2000 to 2005 is larger than that from 2005 to 2010, while the year 2010 is below the curve. This might suggest that not much has happened between 2005 and 2010 as far as computing capability is concerned, and the world may be poised for another advance! The rather large leap in the plot between 2000 and 2005 inspires an investigation of computing history as far back as 2000.

- 2000: Intel releases the Pentium 4.
- 2003: Intel releases Pentium M.
- 2005: Intel releases Pentium D.
- 2006: Intel releases Core 2.
- 2007–2009: Intel releases several advancements to the Core 2.

These advancements, while rapid and significant, do not relate specifically to the world of simulation as to suggest that they play the most important role in simulation's growth. They have certainly improved computers as far as processing power and overall speed are concerned, but perhaps the simulation community is about to witness a breakthrough that is more than a leap in technology.

### 3.4 EBSCOhost Results

Figure 4 shows the results from the EBSCOhost search engine. As for the ACM-DL search engine, the growth is quite dramatic. The final model is

$$\log(\text{EBSCOhost\_Sim}) = 2.8499 + 0.1194 * \text{Year (p-value} < 0.0001, R^2 = 0.966).$$

The influential years (according to Cook's distance) are 1961, 1962, 1966 and 1968; 1963 (with Cook's distance 0.0768) is also very close to the influential cutoff ($4/n = 0.0784$). This set of years is remarkable in that they represent early days of computer simulation other than the "bookend" year of 1960. This particular analysis motivates a look at developments from the early to late 1960s that were influential.

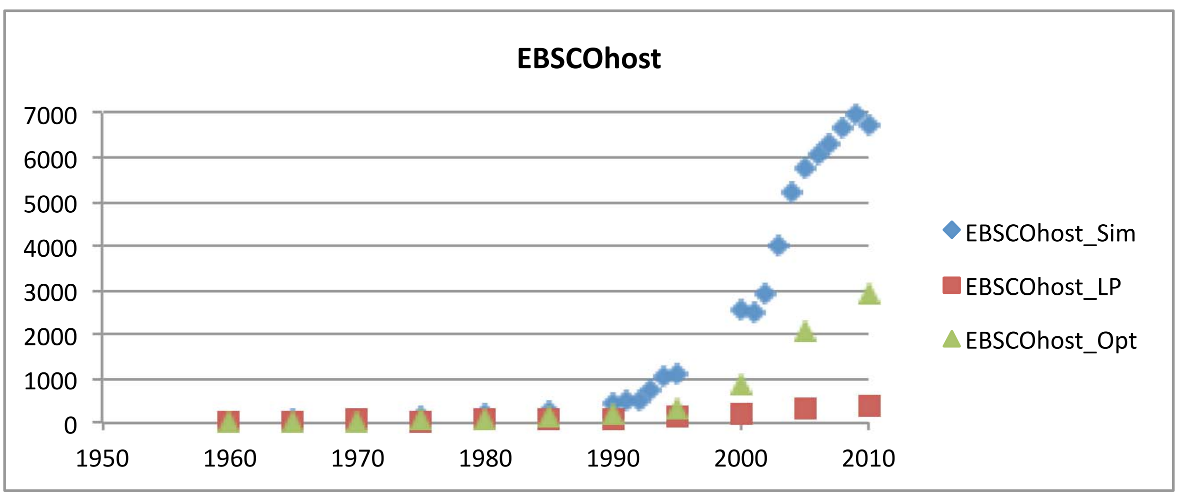


Figure 4: EBSCOhost data scatter plot. The EBSCOhost search engine allowed for separation of "simulation" from "optimization" searches. The "optimization" (Opt) curve, while representing smaller return values, is also exponential.

With 1961 through 1963, 1966, and 1968 identified as the influential years for this fit, it was necessary to look at developments in the computing world *and* the world of academia as it pertained to simulation. With hindsight being what it is, this necessity is because common knowledge tells us that technological advances could not have been the only driving force behind the advancement of simulation modeling in the 1960s.

- 1961: The programming language FORTRAN IV is created.
- 1963: IEEE is founded. IEEE will be responsible for publishing many simulation-based articles.
- 1964: BASIC is run for the first time.
- 1964: IBM introduces System/360, which uses interchangeable software. This is an example of a "third generation computer."
- 1965: Gordon Moore publishes Moore's law.
- 1969: Lewis, Goodman, and Miller publish the paper, "A pseudo-random number generator for the System/360." This paper describes "pseudo-random number generator that uses the full capacity of the 32-bit registers of IBM SYSTEM/360 computers," thereby addressing a hot topic of the day that was common to critiques of simulation.

The efforts of Peter A. W. Lewis were not the first attempt to develop random numbers and variates that behaved according to accepted statistical properties. Such efforts dated as far back as 1949, with the multiplicative congruential generator originally introduced by Lehmer. In fact, by 1971, over 200 papers had been written on the subject of random/pseudorandom number generation (Craddock and Farmer 1971). This amount of publications was indicative of the magnitude of attention that stochastic modeling was receiving. So, while he may not have broken ground in the random number generation field, Dr. Lewis was a pioneer in the simulation community mostly because he was a respected scholar who took it seriously.

As previously mentioned, one of the most prohibitive factors that had been holding back the advancement of simulation was the negative attitude that the Operational Research community expressed towards it. Dr. Lewis was one of the first highly respected scholars to visualize simulation as a valid method for modeling and research. His endorsement played a tremendous role in the eventual acceptance of simulation as a noble pursuit (Schruben 2011). Dr. Lewis's impact was so great, in fact, that he was recently awarded the 2012 INFORMS Lifetime Professional Achievement Award (LPAA) in recognition of his contributions.

## 4 DISCUSSION

The previous results show that simulation publications in two of the search engines (ACM-DL and EBSCOhost) have roughly kept pace with Moore's Law. In the other two search engines (JSTOR and INFORMS) they have polynomial growth patterns over time. In addition, deterministic analytic models are no longer achieving the popularity of stochastic models that are simulation based. A comparison of search engine searches for the analytic keywords "linear programming" and "optimization" shows that the growth of these particular topics has not kept pace with that of simulation.

### 4.1 Summary of Exponential Simulation Growth Curves

The four data sets resulted in four separate and distinct models that were used to determine the most influential years in simulation history. While some of the models share influential years, they were otherwise completely different models. They also share an obvious exponential trait. As such, they each contribute some validity to a theory offered by B. W. Hollocks in his 2006 paper, "Forty years of discrete-event simulation—a personal reflection." Hollocks provided an in-depth look at technological advances that he has observed throughout his time in the OR community. He suggested a tweak to Moore's Law as it applies to simulation. Instead of a trend based on values that would double every 18 months "until constrained by the laws of physics," Hollocks predicted that simulation's evolution would follow more of an "S-curve," as shown in Figure 5 (Hollocks 2006).

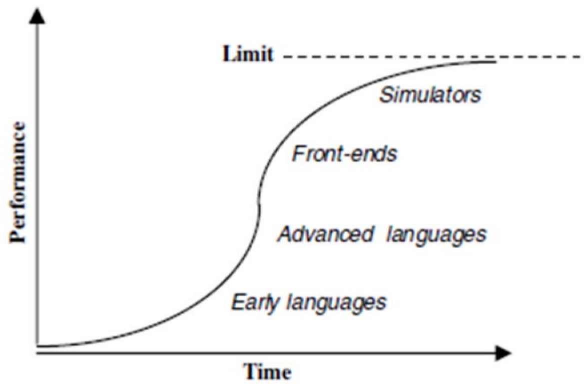


Figure 5: S-curve of simulation growth (Hollocks 2006).

The curve proposed by Hollocks says that, as computing capability reaches its physical upper-bound—a bound that Gordon Moore himself predicted would occur around 2015 to 2020—limited scope for improvement might be left. What room does remain may be user-oriented improvements such as ease of model building and display capabilities. Such a theory, however, would mean that simulation has enjoyed success and expansion over time mainly because of technological advances. A "squinty-eyed" look at the curves presented in this research may suggest that Hollocks is correct in giving so much credit to improvements in processing speed and software. Of advanced processing speed, Hollocks said that "[i]n addition to permitting the same tools to run faster, it has also permitted the tools to carry more function and feature, leading to the current status of simulators." Simply put, Hollocks is suggesting that the simulation field is getting very close to being as advanced as it will ever be (Hollocks 2006). The authors of this paper have another suggestion.

## 4.2 What is Next For Simulation

Computational power provides benefits for both modeling and analysis. As we mention in the analysis of the ACM DL data, the simulation community may be poised for breakthroughs that augment enhanced processing speed. The technological ceiling that Moore has predicted to be right around the corner may still hold true for the physical limits of computers and speed, but the future is wide open for simulation. At least it will be when improved analysis approaches, such as simulation optimization and efficient design of experiments, are readily available to the simulation analyst and in widespread use.

A recent leap of note was the June 2012 unveiling of a supercomputer known as IBM's "Sequoia," a bank of over 1.5 million processing cores capable of performing over 16 quadrillion operations per second (16 petaflop/s) (Wait 2012). Such capability is so difficult to conceptualize that it is not unreasonable to say that it may be approaching the limits of physics. It is difficult to imagine a model that can act more efficiently than one that is being executed on the type of technology that can support petaflop-speed calculation. It would seem that such massive computing power would be enough to explore the limits of even the most complex model. However, due to the "curse of dimensionality" even this level of computational power is not sufficient to provide a "brute-force" analysis for, e.g., conducting thorough sensitivity analyses of the complex simulation models that are pervasive in operations research, industry, business, and military simulations. In fact, a "brute-force" approach involving a single replication of a two-level experiment that involves 100 factors (examined at all $2^{100}$ potential combinations) on a model consisting of a single elementary operation would take over 2.5 million years to complete. The moral is that advances in simulation cannot rely on advances in technology alone.

Fortunately, we need not wait for suitable analysis approaches to be developed. If simulation has started to level out in terms of technology-based advancements, then the design of experiment (DOE) methods have the potential to break the ceiling. Imagine the aforementioned two-level, 100 factor experiment as the "ceiling" for a machine as capable as IBM's Sequoia. This is a stretch of the imagination, as not even the most patient analyst can spare millions of years for a single replication. Nonetheless, smart experimental designs allows an analyst to identify the significant main effects and a modest number of interactions among these 100 factors using as few as a few hundred carefully-specified combinations. For example, thanks to the DOE method of fractional factorials, commonly known as "screening designs" for identifying important factors from an experiment, there exists a resolution V $2^{120-105}$ design for two-level experiments consisting of up to 120 factors that allows for all main effects and two-way interactions to be estimated in 32,768 runs, and this can easily be expanded into a design permitting the estimation of full second-order metamodels (Sanchez and Sanchez 2005).

Similarly, imagine a simulation model running on a computer with processing speed that allows for each design point to take only one second to run. Such a scenario is often feasible considering the processing speeds of commercially available systems. Now suppose that this model is comprised of 29 factors. The "brute force" simulation approach would require over 17 years using a $2^{29}$ full factorial design. This takes the wind out of the ability to simply ride the technological wave. Now, apply the benefits of Latin hypercube sampling and the same model would take under five minutes using a 257 design point NOLH design (Cioppa and Lucas 2007). In other words, one can efficiently squeeze a substantial amount of experimental information from such a 29-factor experiment in less than five minutes. Efficient designs also allow for flexibility in modeling, which is particularly useful in a world where the analyst must account for last-minute "good ideas" offered by his or her clients and there may be considerable uncertainty about the significant factors and the response forms.

The theories behind DOE cannot take full credit for such flexibility. It is a combination of the computational capability available on modern computers and the "art" of experimental design. This marriage of the processing power of today's machines and the power provided by efficient experimental design is an example of both sides of the simulation argument playing nice. The idea of optimality is under the hood of many efficient designs in that the combination of factor settings provides the "best" estimation of a specified response. Furthermore, the concept of "optimality" permeates the practical real world where "sampling is expensive—the goal is to take no more samples than absolutely necessary." That is, even if you could spare the time to run as many replications of your complex model as you wanted, you do not have to (Sanchez and Wan 2012). The optimality of efficient design is holding hands with the impressive capabilities of modern computers to create simulation models that represent a powerful force that is anything but "brute." Of course, another advantage of many space-filling designs, such as NOLHs, is that they are robust in the sense that they allow analysts to explore a breadth of diverse possible metamodels (Kleijnen et al. 2005; Vieira Jr. et al. 2011). For more on the use of experimental design for simulation (including additional references), please see the tutorial by Sanchez and Wan (2012) earlier in this Proceedings. Advances in simulation optimization (Fu 2002) are also providing new opportunities for simulation analysts; there are several sessions in the 2012 WSC Proceedings, and an entire track in the 2011 WSC Proceedings.

In order for analysts to take advantage of new design and analysis capabilities, they need the proper software tools. Fortunately, new simulation environments are making it easier to build simulations, conduct many experiments in parallel using efficient experimental designs, and analyze the output with statistical tools and graphical playbacks. The future of simulation is moving beyond the emphasis on programing and conducting a small number of experiments. We see a future in which modern design and analysis capabilities allow researchers to get orders of magnitude more experimental information from their models—and that these possibilities become the standard practice. Indeed, the simulation community is just beginning to utilize these powerful capabilities.

## 5 CONCLUSIONS

The exponential nature of simulation's growth over time has been made apparent without a need for deep exploration or analysis. The model fitting and analysis of influential years has pointed out some possible candidates for the most significant advances in the computing *and* academic fields. The takeaway is that simulation did not simply ride the technological wave and only take advantage of improved processing speeds. There have been serious contributions in terms of elegant thought, such as new algorithms for pseudo-random number generation, simulation optimization, and efficient design. As we educate the next generation of simulation practitioners and researchers, it is important to let them know that the "last resort" stigma that has been so aggressively applied to simulation in the past is not an accurate reflection of the field. Furthermore, as technologies that leverage higher processing capabilities, such as simulation software and efficient high-dimensional design of experiments, continue to advance, we expect the exponential growth in the use of simulation to continue for the foreseeable future. For many complex real world problems requiring complex models, simulation will increasingly be the tool of "first resort."

## REFERENCES

Cioppa, T. M., and T. W. Lucas. 2007. "Efficient Nearly Orthogonal and Space-filling Latin Hypercubes." *Technometrics* 49(1): 45–55.

Computerhope. 2012. Computer History 1960–1980. http://www.computerhope.com/history/196080.htm [Accessed July 16, 2012].

Craddock, J. M., and S. A. Farmer. 1971. "Two Robust Methods of Random Number Generation." *The Statistician* 20(3): 55–66.

Fu, M. 2002. "Optimization for Simulation: Theory vs. Practice." *INFORMS Journal on Computing* 14(3): 192–215.

Harling, J. 1958. "Simulation Techniques in Operations Research." *Operations Research* 9(1): 9–21.

Hollocks, B. W. 2006. "Forty Years of Discrete-event Simulation: A Personal Reflection." *Journal of the Operational Research Society* 57: 1383–1399.

Hurd, C. C. 1954. "Simulation by Computation as an Operations Research Tool." *Journal of the Operations Research Society of America* 2(2): 205–207.

INFORMS Simulation Society. 2012. Meeting Minutes. Last modified December, 2011. http://www.informs.org/Community/Simulation-Society/Society-Information/Meeting-Minutes.

Kleijnen, J. P. C., S. M. Sanchez, T. W. Lucas, and T. M. Cioppa. 2005. "A User's Guide to the Brave New World of Designing Simulation Experiments." *INFORMS Journal on Computing* 17(3): 263–289.

Lewis, P. A. W., A. S. Goodman, and J. M. Miller. 1969. "A Pseudo-random Number Generator for the System/360." *IBM Systems Journal* 8(2): 136–146.

Moore, G. E. 1965. "Cramming More Components onto Integrated Circuits." *Electronics Magazine* 38(8): 4.

M&SCO (Modeling & Simulation Coordination Office). 2012. Description of M&SCO. http://www.msco.mil/descMSCO.html [Accessed July 16, 2012].

Nance, R. E., and R. G. Sargent. 2002. "Perspectives on the Evolution of Simulation." *Operations Research* 50(1): 161–172.

Parlar, M., and M. Sharafali. 2008. "Dynamic Allocation of Airline Check-in Counters: A Queueing Optimization Approach." *Management Science* 54(8): 1410–1424.

Petersen, C. C. 1969. "GASP II Simulation of Parts Inventory for Electronic Fuze Production." In *Proceedings of the Third Conference on the Applications of Simulation,* 454–469.

Powers, M. J. 2012. "The Exponential Expansion of Simulation: How Simulation has Grown as a Research Tool." M.S. thesis, Department of Operations Research, Naval Postgraduate School, Monterey, California.

Raskin, J. R. 1970. "A Tutorial on Random Number Generation." *Computers and the Humanities* 4(5): 307–311.

Rich, R. P. 1955. "Simulation as an Aid in Model Building." *Journal of the Operations Research Society of America* 3(1): 15–19.

Sanchez, S. M., and P. J. Sanchez. 2005. "Very Large Fractional Factorials and Central Composite Designs." *ACM Transactions on Modeling and Computer Simulation* 15(4): 362–377.

Sanchez, S. M., and H. Wan. 2012. "Work Smarter, Not Harder: A Tutorial on Designing and Conducting Simulation Experiments." In *Proceedings of the 2012 Winter Simulation Conference*, Edited by C. Laroque, J. Himmelspach, R. Pasupathy, O. Rose, and A.M. Uhrmacher, forthcoming. Piscataway, New Jersey: Institute of Electrical and Electronic Engineers, Inc.

Schruben, L. W. 2011. Letter nominating Peter Lewis for the INFORMS Simulation Society's Lifetime Professional Achievement Award.

Student. 1908. "The Probable Error of a Mean." *Biometrika* 6(1): 1–25.

Teledyne Brown Engineering, Inc. 2009. Extended Air Defense Simulation (EADSIM). Last updated June 2, 2009. http://www.eadsim.com [Accessed July 16, 2012].

Wait, P. 2012. "IBM's Sequoia is World's Fastest Supercomputer." *Information Week*, June 19, 2012. http://www.informationweek.com/news/government/info-management/240002268.

Vieira Jr., H., S. M. Sanchez, K. H. Kienitz, and M. C. M. Belderrain. 2011. "Improved Efficient, Nearly Orthogonal, Nearly Balanced Mixed Designs." In *Proceedings of the 2011 Winter Simulation Conference*, Edited by S. Jain, R. R. Creasey, J. Himmelspach, K. P. White, and M. Fu, 3600–3611. Piscataway, New Jersey: Institute of Electrical and Electronics Engineers, Inc.

## AUTHOR BIOGRAPHIES

**MATTHEW J. POWERS** is a Flight Officer in the United States Navy. He received his B.S. in English from the United States Naval Academy. Upon graduation he attended flight school in Pensacola, Florida. He has completed two operational tours with two separate jet types. He flew the S-3 Viking while deployed with The USS George Washington Carrier Strike Group and the EA-6B Prowler while deployed with the USS John C. Stennis Carrier Strike Group. He is working on his M.S. in Operations Research at the Naval Postgraduate School. The work presented here is part of his thesis on the exponential rise in the use of simulation. His e-mail is mjpowers@nps.edu.

**SUSAN M. SANCHEZ** is a Professor in the Operations Research Department at the Naval Postgraduate School (NPS), with a joint appointment in the Graduate School of Business & Public Policy. She received a B.S. in Industrial & Operations Engineering from the University of Michigan, and an M.S. and Ph.D. in Operations Research from Cornell University. She is a Co-director of the Simulation Experiments & Efficient Designs (SEED) Center for Data Farming at NPS. Professor Sanchez leads the Design of Experiments Subgroup of NATO's MSG-088: Data Farming in Support of NATO. She has been active in the simulation community in a variety of capacities, including positions on the WSC Board of Directors, and is currently the Chair Elect of the American Statistics Association's Section on Statistics in Defense and National Security. Her e-mail address is ssanchez@nps.edu and more information can be found at the SEED Center's web pages at http://harvest.nps.edu.

**THOMAS W. LUCAS** is a Professor in the Operations Research Department at the Naval Postgraduate School where he has been a leader in advancing the development and use of simulation experiments and efficient design since 1998. As part of this, he co-founded and is the Co-Director of the Simulation Experiments and Efficient Designs (SEED) Center (http://harvest.nps.edu). Professor Lucas has a B.S. in Industrial Engineering and Operations Research from Cornell University, an M.S. in Statistics from Michigan State University, and a Ph.D. in Statistics from the University of California at Riverside. A detailed vita can be found at http://faculty.nps.edu/twlucas/. His email address is twlucas@nps.edu.