Dynamic System Simulation for Decision Support

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Simulation is a powerful methodology for decision support because it allows managers to experiment with models prior to implementing a policy or decision. There are several approaches to computer simulation: continuous event simulation, discrete event simulation, and Monte Carlo simulation. Continuous event simulation can be used to model dynamic system which cannot otherwise be easily modeled.

INTRODUCTION

Simulation is a technique that uses models that imitate the behavior of the real system. There are several ways to describe simulation models (Winston, 1994).

- Static models describe the behavior of the system a specific point in time.
- Dynamic models describe the behavior of the system as it evolves over time.
- Deterministic models allow for no random behavior.
- Stochastic models use Monte Carlo techniques to model random behavior.
- Discrete event simulations model systems in which events change the state.
- Continuous simulations model systems in which the state variable changes continuously. Such systems can sometimes be described with systems of differential equations.

Simulation is valuable because it allows decision makers to experiment with models before they implement decisions or policies. They then may be able to better understand the impacts of their decisions before implementing them.

The remainder of the article is organized as follows. The second section discusses simulation as a mode of inquiry. The third section presents some background on Monte Carlo and discrete event simulation. The fourth section has the main discussion of continuous event simulation and systems dynamics. The fifth and sixth sections offer a discussion of current efforts and future trends. These are followed by definitions and references.

BACKGROUND

Simulation as a Mode of Inquiry

Scientific inquiry has traditionally had two components: theory and experimentation. Lax (1986) suggested that computer simulation constitutes a third form of inquiry. In particular, simulation provides the ability to study complex systems. Pagels (1988) suggested that this new mode of inquiry would have a great impact on decision making in a broad range of areas ranging from medicine to finance.

Since Lax made his prediction, an extensive literature on complex systems and nonlinear dynamics has arisen (see Sterman, 2000 for example). Complex systems are characterized by nonlinear behavior typically caused by feedback. Forrester (1961) notes that information feedback is present in every decision made by people. When the interaction between the components of a system dominates the aggregate behavior, the system can be described as complex. Further, such systems frequently display behavior that may vary radically depending on the values of the parameters.

Biological and social systems are inherently complex as are many physical systems. They typically do not achieve the "equilibrium" traditionally studied by economists. Even if they do, it is frequently their transient behavior that is interesting to decision makers. Some of these systems can be modeled with

Figure 1. Limits to growth (adapted from Senge)
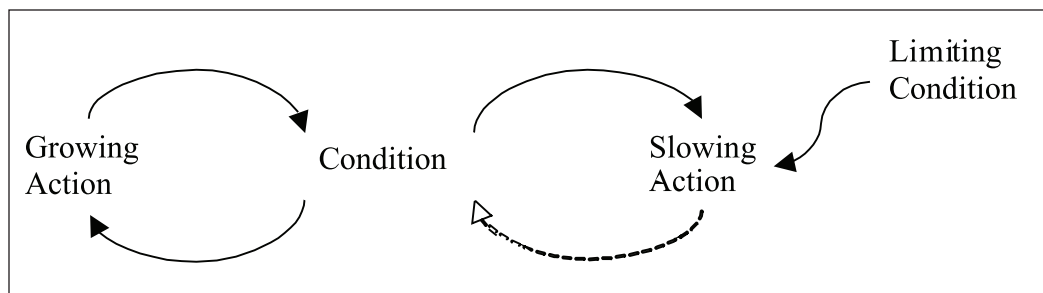
differential equations, but they are typically hard to solve analytically, simulation has become an attractive way to study their time evolution. Continuous event simulation (sometimes called "system dynamics" in this context) is well suited to studying such systems. These simulations use models consisting of systems of finite difference equations which are solved iteratively to model the dynamic behavior of the system. Until recently, numerical solution of such systems was expensive and required advanced programming skills. Recent advances in computer technology have made solutions of such systems much easier.

Senge (1990) presents an extensive discussion of dynamic models of social systems. He identifies several prototypes that describe common organizational problems. For example, his prototype I is "Limits to growth" (Figure 1). The management lesson that he extracts from the prototype is: "Don't push growth; remove the factors limiting growth." (Senge, 95ff.)

Discrete Event and Monte Carlo Simulation

In Monte Carlo simulation, some values are taken to be random variates. These are generated using some sort of pseudo random number generator. For example, a spread sheet calculating present value of an income stream might take the discount rate in each year to be random. In a queuing model, service and inter arrival times might be stochastic, and discrete event simulation is often useful. In such simulations the state of the system changes periodically due to the occurrence of events. In a queuing problem, the state could be the number of customers in the system and the busy/free states of the servers. Events would include:

customer arrival, start of service, and completion of service. Each of these could cause the state to change. Typically, discrete event simulations use Monte Carlo methods to determine the times at which events occur and statistical means are used to evaluate the results (See Winston, 1994).

DYNAMIC SYSTEM SIMULATION

While Forrester (1961) did not invent simulation nor introduce it to management, his seminal *Industrial Dynamics*, may be the first comprehensive introduction to the use of computer simulation in support of management. He discusses key ideas like stock and flow models, information flows, and delays in flows. Stock and flow models are still a standard way of visualizing dynamic system models. Stocks represent the state of the system while the flows represent activities that result in changes to the state.

Forrester implemented his models in the computer language DYNAMO. More modern tools like IThink allow the user to write the code by manipulating graphical symbols on the computer screen. The program then translates those symbols into lines of code. The result in both cases is a set of finite difference equations which are solved iteratively using standard numerical algorithms.

Systems dynamics (SD) has been used to support decision making in a wide variety of fields. Strohhecker (2005) describes a project to support a bank planning for the euro conversion. Otto and Struben (2004) created a model to improve understanding of a fishery management problem. Stephens, Graham, and Lyneis (2005) describe the use of SD in a variety of legal disputes.

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