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SIMULATION MODELING IN ORGANIZATIONAL AND MANAGEMENT RESEARCH

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Simulation modeling provides a powerful methodology for advancing theory and research on complex behaviors and systems, yet it has been embraced more slowly in management than in some associated social science disciplines. We suspect that part of the reason is that simulation methods are not well understood. We therefore aim to promote understanding of simulation methodology and to develop an appreciation of its potential contributions to management theory by describing the nature of simulations, its attractions, and its special problems, as well as some uses of computational modeling in management research.

Managerial behaviors and organizational outcomes increasingly are recognized to be the result of the interaction of multiple interdependent processes. Progress in understanding these phenomena depends, in part, on the ability to incorporate more complexity into management theory and to conduct research on the consequences of the resulting theory.

Traditional approaches to theory development are limited in their ability to analyze multiple interdependent processes operating simultaneously. Even when the individual processes are well understood, analyzing their interdependent behavior poses difficulties, because the processes involved may interact in complicated and unforeseen ways. And because the interactions typically produce nonlinear system behavior with feedback, empirical analysis using the general linear model has limited value, especially when (as is typical) samples are sparse in the regions of greatest interest.

In studying the complexities of managerial and organizational behavior, a more systematic methodology for theory development and analysis may prove useful. Specifically, we believe that simulation or computational modeling has unique advantages in this respect (Axelrod, 1997; Taber & Timpone, 1996). Well suited for the study of complex behavioral systems, simulations show greatest utility for gaining theoretical insight through developing theories and exploring their consequences (Cohen & Cyert, 1965).

Yet researchers in the academic field of management have been slow to take advantage of simulation methods. Scholars in some related social science disciplines, most notably psychology, seem to be far ahead, and the application of simulations by management practitioners to set policy and study organizational problems is quite extensive (Carley, 2003). So management theorists have the opportunity to benefit by taking fuller advantage of simulation methods.

Our aim in this article is to provide an explanation and overview of simulation methodology. By doing so, we seek to encourage management scholars to become users of simulation methods and to become better informed consumers of simulation-based research. An understanding of what simulations are and how they work is a prerequisite for appreciating the potential contributions of simulation analysis to management theory, as well as for identifying problems and shortcomings in simulation work.

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We begin by providing some background on the science of simulation. We then show that simulation research in management has had less impact than in other social sciences, at least as indicated by publications in leading journals. After addressing the benefits of formal models in general, we consider simulation modeling in detail. We discuss what simulations are and how they work. We describe different types of simulation models, discuss some common research uses of simulations, and consider some key issues and problems in the process of doing simulation research. We conclude by summarizing the benefits and limitations of simulation-based work.

A BRIEF HISTORY OF COMPUTER SIMULATIONS

Historically, scientific progress has relied on two methodologies: (1) theoretical analysis or deduction and (2) empirical analysis or induction. In the deductive form of science, a set of assumptions is formulated and the consequences of those assumptions are then deduced. Often, the assumptions are stated as mathematical relationships, and their consequences are deduced through mathematical proof or derivation. This strategy has led to some extraordinary successes, particularly in physics—the general theory of relativity being the prime example. A major problem with this approach, however, is that derivation can be mathematically intractable—mathematical techniques may be inadequate to determine the consequences of assumptions analytically. This problem seems to be common in the social sciences, perhaps because of the complexity and stochastic nature of social processes, and it has led researchers to choose assumptions (such as perfect rationality, perfect information, and unlimited budgets) on the basis of their usefulness for deriving consequences rather than because they correspond to realistic behavior. Even when elegant results can be obtained in the form of mathematical equations, these equations can sometimes be solved only for special cases; for example, the equations of general relativity can be solved for the case of spherical symmetry, but no general solutions are known.

In the inductive form of science, researchers proceed by obtaining observations of variables (data) and then analyzing the data to uncover relationships among the variables. This approach has also been highly successful—an important example being the development of the periodic table of the elements before atomic structure was understood. A variant of this approach has been used to test the predictions of theoretical analysis. A major problem with empirical work, however, is the availability of data. Variables may be unobservable (e.g., secret agreements) or difficult to measure (e.g., the power of organizational subunits); the problems compound with the need for comparable measures across a sample and, in the case of dynamic analysis, across an extended time frame. Consider the prospects for obtaining reliable data on subunit power across a sample of organizations over a period of many years.

Computer simulation is now recognized as a third way of doing science (Axelrod, 1997; Waldrop, 1992).[1] It renders irrelevant the deductive problem of analytic intractability—mathematical relationships can be handled computationally using numerical methods. It also partially overcomes the empirical problem of data availability, since a simulation produces its own "virtual" data. Because of these features, computer simulation can aid enormously in theory construction. It allows theorists to make realistic assumptions rather than to compromise with analytically convenient ones, as is common in deductive theory. Finally, a computer simulation can be used to generate hypotheses that are integrated and consistent (Carley, 1999).

While simulation can be distinguished from deduction and induction, it does have similarities to these other methods. Simulations resemble deduction in that the outcomes follow directly from the assumptions made (without the constraint of analytic tractability). Simulations resemble induction in that relationships among variables may be inferred from analyzing the output data (although the data are generated by simulation programs rather than obtained from "real-world" observations).

The first well-known computer simulation involved the design of the atomic bomb in the Manhattan Project during World War II. The complex systems of equations used in the de-

[1] Physical scientists, who have used simulations for over half a century, are now adding a fourth way of doing science—data mining (Schechter, 2003).

sign process could not be solved analytically, and data were impractical; besides the unknown risks of attempting to set off atomic explosions, there was not enough fissionable material available at the time for even one test. The atomic bomb simulations began before the advent of programmable digital computers and involved a complex process of using punch card sorters (Feynman, 1985; Gleick, 1992). The modern method for conducting simulations on programmable computers using Monte Carlo techniques (described later in this article) was developed by Stanislaw Ulam in 1946 in conversations with John von Neumann and implemented shortly thereafter when the digital computer MANIAC arrived at Los Alamos (Ulam, 1991). Over the decades following the war, simulation became an accepted and widely used approach in physics, biology, and other natural sciences, with the social sciences lagging behind.

In the social sciences the use of computer simulation methodology was pioneered by James March and colleagues (Cohen, March, & Olsen, 1972; Cyert & March, 1963). Early computational work played a central role in developing theories of organizations (Lomi & Larsen, 2001). But during the 1970s and 1980s, computer simulation "settled into a tiny niche, mostly on the periphery of mainline social and organizational science" (March, 2001: xi).

One reason for this may be accessibility; simulation is given short shrift in most social science methodological training curricula, so many researchers lack the background to evaluate and interpret simulation studies. Many social scientists—in contrast to most natural scientists—may also be averse to the level of abstraction involved in simulations (as well as in mathematical modeling in general). In addition, the development of simulation models requires a theoretical grasp of underlying microlevel processes, which are often better understood for natural science phenomena than for social behavior.

Social simulation has gradually become more accepted because of a variety of developments. These include the spreading recognition of the efficacy of simulation methods, the increasingly sophisticated simulation infrastructure, the growing base of researchers with simulation training, and the development of specialized journals supporting simulation work. But, in our view, it still falls short of the methodology's potential for contributing to management theory.

THE IMPACT OF SIMULATION RESEARCH IN MANAGEMENT

Although some simulation studies were published in major management journals in the 1980s (e.g., Burton & Obel, 1980; Malone, 1986; Masuch & LaPotin, 1989; Padgett, 1980), as well as in books (e.g., Nelson & Winter, 1982), simulation-based work did not begin to appear in management and social science journals with any regularity until the 1990s. To assess the impact of simulation, we examined its use in management journal articles and compared that with its use in journals of other social sciences. Specifically, we calculated the proportion of simulation-based articles appearing in leading journals across various disciplines for the ten-year period 1994 to 2003. We counted all those articles using computer simulation methods, including papers where simulation was used in conjunction with other methods, such as experiments and empirical analysis, but excluding simulation-assisted human experiments, comments, replies, and so forth. Our findings are summarized in Table 1.

Table 1 shows that, in the leading management and social science journals, about 8 percent of the published papers used simulation methodology. Among leading management journals, *Management Science* has published a substantial proportion of simulation papers. This is somewhat misleading, however, since many of these simulations do not address social or behavioral issues. Except for *Management Science,* the rate for management journals is much lower, varying from 3.7 percent in *Organization Science* to 0.3 percent (only two papers in ten years) for the *Academy of Management Journal*.

Among the social science journals, sociology shows a low-frequency pattern similar to management. But simulations are more prevalent in the other social science disciplines, led by psychology's *Psychological Review,* where, in some years, more than half of the articles were simulation papers. The results for economics may actually understate the use of simulation in this field, since these journals typically publish more papers; for the ten-year period we examined, the *American Economic Review* published 118 simulation papers.

TABLE 1
Proportions of Simulation Articles in Social Science Journals, 1994–2003

Discipline	Journal	Proportion of Simulation Articles[a]
Management	*Academy of Management Journal*	.003
	Administrative Science Quarterly	.022
	Management Science	.236
	Organization Science	.037
	Strategic Management Journal	.010
Sociology	*American Journal of Sociology*	.024
	American Sociological Review	.024
Psychology	*Psychological Bulletin*	.034
	Psychological Review	.378
Economics	*American Economic Review*	.073
	Journal of Political Economy	.074
Political science	*American Journal of Political Science*	.065
	American Political Science Review	.047
Total		.079

[a] These numbers are ten-year averages.

It is unclear why management and sociology lag behind psychology, economics, and political science in simulation papers in leading journals. But the pattern implies that simulation methods have made less of an impact in management than in most social sciences. While the emergence of specialized simulation journals (such as *Computational and Mathematical Organization Theory, Journal of Artificial Societies and Social Simulation,* and *Simulation Modelling Practice and Theory*) has been a boon to simulation work, the readership of these journals tends to be limited to simulation specialists. Publication in leading journals is necessary for simulation research to disseminate to a wider audience and to inform the development of management theory more generally.

We believe that the field of management will benefit from a better understanding of what simulations are and a broader recognition of what they can contribute to theory development. We further suggest that the payoffs are expected to be especially high for research involving complex interactive systems. By requiring formal modeling, simulations also impose theoretical rigor and promote scientific progress (Burton & Obel, 1995). So before describing simulations and their uses, we briefly discuss formal models in general.

FORMAL MODELING

Simulations are based on formal models. For our purposes, we define a formal model as a precise formulation of the relationships among variables, including the formulation of the processes through which the values of variables change over time, based on theoretical reasoning. The formalism may specify mathematical relationships, such as *equations,* or sets of explicit *rules,* such as "when X occurs, then do Y," or a combination of the two. We find great value in using formal models, although we would be the first to admit that they provide only one of several possible avenues for theory development and are no substitute for substance and insight.

Consider, for instance, the views of David Kreps, a distinguished economist who is widely considered a premier formal model builder. According to Kreps (1990: 6–7), the main advantages of a good formal model are

- *clarity* ("It gives a clear and precise language for communicating insights and contributions");
- *ease of comparability* ("It provides us with general categories of assumptions so that insights and intuitions can be transferred from one context to another and can be cross-checked between different contexts");
- *logical power* ("It allows us to subject particular insights and intuitions to the test of logical consistency"), and
- *transparency* ("It helps us to trace back from 'observational' to underlying assumptions to see what assumptions are really at the heart of particular conclusions").

In a more casual vein, we would add that a model provides a different perspective on a research problem, and this fresh look often proves insightful in and of itself.

Kreps' list makes clear that model building and models are tools of research, not ends unto themselves. It is hard for us to understand why anyone would object to the use of potentially useful tools. This is not to say, of course, that models will necessarily lead to Kreps' outcomes, or that such a list will always provide the only direction for today's computational models, which increasingly have been focusing on multilevel phenomena that are often mathematically intractable. The point is to evaluate what can be gained from using the model, not the model-building enterprise itself.

SIMULATION MODELING

What is a computer simulation? How is it used? What special issues are associated with its use? While experienced simulators may find these questions unproductive, we believe it is important to make simulation understandable to researchers without extensive backgrounds in computer programming or mathematical analysis.

Simulations As Formal Models

As with any formal model, the development of a simulation model constitutes an exercise in theory development. Constructing a simulation model involves identifying the underlying processes thought to play key roles for the behavior of an actor (or organizational system) and formalizing them as mathematical equations or sets of computational rules. Determining the key processes and how they interact is essentially a theoretical endeavor; formally specifying the operation of the underlying processes is also such an endeavor, since previous research rarely provides a formal specification of the processes, necessitating the development of new ideas. The resulting model not only is the outcome of theoretical development but also *is* the theory in the sense that it embodies the theoretical ideas (Carley & Gasser, 1999; Cohen & Cyert, 1965), just as the field equations embody the theory of general relativity or the Black-Scholes model embodies the theory of option pricing. Hypotheses are not normally offered in simulation research, since the consequences of the complex interactions of the model's components are not logically obvious (if they were, a simulation would not be necessary); instead, the model's consequences are determined computationally, and the findings may themselves be regarded as hypotheses or theoretical conclusions. In other words, the entire simulation process constitutes a methodology for theory development, starting with assumptions and model construction and ending with predictions of the theory (findings).

A strength of simulation is the theoretical rigor introduced by formal modeling. A process may appear to be well understood, but an attempt to specify an equation for the operation of the process over time often exposes gaps in this understanding. Formalizing processes imposes a discipline on theorizing, forcing researchers to come to grips with thorny issues that have previously been dealt with only by handwaving, or that have not even been recognized. At a minimum, formalization promotes scientific advancement by forcing cloudy areas to be addressed, resulting in a clear specification that can be subjected to analysis and subsequent refinement.

What Is a Computer Simulation?

A computer simulation begins with a model of the behavior of some system the researcher wishes to investigate. The model consists of a set of equations and/or transformation rules for the processes by which the variables in the system change over time. The model is then translated into computer code, and the resulting program is run on the computer for multiple time periods to produce the outcomes of interest.[2]

We focus here on computer simulations of organizational processes using formal simulation models with discrete-time designs. While a few simulations use or approximate continuous time (Sastry, 1997), most simulations model time in discrete intervals, where the simulation uses predetermined time intervals (e.g., a simulation day, month, or year), with the state of the simulated system updated each time interval as the simulation clock advances during the computer run.

Simulation models may be either stochastic or deterministic. Stochastic models contain probabilistic components so that the behavior of a model in any particular instance depends, to some extent, on chance. Stochastic simulations

[2] Actually, the model could consist of a single process, although simulations are usually used to study systems in which multiple processes operate simultaneously. Also, one could use a static model—for example, to generate probability distributions for variables lacking analytic density functions (as in Harrison & March, 1984)—but most simulations in organizational research are dynamic.

typically use Monte Carlo methods. Essentially, a Monte Carlo approach relies on the idea that the probabilistic components have distributions that can be sampled to obtain values used as inputs for the computations in a model, using random number generators. Single draws from these distributions may not, of course, produce representative outcomes for the model. But by repeating the process a large number of times, a simulation produces sets of output values with distributions that characterize the model's behavior. Deterministic models have no probabilistic elements and produce the same outputs each time, so they need to be run only once for a given model.

To illustrate some simulation concepts, we use Harrison and Carroll's (1991, 2006) simulation of cultural transmission in organizations. This simulation model consists of three basic processes. New members enter the organization (first process), current organizational members socially influence one another (second process), and some members exit the organization (third process). Although each of these three processes has been investigated thoroughly, most research on organizational culture has focused (at least implicitly) on the socialization of current organizational members. New insights into organizational culture can likely be gained by studying an organizational system that includes entry and exit as well as socialization. The simulation makes it possible to do this, including understanding how the three basic processes interact to generate the behavior of the organization's cultural system.

This kind of investigation does not square neatly with many social scientists' ideas about cumulative research programs. Many methods textbooks state that successful development of cumulative knowledge about a phenomenon proceeds linearly and sequentially down a path, from less structured qualitative approaches to the highly structured approach of formal modeling. Ragin's (1994) textbook, for example, claims that qualitative research methods work best for developing new theoretical ideas and making interpretations of a theory or a phenomenon's significance; quantitative research is directed toward identifying general patterns and making predictions.

Our view is that the presumed linear sequence of cumulative knowledge development from qualitative (and informal) to quantitative (and formal) may be debilitating and even counterproductive. Some phenomena are inherently more difficult to measure, and although we admire attempts to do so, we do not believe that theoretical progress needs to wait for breakthroughs in measurement technology. In particular, we see no reason why theoretical insights from qualitative and other observations might not be directly translated into formal models. Indeed, we believe that doing so potentially improves the theory in many ways and that formalization efforts may, in turn, help empirical researchers better target their efforts. For instance, such a strategy has been pursued with great success by researchers in organizational ecology (see Carroll & Hannan, 2000).

Definition

Formally, we define a computer simulation as a computational model of system behavior coupled with an experimental design; the execution of the design is sometimes called a "virtual experiment" to distinguish simulation experiments from traditional laboratory experiments. The computational model consists of the relevant system components (variables) and the specification of the processes for changes in the variables. The equations or rules for these processes specify how the values of variables at time $t+1$ are determined, given the state of the system at time t. In stochastic models these functions may depend partly on chance; the equation for the change in a variable's value may include a disturbance term to represent the effects of uncertainty or noise, or a discrete process such as the turnover of an organizational member may be modeled by an equation that gives the probability or rate of turnover.

The model's functions typically require the investigator to set some parameters so that computations can be carried out. For example, in the Harrison and Carroll (1991, 2006) simulation of cultural transmission in organizations, one process is the arrival of new members of the organization in each time period. These new members arrive at a certain rate with certain enculturation (fitness) scores. The arrival rate, as well as the mean and standard deviation of the enculturation scores of the pool from which new members are selected, are all parameters of the process.

The experimental design consists of five elements: the initial conditions, the time structure, the outcome determination, iterations, and variations. The computational model specifies how the system changes from time t to time $t+1$, but not the state of the system at time 0, so initial conditions must be specified. For example, in the cultural transmission simulation, initial conditions include the number of members in the organization at the beginning of the simulation and their individual enculturation scores.

The time structure sets the length of each simulation time period and the number of time periods in the simulation run. The length of the time period links the simulation to observation; for example, it may be desirable for turnover rates in a simulation to correspond the realistic turnover rates for an organization. Once the time period is determined, the number of time periods to be simulated can be set to obtain the desired total duration of the simulation run, or a rule may be established to stop the run once certain conditions (e.g., system equilibrium) are met.

The outcomes of interest are often some function of the behavior of the system and need to be calculated from system variables. Outcomes may be calculated for each time period or only at the end of the run, depending on the simulation's purpose. In the cultural transmission simulation, the outcomes of interest are the mean and standard deviation of the enculturation scores of the organizational members and the number of periods it takes the system to reach equilibrium.

In stochastic models the simulation outcomes will vary somewhat from run to run, depending on the random numbers generated, so the results of one run may not be representative of the average system behavior. To assess average system behavior as well as variations in behavior, multiple iterations are necessary—that is, the simulation run must be repeated many times (using different random number streams) to determine the pattern of outcomes.

Finally, the entire simulation process described above may be repeated with different variations. Both the parameter values and the initial conditions can be varied for two reasons. First, the behavior of the system under different conditions may be of interest; the examination of such differences is often a primary reason for conducting simulation experiments. In the cultural transmission simulation, for example, turnover rates of organizational members are varied to examine differences in system behavior under conditions of low turnover and high turnover. This type of variation is analogous to standard strategies for experimental design. In both simulations and laboratory experiments, the context can be controlled and manipulated to assess the effects of variations (Burton, 2003). Simulations obviously have disadvantages relative to laboratory experiments, since the "actors" are artificial agents rather than human subjects. But they also have some advantages, including perfect control (unobserved heterogeneity and unwanted influences are eliminated), less constraint on sample size, the ability to manage greater complexity in experimental design, and the ability to precisely track the behavioral steps leading to the outcomes of interest (the computer's memory is not subject to the biases of subjects' recollections and to other problems of reconstructing causes of human and organizational behavior). As with laboratory experiments, sound experimental procedures are essential in designing simulation experiments.

The second reason for introducing variations involves examining how sensitive the behavior of the system is to the choices of parameter settings and initial conditions. If the behavior does not change much with small variations in conditions, then the system's behavior is robust, increasing confidence in the simulation process. Alternatively, observing significant behavioral changes when conditions vary slightly may indicate discontinuities or bifurcation points due to nonlinearities in the model's behavior, warranting further investigation and perhaps new insights. This type of variation is called "sensitivity analysis."

After the simulation runs are completed, the results may be subjected to further analysis. Simulations can produce a great deal of data for each variation, including the values of system variables and outcomes for each time period and summary statistics across iterations, as well as the parameter settings and initial condition settings. These data may be analyzed in the same manner as empirical data, with some caveats. Since interactive systems typically produce nonlinear behavior, as noted earlier, estimation using the general linear model may not be appropriate, except for comparing the model findings with empirical work using linear models. Instead, nonlinear statistical tools or graphical analysis may be called for—and there is much room for developing better techniques for nonlinear data analysis. Because simulation models can produce a wealth of data, statistical measures take on a different meaning than they do in the analysis of empirical data. For example, when appropriate statistical techniques are applied to simulated data, most variables in the model are likely to yield statistically significant coefficient estimates because of the large sample size. Accordingly, the usefulness of the estimated coefficients is usually to show the directions of the effects of variables, and significance tests mainly help in identifying variables that make no behavioral contributions.

A Simple Example: Coin Tossing

A very simple example of how a simulation is carried out may be instructive at this point. Suppose you wish to use a simulation to find the probability of getting first a head and then a tail in two independent coin tosses. The processes of the computational model are coin tosses. Variable values are assigned by determining whether a toss is a head or a tail. Computationally, we can define a parameter p as the probability of getting a head and set it to some value between 0 and 1 (not necessarily assuming that the coin is "fair"). The simulation program can then call a random number generator for the uniform distribution, which will yield any number between 0 and 1 with equal probability, to produce a number. If this number is less than p, the program concludes that the toss was a head; if otherwise, the toss was a tail. (To see why this works, say we have a biased coin with $p = 4$; the probability that the generator will produce a number less than .4 is precisely .4, since all numbers between 0 and 1 are equally probable.)

In the experimental design, no initial conditions need be specified since the outcome of the first toss depends only on the parameter p. The time structure is two periods, one for each toss (although in this example their length does not matter). The program can determine the outcome by examining the results of the run to see whether the first toss was a head and the second a tail. The run can be repeated many times with different random numbers supplied by the generator—say, for 10,000 iterations—to determine the percentage of head-then-tail outcomes. Finally, variations can be introduced by changing the parameter p and repeating the entire process. Further analysis could consist of plotting the percentage of head-then-tail outcomes for different values of p to produce a graph of the relationship.

Comparison of Modes of Inquiry

Differences in the three forms of scientific inquiry can be illustrated with the simple coin tossing example. The question can be addressed deductively by using probability theory to derive the answer. It can be addressed empirically by performing a coin toss experiment with many trials; this procedure is simple for $p = .5$, assuming that a normal coin is fair, but it may be difficult in practice to obtain coins with different p values. Or a simulation can be used to address the question computationally, as described above.

Simulation is similar to theoretical derivation or deduction in a very fundamental way. Both approaches obtain results from a set of assumptions. The results are the logical and inevitable consequences of the assumptions, barring errors. If one accepts the assumptions, then one must also accept the results; put another way, the results are only as good as the assumptions. So a simulation may be thought of as a numerical proof or derivation.

Simulations differ from deduction in three significant ways, however. We have already mentioned the first difference: simulations can examine the consequences of formal models computationally when derivations cannot be carried out because of analytical intractability. This is the primary reason that simulation methods are particularly useful for studying complex models.

The second difference is more subtle. As discussed above, good formal models generally have four advantageous features (Kreps, 1990): clarity, ease of comparability, logical power, and transparency. The first three advantages also apply to formal simulation models. But the fourth advantage, transparency, may not. It would seem that models must be analytically tractable in order to trace the sequence of reasoning connecting assumptions with conclusions, whether forward or backward. In simulations the formal model may involve the complex interaction of multiple interdependent processes where outcomes emerge from the interactive processes but cannot be predicted or derived in advance. Even with the results in hand, it may not always be possible to understand how the sequence of process behaviors produced the results; this may be an intrinsic property of truly complex systems. Although the precise manner in which the theoretical processes specified in the model produce the results may not be clear, simulations might still inform theory and research by demonstrating a relationship between model assumptions and components on the one hand and system outcomes on the other.

The third difference between simulation and deduction involves the nature of the intuition of the investigator that shapes the formal model. A common misconception about mathematical deduction comes from the way formal derivations are presented. In the usual presentation, definitions and assumptions are laid out first, and these are then used to derive lemmas and theorems, suggesting a mechanical process whereby insights follow from sterile assumptions. An alternative view, which more closely resembles deductive work as we know it, holds that the initial insights of the scientist are contained in theorems (Lakatos, 1976). Once the theorem embodying the insight is specified, the formalization enterprise then consists of attempting to identify assumptions that might be used to derive it. Because realistic assumptions may lead to intractable models, the theorist sometimes resorts to convenient but unrealistic ones. The point is that although deductive work is presented as a sequence of reasoning from assumptions to theorems, the initial insight is often contained in the theorem rather than in the way the model is constructed.

The process of envisioning the result and then figuring out how to produce it is unlikely to succeed for many complex interactive models. Instead, we believe that the intuition of simulators is more likely to play a role in the model construction phase—specifically, in identifying the key processes thought to be relevant to the behaviors under study and in determining the form of interaction of these processes. To be more precise, we believe that many good simulations arise in contexts where the analyst has a valid insight about how certain behavioral or other processes interact with each other but cannot trace through the impact of the interactions because of the potential complexity. Of course, simulators, like deductive theorists, can tinker with model assumptions to try to get desired results, but this is more difficult for simulations, because it is less apparent how assumptions may affect the complex behavior of interactive processes.

Types of Simulation Models

While a number of typologies of simulation models have been proposed (e.g., Burton, 2003; Cohen & Cyert, 1965; Macy & Willer, 2002), it is perhaps helpful to discuss three commonly used types: (1) agent-based models, (2) systems dynamics models, and (3) cellular automata models. Although many current simulations in management theory use agent-based models, we briefly describe the defining characteristics of each type of model and provide a few examples.

Agent-based models. Agent-based models focus on modeling the behaviors of adaptive actors who make up a social system and who influence one another through their interactions (Macy & Willer, 2002; Parunak, Savit, & Riolo, 1998); the behavior of the system is an emergent property of the interaction of the agents. Examples include individuals interacting in an organizational system or organizations interacting in an industry. For instance, in the organizational culture simulation (Harrison & Carroll, 1991, 2006), the agents consist of the members of an organization who influence each other's enculturation and turnover behavior through social influence, and an emergent organizational property is the cultural heterogeneity of the organization. March (1991) models the learning behavior of individual and organizational agents to examine the effects of exploration and exploitation on organizational knowledge and competitive advantage. Strang and Macy (2001) examine cascades in the organizational adoption of fads by modeling the manner in which organizational agents are influenced by one another to adopt innovative practices. And Rivkin and Siggelkow (2003) model the decision behavior of top management agents to examine the interdependence of organizational design elements, organizational search and stability, and decision characteristics.

In agent-based models the model simulates the behaviors of the actors (agents) who make up a social system—including, in particular, how they interact to influence one another—and the outcomes of interest typically are the consequences of the agent behaviors for the social system as a whole. The behavior of the social system is not modeled directly; rather, the system's behavior emerges from the interactive behaviors of its constituent agents.

Systems dynamics models. Systems dynamics models focus on modeling the behavior of the system as a whole, rather than modeling the behaviors of actors within the system (see Forrester, 1961). At the system level these models simulate the processes that lead to changes in the system over time. Systems dynamics models are typically presented in diagrams of variables connected with arrows—including feedback loops—that show the directions of influence of variables on one another, and each influence component is then formalized. For example, Sastry (1997) studied discontinuous or punctuated organizational change by modeling organizational change as a function of organization-environment fit and of trial periods following reorientations during which the change process is suspended. Repenning (2002) examined organizational implementation of innovations by modeling the process whereby participants collectively develop commitment to newly adopted innovations.

Cellular automata models. Cellular automata models are based on an $n \times n$ lattice, or grid, with each square in the grid representing a cell.[3] The model specifies how each cell changes from being occupied or not (i.e., either an actor occupies the cell or it is vacant) in each time period as a function of the characteristics of neighboring cells; in other words, influence is limited to local interactions. Since individual cells change through interaction with other cells, cellular automata models can be seen as a special case of agent-based models if cells are viewed as agents—but they differ fundamentally from agent-based models in that unoccupied or vacant cells still exercise influence on their neighbors. The cellular automata approach has been popularized by work on a wide range of topics at the Santa Fe Institute. Lomi and Larsen (1996) used cellular automata models to explore how localized competition can be linked to founding and mortality processes in an organizational population.

Agent-based models are usually specified using either equations or rules, or a combination of the two. Systems dynamics models typically use differential equations for their formalizations. And cellular automata models tend to be rule based. But there is no intrinsic reason for a particular type of model to be formalized using either equations or rules. The choice of using equations, rules, or both depends on the nature of the processes being modeled and the preferences of the researcher.

THE USES OF SIMULATION MODELING

Once a simulation model has been developed, it can be used for a variety of research purposes. Axelrod (1997) identified three, as follows.

Prediction

Analysis of simulation output may reveal relationships among variables. These relationships can be viewed as predictions of the simulation model or hypotheses that can perhaps be subjected to empirical testing. Even if some variables in the computational model cannot be easily observed, the output variables often can be. For example, in their computer simulation, Carley and Lin (1997) theorized about how organizations can design effective structures to mitigate the impact of information distortion. Empirical confirmation of a simulation's predictions provides indirect support for the theory embodied in the model of the underlying (unobserved) processes.

Proof

Axelrod discussed proofs in terms of "existence" proofs; a simulation can show that it is possible for the modeled processes to produce certain types of behavior. For example, Lant and Mezias (1992) showed that a learning model of organizational change can produce patterns of punctuated equilibria in organizations. This strategy can be used to examine the feasibility of models and to demonstrate that the resulting system behaviors meet certain conditions (such as boundary conditions).

[3] We discuss two-dimensional grids here, although higher-dimensional (or one-dimensional) "grids" can also be used.

Discovery

Simulations can be used to discover unexpected consequences of the interaction of simple processes. In a simulation of competition between populations of organizations, Carroll and Harrison (1994) discovered path-dependent effects that sometimes made it possible for structurally "weaker" populations to win out over populations that were competitively superior.

In our view, Axelrod's list can be complemented by four additional uses for simulations.

Explanation

Frequently, behaviors are observed, but it is not clear what processes produce the behaviors. Specific underlying processes can be postulated and their consequences examined with a simulation; if the simulation outcomes fit well with the observed behaviors, then the postulated processes are shown to provide a plausible explanation for the behaviors (Mark, 2002). A simulation of R&D investment in innovation and imitation (Lee & Harrison, 2001) shows that the process of adaptive firm search over a stochastic landscape for returns to innovation and imitation can explain the emergence of strategic groups in an industry under some conditions. The explanatory use of simulations is related to the use of simulation as existence proof, but it typically goes beyond just showing that it is possible for the model to produce certain outcomes and also illuminates the conditions under which such outcomes are produced.

Critique

Simulations can be used to examine the theoretical explanations for phenomena proposed by researchers, and to explore more parsimonious explanations for these phenomena (Denrell, 2004). This is similar to the explanatory use of simulation, except that, in this case, simulation is used to assess preexisting explanations and, possibly, to find simpler explanations. For example, Levinthal (1991) demonstrated that a simple random walk over capital levels is capable of producing declining age dependence in organizational mortality, without making any assumptions concerning internal organizational processes.

Prescription

A simulation may suggest a better mode of operation or method of organizing. Many simulations in operations research—queuing simulations, for example—indicate more efficient ways of organizing the work flow, which sometimes serve as a basis for changes in organizational procedures. Some prescriptive models may also be associated with a set of management wares, such as graphic user interfaces, database management and accesses for input and output, statistical analysis tools for the generated data, and output visualization tools. These tools are not a core part of a simulation model but are becoming critical to the usefulness of the model in many applications.

Empirical Guidance

The development of theories and models using simulation methods may also generate new empirical strategies. Establishing a formal model holds out the possibility of uncovering systematic connections among previously unconnected observables—a consequence of the logic of the model. In other words, tracing through and understanding the implied connections among variables may show an expected covariation between two or more observable variables that can be used as a hypothesis in systematic empirical research. Further, by demonstrating nonlinear relationships among observables, a simulation model may indicate the inappropriateness of standard statistical testing and suggest alternative empirical approaches.

Of course, it is possible for a simulation to serve multiple purposes, as may be clear from some of the above examples. Indeed, a simulation project probably starts with one of these purposes in mind, but, since the outcomes of simulating complex systems may yield surprises, it could end up serving other purposes. For example, a simulation originally envisioned as a critique could lead to a discovery. In using their cultural transmission model to critique demographic research linking the tenure (length of service [LOS]) distribution to organizational outcomes, Carroll and Harrison (1998), for example, observed a "disruption effect" whereby employee entry and exit events frequently produce substantial fluctuations in measures of LOS distribution heterogeneity that are weakly or even negatively correlated with changes in measures of intraorganizational social process diversity. This discovery showed that the widely used assumption that heterogeneity in the LOS distribution tracks diversity effects based on social processes is often invalid. So the seven research purposes described above illustrate the variety of ways in which simulations can be used, but there could be overlap in the purposes of specific simulation studies.

The role of simulation modeling in management research is summarized in Figure 1. We have emphasized the link between complex problems and simulation modeling as a theory development process. Theory development and model construction are informed, of course, by previous theory and empirical research, and new theory and research feed back into the process. Model construction is also linked to computational technology: technology provides the means to implement and run the models, and it also constrains computational possibilities because of limitations on computer speed, storage, and programming features (constraints that are, fortunately, loosening with technological advances).

SOME ISSUES IN SIMULATION RESEARCH

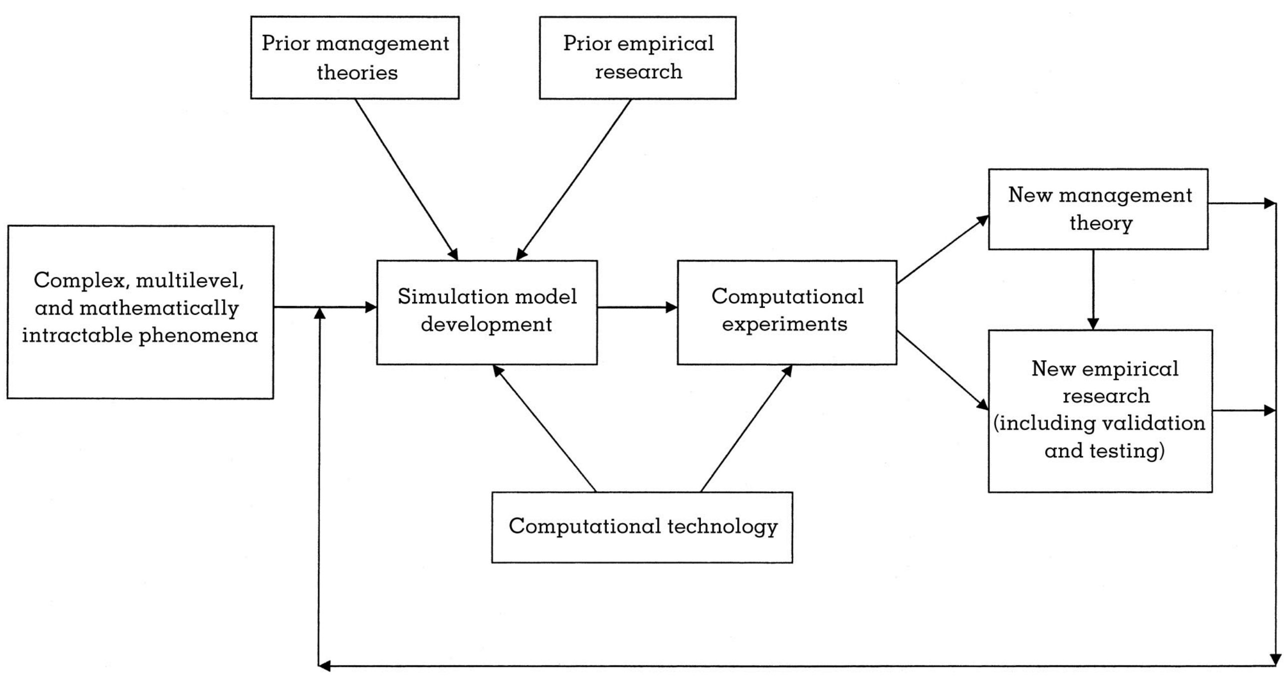
What special issues are raised in simulation research? We address three sets of issues involved in the simulation research process: the degree of complexity in simulation models, empirical grounding of simulations, and some problems and limitations of simulation work.

Model Complexity

Construction of a simulation model involves a tension between simplicity and elaboration. When we give talks on our simulations, a frequent (perhaps the most frequent) question we get is "Why don't you add variable X to the model?" Undoubtedly, a model can be made more realistic by adding more variables or processes. At the same time, it usually becomes more difficult to understand what drives the results in more complex models. The more elaborate or realistic a model of an organization is made, the more it comes to resemble a real organization, including aspects of the organization's incomprehensibility and indescribability (Starbuck, 1976; Weick, 1969).

For theory development purposes, the objective is to construct a model based on a simpli-

FIGURE 1
The Interactive Process of Management Theory and Simulation Modeling



fied abstraction of a system—guided by the purpose of the simulation study—that retains the key elements of the relevant processes without unduly complicating the model (Burton & Obel, 1995). According to Nelson and Winter:

> Willingness to recognize complexity is not an unmitigated virtue. Models in economics must be greatly simplified abstractions of the situation they are intended to illuminate; they must be understandable and the logic must have certain transparency. Artful simplification is the hallmark of skillful modeling (1982: 402).

Axelrod (1997) suggests the KISS principle: keep it simple, stupid. The simpler the model, the easier it is to gain insight into the causal processes at work.

This is sound advice but more appropriate for some simulation uses than for others. The findings from simple models help in understanding the phenomenon studied to the extent that the focal processes play an important role in influencing it. The downside of this approach is that important elements may be inadvertently excluded from the model, including some elements that interact with the simplified model in important ways, thus limiting the usefulness of the insights for understanding the system's behavior. Of course, it is not really possible in models of complex interactions to determine what is important without actually modeling and testing the omitted processes. Deciding which processes are relevant is part of the theoretical exercise of model construction, and the intuition and objectives of the modeler determine what is included in the model. So the applicability of the KISS principle depends, to some extent, on the nature of the phenomenon under investigation and on the investigator; in modeling multiple interactive processes, a delicate balance must be struck between keeping the model simple and including enough elements to get adequate leverage for understanding the behaviors of interest. This might be considered part of the "art of simulation."

A simulation-based research program may start with a simple model and then elaborate it. This might be referred to as a *building block approach,* which amounts to adding complexity in a stepwise fashion. It enables the researcher to understand the behaviors of simple models and then to study the consequences of extending them. Research programs using the building block approach often produce a series of articles; as with other forms of programmatic research, a full understanding and appreciation of later articles in the program may depend on familiarity with the earlier ones, since complete details of the program's history cannot be repeated in each article. But as the complexity of the underlying model increases, it becomes increasingly difficult to interpret the findings.

Simulations sometimes have purposes other than purely the development of theory. They may seek to develop realistic models of behavior that can be applied, for example, to policy analysis or to prescriptions for managing organizational processes. These simulations tend to use a building block approach. One example is the virtual design team (VDT) platform (Jin & Levitt, 1996; Levitt et al., 1994; Levitt at al., 1999), which achieved high realism and has allowed researchers to apply their work to a broad set of real-world projects, including risk analysis for the U.S. space shuttle program.

Model Grounding

Simulation experiments are artificial in that they are based on computer models and their data are generated by a computer program. Artificiality naturally prompts the question of how the simulation relates to real-world behavior. There are several possibilities. The model's processes could be based on empirical work; for example, in a simulation of competing populations (Carroll & Harrison, 1994), both the model's functional forms and their parameter settings were based on empirical studies. The only ungrounded parameters were the competition coefficients, which were systematically varied to demonstrate that the basic findings of the simulation did not depend on the specific settings. In many cases formal models with empirical estimates are not available, but empirical work can still provide much information for model construction, and variations and sensitivity analysis can be used to examine the robustness of the results.

Empirical grounding can also be established through the results of the simulation. The results can be compared to empirical work, as was the case with Lin's (2002) simulation of network activation during crises. Alternatively, the simulation results can serve as a basis for subsequent empirical work to assess their correspondence with observable behavior. Empirical feedback of this nature can also aid in determining an appropriate level of model complexity.

The type of grounding may differ with the purpose of the simulation. For a simulation used for prescription, grounding of the processes increases the likelihood that the results will lead to useful applications. For predictive purposes, empirical testing of the results is an appropriate form of grounding. Still other uses may involve grounding of both the processes and the results; for example, Carley (1996) demonstrated the validity of her computer simulation model by exploring empirical evidence for both the processes and the results.

In our opinion, however, simulation can be a valuable research tool even when grounding is not possible. Simulations can be used to explore the consequences of theoretically derived processes, for example, even if the outcomes cannot be readily assessed empirically. This may be viewed as a form of discovery and is characteristic of much theoretical work in both the natural and social sciences. For example, Wolfgang Pauli predicted the existence of the neutrino in 1931 using theoretical methods, although there was no realistic prospect at the time of observing this hypothetical particle. One would hope, of course, that theoretical work would eventually lead to some empirical validation (indeed, the neutrino was discovered in 1956 using advanced experimental methods, at which time Pauli was awarded the Nobel Prize for his prediction). Purely theoretical simulation work should not be avoided simply because grounding is not available; it is still a legitimate scientific endeavor with the potential to make important contributions to management theory (but needs to be regarded as purely theoretical).

Problems and Limitations

Simulation-based research, like other research methodologies, has problems and shortcomings. Obviously, simulation work can be poorly done, articles can be poorly written, and theoretical justifications can be inadequate. As with formal modeling in general, simulation models may not be specified in a way that convincingly captures the essence of the underlying theoretical reasoning. But simulations have other problems and limitations that are particularly salient for simulation research. Some of these issues were addressed earlier; we take up others here.

One issue involves presentation of the model. In some articles the modeling and experimental structures are not presented in sufficient detail to provide understanding of what was actually done, making it impossible to evaluate the work and to develop any level of confidence in the conclusions. In other cases the researcher may have failed to conduct enough analysis to illuminate the relationships implied by the model. Ideally, problems of this nature would be addressed in the review process. But when an article with inadequate description or analysis is published, the reader must decide what, if any, weight should be given to its claims.

A special set of issues emanates from the fact that the consequences of the model are determined by writing and running computer programs. The most obvious problem is that programming errors (bugs) can occur—management simulators are as vulnerable to this problem as the teams of computer scientists at NASA who made errors in the software for one of the Martian probes. Bugs in the program may not be obvious and can produce spurious results. Eliminating bugs is a major concern of simulators, who may conduct a variety of tests to ensure that the program is operating appropriately, but some researchers are more conscientious than others in this respect, and, as with other methodologies, even the best researchers can still make mistakes. The ultimate test is whether other simulators can replicate the simulation findings. This requires that the original researchers provide sufficient detail of the simulation—or make the actual computer code available—which is often not the case, and, unfortunately, incentives to attempt replications are lacking.

A related potential problem arises from the translation of the formal model into computer code. Even with a clearly specified formal model, there may be choices regarding how the code is written. For example, if three interdependent processes are involved in the model and the computer executes instructions sequentially, the order in which these three processes are carried out in a given time period may make a difference in the results. Different researchers could conceivably write different code and get different results using the same formal model. Particularly for simulation work with important theoretical implications, it is risky to put too much confidence in the findings of one article, and independent verification is called for (as with findings using other methodologies).

Independent verification has been attempted for some important simulation work—for example, Cohen et al.'s (1972) garbage can model and Axelrod's (1984) tit-for-tat work—with mixed results. Failure to replicate a finding does not necessarily mean that it is wrong, however. It may be that the original finding holds only under certain conditions or only for certain ways of operationalizing the formal model. So efforts of this type can help to extend and refine theory, in addition to weeding out errant results.

A final set of issues concerns the inferences drawn from simulation findings. Simulation experiments vary model parameters in an attempt to assess the model's behavior over a range of conditions. While it can be tempting to generalize to other conditions, the simulation findings are only demonstrated for the region of parameter space examined experimentally; generalizations beyond this space can at best be considered conjectures (while inferences based on the parameter values studied can be considered hypotheses of the model). A further problem is associated with models of interdependent processes; since the complexity of the interactions may lead to nonlinear behavior, important effects such as discontinuities may be missed even within the parameter space examined if the parameter variations are not fine grained enough (Kitts, 2003). Finally, it is difficult to make inferences about the relative strengths of the effects of different model components on the outcomes. These effects depend, in part, on the scaling of parameters and variables in the model and on the range of values examined; when these scales and ranges lack empirical grounding—and at least some do in almost all simulation work—the strengths of component effects may not be comparable. With sufficient variation, simulation experiments can sort out which model effects matter and which do not, but comparisons of the relative strengths of effects with observable impacts may lack a substantive foundation.

CONCLUSION

Computer simulation can be a powerful way to do science. Simulation makes it possible to study problems that are not easy to address—or are impossible to address—with other scientific approaches. Because organizations are complex systems and many of their characteristics and behaviors are often inaccessible to researchers, especially over time, simulation can be a particularly useful research tool for management theorists.

Simulation analysis offers a variety of benefits. It can be useful in developing theory and in guiding empirical work. It can provide insight into the operation of complex systems and can explore their behaviors. It can examine the consequences of theoretical arguments and assumptions, generate alternative explanations and hypotheses, and test the validity of explanations. By relying on formal modeling, simulation imposes theoretical rigor and promotes scientific progress.

Simulation research, like any other research method, also suffers from problems and limitations. The value of simulation findings rests on the validity of the simulation model, which frequently must be constructed with little guidance from previous work and can be prone to problems of misspecification. Simulation work can be technically demanding and susceptible to errors in computer programming. The data generated by simulations do not represent real observations, and techniques for their analysis are limited. And it is risky to attempt generalizing simulation findings to areas of the parameter space not examined in the simulation. So claims based on simulation findings are necessarily qualified.

The role of simulation is not well understood by much of the management research community. Simulation is a legitimate, disciplined, and powerful approach to scientific investigation, with the potential to make significant contributions to management theory. Properly used and kept in appropriate perspective, computer simulation constitutes a useful theoretical tool that opens up new research avenues. The computer simulations discussed in this article provide a sample of a future direction in management research, and many samples in future management research are likely to be generated by computer simulations.

Only in the 1990s did simulation-based research begin to appear with any regularity in leading management journals. With the increasing acceptance of computer simulation as a legitimate research methodology, the rise in simulation-based journal articles, and the expanding number of newly trained scholars using simulation techniques, computer simulation promises to play a major role in the future of management theory.

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