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Editorial

System dynamics perspectives and modeling opportunities for research in operations management

1. Introduction

It is an exciting time to work in operations management. Advances in theory and methods, including behavioral operations, dynamic modeling, experimental methods, and field studies provide new insights into challenging operational contexts. Yet the world of operations continues to change rapidly, creating new and difficult challenges for scholars. Increasingly, operations management requires theory, models and empirical methods to address the cross-functional, interdisciplinary character of modern operational systems and the complex nonlinear dynamics these systems generate.

The OM research community has a long tradition of dynamic modeling, going back at least to the pioneering work of Forrester (1958) and Holt et al. (1960). These innovators recognized that even core processes in organizations, such as production and supply chain management, involve critical feedbacks with other organizational functions and with other organizations and actors including customers, suppliers, workers, competitors, financial markets, and others. They recognized that these interactions and feedbacks often involve significant time delays, nonlinearities, information distortions, and behavioral responses that often cause dysfunctional, suboptimal behavior and slow learning and process improvement. The challenge, however, has been to develop, articulate and test parsimonious theories to explain the behavior of complex systems, to test policies for improvement, to implement these in real organizations, and to assess their impact over time.

Forrester's insight was to use ideas from control theory to map and explain industrial problems (Forrester 1958; 1961; Richardson 1991 traces the history of feedback control and systems theory from the Greeks through the development of nonlinear dynamics). Forrester's first system dynamics model explained persistent oscillations of production and sales in a manufacturing supply chain. Forrester's model integrated aspects of operations that had not previously been considered — e.g., limited information flow across organizations and functions within organizations, delays in gathering information, making decisions and in the implementation and impact of those decisions, and the behavioral, sometimes suboptimal decision rules managers used to make inventory and production decisions at each level of the supply chain. Forrester (1961) also integrated advertising and consumer behavior into the model, expanding the boundary of analysis beyond conventional inventory theory at the time. Forrester's goals were broader than explaining an important operations issue; rather, he created a general approach to dynamic modeling any management system, indeed, any dynamic system, along with the conceptual and software tools to develop, test, and improve behavioral, dynamic models of human systems, and implement the recommendations arising from them. Soon after the publication of *Industrial Dynamics*, these concepts were applied to a variety of contexts, first in management, and soon after to ecological, urban, and societal problems, among others. By the late 1960s the breadth of the field led to a name change, from industrial dynamics to system dynamics (SD), and the growth of a vibrant field of study, taught around the world (see e.g. http://systemdynamics.org).

There are many conceptual overlaps and synergies between OM/OR and SD; these can be traced to the origins and stated goals of both fields (see Lane, 1997; and Größler et al., 2008). Here we focus on the methodological elements of SD that are most distinctive and relevant to the OM community.

First, system dynamics models are *structural*, *behavioral* representations of systems. The behavior of a system arises from its structure. That structure consists of the feedback loops, stocks and flows, and nonlinearities created by the interaction of the physical and institutional structure of a system with the decision-making processes of the agents acting within it (Forrester, 1961; Sterman, 2000). The physical and institutional structure of a model includes the stock and flow structures of people, material, money, information, and so forth that characterize the system. The decision processes of the agents refer to the decision rules that determine the behavior of the actors in the system. The behavioral assumptions of a simulation model describe the way in which people respond to different situations, for example, the way managers perceive inventory, forecast demand, assess the delivery time for materials, and use these perceptions and expectations to schedule production, hire workers, adjust prices, and so on. Accurately portraying the physical and institutional structure of a system is relatively straightforward. In contrast, discovering and representing the decision rules of the actors is subtle and challenging. To be useful, simulation models must mimic the behavior of the real decision makers so that they respond realistically, even when they deviate from optimality, and those decision rules must be globally robust so that the simulated actors behave appropriately, not only for conditions observed in the past but also for circumstances never yet encountered. SD models therefore have much in common with models in the behavioral operations tradition (See Bendoly et al., 2010a,b for a partial review): in both communities, decision makers are boundedly rational, rely on heuristics, and are often influenced

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by emotion and stressors that affect physiological arousal.

Second, SD models capture *disequilibrium*. Since different decision processes govern the inflows and outflows to the stocks that characterize the state of the system, disequilibrium is the rule rather than the exception (Sterman, 2000). For example, the rate at which customers arrive at a hospital emergency department, or place orders for new products, differs from the rate at which they are treated, or orders fulfilled, leading to queues and delays in medical treatment, or wait lists of unsatisfied customers. The reactions of actors to these imbalances create feedbacks, both negative and positive, that then alter the rates of flow. If the negative feedbacks are strong and swift, the system may quickly settle to an equilibrium. If, however, there are long delays in the negative feedbacks, the system may oscillate; if there are positive feedbacks, the system may become locally unstable (for example, if a wait list triggers fear of shortages people may order more, lengthening the wait list still further; see Sterman and Dogan in this issue). Modelers should not presume that a system has an equilibrium or that any equilibria are stable. Instead, SD modelers represent the processes through which decision makers respond to situations in which the states of the system differ from their goals. Model analysis then reveals whether these decision rules, interacting with one another and with the physical structure, result in stable or unstable behavior. Equilibria, and the ability of a system to reach them, are emergent properties of the dynamic system, not something to be assumed.

Third, SD stresses the importance of a *broad model boundary*. Research shows decisively people's mental models have narrow boundaries, omitting most of the feedbacks and interactions that generate system behavior (see e.g., Sterman, 2000 and the law of prägnanz, a fundamental principal of gestalt perception, reinforcing our tendency to simplify the world, e.g., Sternberg, 2003). We tend to assume cause and effect are closely related in space and time, ignoring the distal and delayed impacts of decisions. The result is *policy resistance* — the tendency to implement policies that fail, or, more insidiously, that work locally or in the short run, only to worsen performance elsewhere or later (Meadows, 1989; Sterman, 2000). Although the sensitivity of model results to uncertainty in parameter values is important, and system dynamics uses a wide range of tools to assess such uncertainty, both model behavior and policy recommendations are typically far more sensitive to the breadth of the model boundary than to uncertainty in parametric assumptions. SD modelers are therefore also trained to challenge the boundary of models, both mental and formal, to consider feedbacks far removed from the symptoms of a problem in space and time. For example, models of traffic flow with exogenous trip origination, destination and departure times typically show that expanding highway capacity (adding lane-miles, optimizing traffic light timing, etc.) will relieve congestion. Expanding the model boundary to include endogenous changes in the number and type of trips, trip timing, transport mode choice, and settlement patterns will show that expanding highway capacity is ineffective as people respond to lower initial congestion levels by taking more trips, driving instead of using mass transit, and moving farther from their jobs (Sterman, 2000; Chapter 5).

Fourth, SD models are developed and tested through *grounded methods*. SD and operations management modelers strive to capture the interactions among the elements of a system as they exist in the real world. The resulting models should reflect operational thinking (Richmond, 1993), that is, they should capture the physical structure of the system, the institutional structure that governs information flows and incentives, and the behavioral decision rules of the actors. These must all be tested empirically. Grounded methods, in this context, refers to empirical methods spanning the spectrum from ethnographic work for theory development, to experimental studies, to formal econometric estimation of model parameters and confidence intervals, hypothesis testing, and other statistical tests.

The application of these methodological principles often results in complex models with dozens of interactions and significant time delays that integrate multiple data sources of different kinds (e.g., quantitative data such as panel datasets, archival data, interviews, surveys, participant observation, laboratory experiments, and so on). The result is both a better theory of the structure of the system, and a formal model. Usually that model cannot be solved in closed form so must be simulated. Simulation enables rigorous tests of the ability of the theory to explain the problematic phenomenon and can be used to evaluate and rank policy options, carry out wide-ranging parametric and structural sensitivity tests, and optimize performance.

Much of the leading edge research in operations management is evolving along similar lines. Increasingly, OM scholars are expanding the boundaries of their models to include behavioral decision making, explicit consideration of dynamics, and broader model boundaries including multiple decision makers and organizations (e.g., supply chain coordination; interactions of operations, marketing and pricing) and performance criteria beyond profit maximization (e.g., working conditions and environmental sustainability). With this special issue we highlight relevant developments in system dynamics and empirical studies in operations management, focusing on the increasing alignment between them and complementarities that may lead to mutual benefit in new research. In the next sections we single out those areas of collaboration informed by the articles in this special issue.

2. Supply Chain Management

As discussed above, Forrester (1958, 1961) developed the first integrated supply chain model, showing how limited information and bounded rationality interact with the physics of production and distribution to explain the persistent oscillation in supply chains and the amplification of disturbances up the chain—phenomena that continue to vex operations managers today. Sterman (1989) used an experimental setting (the Beer Distribution Game) to estimate empirically a simple, behaviorally grounded decision rule, showing how "misperceptions of feedback" — mental models with narrow boundaries and short time horizons, specifically the failure to recognize feedbacks, time delays, accumulations and nonlinearities — led to the oscillations and amplification seen in real supply chains, thus articulating an endogenous behavioral theory of the causes of the bullwhip effect. Later experimental studies including Croson and Donohue (2006), Wu and Katok (2006), Croson et al., 2014, Paich and Sterman, 1993, Diehl and Sterman, 1995; to name just a few, have demonstrated how dysfunctional behavior arises endogenously through the interplay of human decision making heuristics with systems characterized by feedbacks, accumulations, time delays, limited information and other structural features of supply chains. Others have explored the interactions between feedback and behavioral response to empirically examine the evolution of trust, or its breakdown, among supply chain players, for example, Autry and Golicic's (2010) analysis of relationship-performance spirals.

In this issue, three papers expand on this experimental tradition. The paper by Sterman and Dogan uses a laboratory experiment with the beer game to explore the causes of hoarding (endogenous accumulation of excessive safety stock) and phantom ordering (endogenous accumulation of excessive on-order inventory) often seen in real supply chains as managers seek to defend themselves against erratic customer demand and poor supplier performance. The authors analyze the data collected in the experiment of