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SYSTEM DYNAMICS: A BEHAVIORAL MODELING METHOD

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ABSTRACT

Nowadays, there is an increasing integration of methods from economics and psychology in simulation that allow more rigorous approaches to addressing behavioral issues. One of these approaches is the use of laboratory and field experiments of individual and group decision making concerning human judgment and decision-making under uncertainty. System Dynamics, as a simulation methodology, has been employed successfully as a behavioral experimental tool. Some researchers suggest that System Dynamics models are behavioral models of business systems which uncover intended rationality (theories in use) in business decision making. This tutorial offers an opportunity to explore the antecedents of System Dynamics as a behavioral simulation modeling method and offers examples of uses of System Dynamics in laboratory experiments, field experiments and evaluation of theories-in-use by decision makers.

1 INTRODUCTION

System Dynamics (SD), founded by Jay Forrester at MIT in 1961 (Forrester 1961), has been described as a "rigorous method for qualitative description, exploration and analysis of complex systems in terms of their processes, information, organizational boundaries and strategies; which facilitates quantitative simulation modeling and analysis for the design of system structure and control" (Wolstenholme 1990). Using SD involves the use of qualitative and quantitative structuring tools such as causal loop diagrams and stock and flows networks respectively. The use of SD can be performed in either isolated or participative modes. Traditionally, the SD modeling approach involves (as extracted from the System Dynamics Society website):

- Defining problems dynamically, in terms of graphs over time.
- Striving for an **endogenous, behavioral view of the significant dynamics of a system**, a focus inward on the characteristics of a system that themselves generate or exacerbate the perceived problem.
- Thinking of all concepts in the real system as continuous quantities interconnected in **loops of information feedback and circular causality**.
- Identifying independent stocks or accumulations (levels) in the system and their inflows and outflows (rates).
- Formulating a **behavioral model capable of reproducing, by itself, the dynamic problem of concern**. The model is usually a computer simulation model expressed in nonlinear

- equations, but is occasionally left without quantities as a diagram capturing the stock-and-flow/causal feedback structure of the system.
- Deriving understandings and applicable policy insights from the resulting model.
- Implementing changes resulting from model-based understandings and insights.

This tutorial provides the participants with an overview of the main tools in SD: causal loop diagrams, feedback loops, stock and flow and data requirements/analytical methods for parameter estimation. Then, I discuss applications of SD as a behavioral simulation method in three areas: laboratory experiments, field experiments and behavioral theories-in-use. Finally, recommendations for modeling behavior are provided.

2 MAIN TOOLS IN SYSTEM DYNAMICS

2.1 Causal Loop Diagrams and Feedback Loops

Atwater and Pittman (2006) suggested that causal loop diagrams are the basic starting point for teaching SD for two reasons. First, drawing these diagrams is fairly simple and can be handled in less than one class. Causal loop diagrams consist of variables linked, either positively or negatively, forming feedback loops. Second, students and participants in workshops enjoy using them as an easy way to describe their understanding about the topics they learned or business where they worked or owned respectively.

Rules for drawing causal loop diagrams are very simple. For an in depth review see Sterman (2000) but for a brief explanation Atwater and Pittman's explanation (2006) is useful: "In each two-variable link, the variable at the back of the arrow is said to cause a change in the behavior of the variable the arrow points to. The type of change is depicted using either '+' or '−' signs. A '+' means the two interconnected variables change in the same direction, and a '−' means the two variables change in opposite directions. For example, if two variables are linked by an arrow with a '+ 'sign, it means that an increase in the cause variable results in an increase in the effect variable. Similarly, two variables linked by an arrow with a '−' sign is read as an increase in the cause variable, resulting in a corresponding decrease in the effect variable. Basic loops are created when two or more variables are linked together using arrows, which result in a closed loop. A closed loop is the basic piece for describing dynamic behavior in a system." (p. 280) Sterman (2000) provides an important clarification in terms of the conceptualization of the links between variables: "Link polarities describe the structure of the system. They do not describe the behavior of the variables. That is, they describe what would happen **IF** there were a change. They do not describe what actually happens." (page 139).

Closed feedback loops can represent two types of behaviors. First, goal seeking or stabilizing behavior arises from a feedback loop when there are odd negative signs in a loop (Sterman 2000). This basic rule of thumb arises from a simple conceptual simulation around the loop: if there is a small change in one variable, the change disseminates around the loop to cancel out the initial change because there is a reversal in the change in one of the links between two variables (which can only occur if the sign is '−' (negative). This type of feedback loops are called 'negative' or 'balancing'. Second, reinforcing or amplifying behavior is obtained when a feedback loop has zero or even negative signs. This type of feedback loops are called 'positive' or 'reinforcing' since a small change is amplified around the loop.

Table 1 offers a brief example of the use of causal loop diagram in class through a simple description of a business problem. As you can infer from the activity posited, the causal loop diagram does not provide the same level of precision as quantitative simulation but it can provide enough intuition through conceptually simulating it to guide your analysis of the results obtained from a model.

Case description: You are invited to advise a manager of a start-up. The manager has implemented a set of actions in the company but the results are not as expected. From his explanation, we can infer he promoted word of mouth from the existing clients to attract new clients. The representation of this explanation is the reinforcing feedback loop on the left. He also suggested an increasing number of client losses, which may be originated by the level of service provided, reducing the growth of the start-up. This explanation is reflected as a balancing feedback loop on the right. After the initial discussion, the manager wants to know the future of his business as measured by the trajectory of the number of clients.

Causal loop diagram:

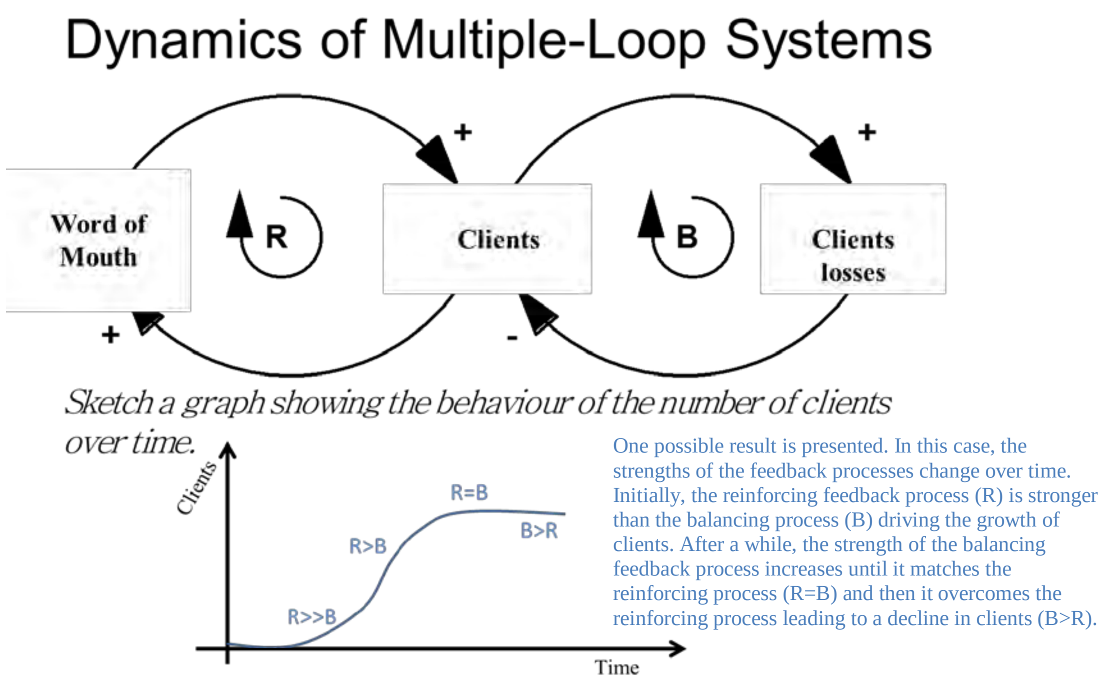

Figure 1. A brief example of the use of causal loop diagram.

There are a number of limitations on the use of causal loop diagrams. First, the diagram is usually not comprehensive, e.g. it does not contain detailed accounts of the systems but perceptions about the system, and it is evolving, e.g. the understanding of the system changes as discussions among stakeholders happen and more research is done (Sterman 2000). Second, the causal loop diagram does not differentiate between stocks and flows (Sterman 2000).

While causal loop diagrams have a number of limitations as explained previously, they have widespread use in different situations related to the conceptualization of SD (and other) models. For example, Kunc (2008a) employed causal loop diagrams to evaluate the selection of indicators in the design of balanced scorecards and the linkages between indicators perceived by decision makers. Kunc and Kazakov (2013) used causal loop diagram to obtain a holistic view of the healthcare system and analyzed the key feedback loops in terms of strength and speed before designing a SD model for one part of the system. Then experiments with different policies were performed using the SD model. Another area of important developments in causal loop diagrams is their use to facilitate groups to achieve consensus on problems, which is known as group model building. There have been interesting advances in evaluating the effectiveness of group model building to change behavior in participants and achieve consensus; for a review see Rouwette et al. (2011). Huh and Kunc (2016) also addressed the impact of group dynamics, e.g. cognitive load and cognitive/affective conflicts, on the development of causal loop diagrams.

2.2 Stocks and Flows

Stocks represent the accumulations existing in a system and characterize the state of the system (Sterman 2000). For example, the number of people waiting in an Accident and Emergency (A&E) area in a hospital can be considered a stock. Stocks increase due to inflows, e.g. people arriving at A&E, and they decrease due to outflows, e.g. people leaving A&E after being treated. Stocks are responsible for the delays as they accumulate the difference between inflows and outflows (Sterman 2000). For example, the capacity utilization of A&E will not decline until all people are treated even if there are no arrivals. Consequently, there is a delay between the action (no more people arriving at A&E) and the result in the system (capacity level); see chapter 5 in Sterman (2000) for an in-depth discussion about delays. In terms of notation, stocks are represented as rectangles, which indicates the accumulation, and flows are pipes pointing into or out of stocks (Sterman 2000, Morecroft 2007). Clouds at the beginning or end of the pipes reflect the limits of the representation of the model since they reflect sources (inflows) and sinks (outflows) (Sterman 2000, Morecroft 2007). Basically, stocks and flows represent integral equations.

$$Stock(t) = \int_{t_0}^{t} \left[Inflows(s) - Outflow(s) \right] ds + Stock(t_0)$$

SD models are essentially a system of integral equations where time is considered continuous and the size of *ds* is reflected in the size of the time step in the modeling software (e.g. Vensim, iThink). One of the key aspects of stocks and flows representation is the differentiation between flows and the information feedbacks controlling the flows, which are responsible for closing the loops in the system (Sterman 2000). Essentially, the material, either tangible (people) or intangible (brand reputation), in the stock and flow network is preserved. For example, a set of stocks and flows describing the dynamics of patients in A&E will only contain patients and not doctors. If there is a need to represent the number of doctors in A&E then a new stock and flow network will have to be developed. The feedback links controlling the flows can be derived either from decision making processes (e.g. how the manager uses the information about the stocks to take action) or from operational/physical/biological processes (e.g. relations that are occurring without any human intervention) (Morecroft 2007). For example, the required inflow of doctors in A&E can be derived directly from the number of patients in A&E or from the average waiting time for patients in A&E. In this example, the choice between the two information links is part of the decision making process of the A&E manager. An example of a biological link can be the amount of virus in A&E which is derived from the number of patients in A&E and an average number of virus per patient (viral load) measured by some scientific method (e.g. blood test). In this case, this link is not an information link or human choice but results from a scientific measurement process and the result may be important to evaluate the risks of infections.

One important corollary from the use of stocks and flows is the coherence of the units employed to describe the quantities in interconnected stocks and flows. Since the material in interconnected stocks and flows is preserved, the measurement units for stocks and flows have to be similar (e.g. patients, doctors) but flows, which also reflect the action of arriving or leaving patients over a period of time (instantaneous rates), have the same units as stocks but per unit of time (e.g. patients per hour or patients per minute). System dynamic modelers also use auxiliary variables to facilitate communication and clarity (Sterman 2000). Auxiliary variables can contain the intermediate results of combining a stock with a certain constant or an exogenous factor. Figure 1 shows the example of the stock and flow network for the A&E case including doctors and patients. Doctors and patients are represented as two separate networks of stocks and flows. The amount of virus in A&E is an auxiliary variable derived from the stock of patients and an estimated amount of virus per patient. The number of doctors required is also an auxiliary that captures the decision making process of the A&E manager based on the situation of the stock of patients and doctors. The connectors from both stocks are considered information feedback links so I draw the links using broken lines (Morecroft 2007) to differentiate from operational links. Then a simple mathematical formula calculates the number of required doctors as the difference between the number of doctors in A&E and the number of patients divided by the number of patients per doctor. However, doctors will not arrive instantaneously to A&E as there are some internal processes, which take time to perform, generating delays (variable time to contact and bring doctors to A&E). Undeniably, this is a simplification of a more complex process to calculate staff roster in A&E, e.g. Gunal and Pidd (2006), but it clearly shows the balancing feedback process between demand (patients in A&E) and supply (doctors in A&E), which occurs at system level, and it is the theory-in-use of the A&E manager. However, the model only reflects short-term pressures since a long-term model will include education delays to have doctors, which is a very important issue in services provided by professionals (Kunc, 2008b)

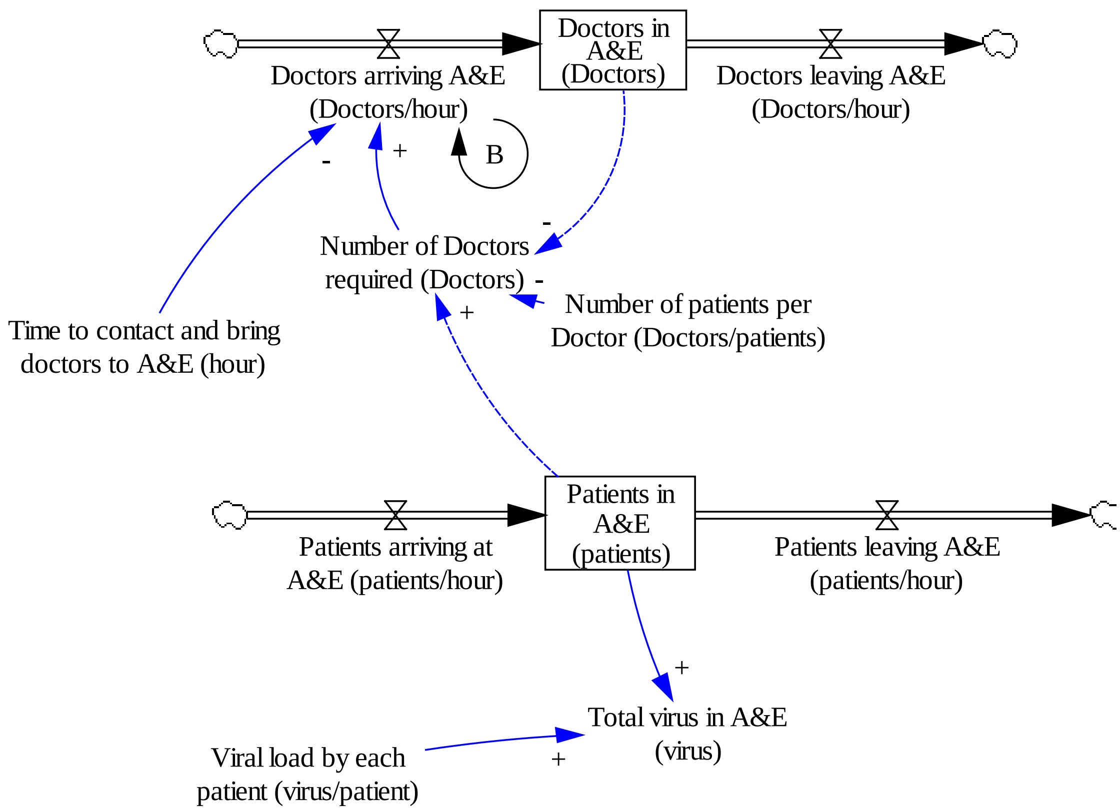

Figure 2. Stock and flow network for a simple representation of an A&E area.

Substantial research in SD has been performed in evaluating the understanding of stocks and flows. This line of research is called *misperceptions of feedback.* One of the most widely cited works (more than 2500 citations) in this area is Sterman (1989). In the paper, Sterman evaluated the impact of failing to understand the stock of orders on the oscillations observed in supply chains. Follow on studies focused on whether subjects can describe the feedback processes existing in dynamic complex systems using a set of tools like the systems thinking inventory (Booth Sweeney and Sterman 2000). Kunc (2012) combined quantitative and qualitative approaches to identify the level of development of well-established concepts in SD such as using graphs of time series, articulation of the problem in terms of endogenous/exogenous variables, identification of feedback loops, and robustness of policies. Kunc (2012) found there were variations in the skills developed so there has to be a gradient in the use of SD adjusted to different people.

Final consideration is related to the similarities between the key components of SD, stocks and flows, and discrete event simulation (DES), queues and activities. Both simulation techniques (SD and DES) are useful to model and compare the performance of a system among various alternatives (Brailsford, Churilov, and Dangerfield 2014). DES is employed in problems where variables change in discrete steps, and it is usually used to solve operational/tactical problems over a relatively short time scale (Brailsford and Hilton 2001). A major strength of DES is to model random events, whereas SD is a continuous deterministic modeling technique aimed at understanding the broad performance of systems (Morecroft and Robinson 2014). Hoad and Kunc (2015) studied the perceptions of students taking a course teaching both methods simultaneously and they found students tend to understand well the tangible components of the system (stocks/flows in SD and queues/activities in DES) but they failed to identify intangible aspects such as information links and feedback loops.

2.3 Data Requirements/Analytical Methods for Parameter Estimation

An important aspect of behavioral modeling is to consider decision makers as subjects with bounded rationality, i.e. subject with limited computational capacity so they are not able to compute the optimal decision. Bounded rationality also implies cognitive limitations and being affected by habits, routines and rules of thumb in terms of the data used. Morecroft (2007) defines the combination of these factors in a process of decision making: ‘policy functions’. While there are some examples of SD models using IF THEN ELSE formulations, good practice tends to avoid the use of this type of formulation as it discretizes decision making process responsible for the dynamics of the system. From a SD perspective, decision making occurs continuously driven by the habits, routines and rules of thumb and not in discrete events.

A behavioral perspective has important implications on the data requirements for a SD model. The model needs information about the initial condition of the system (the initial values of all stocks) to be able to complete the information feedback processes. Flows are results of the initial conditions and policy functions, e.g. the number of doctor arriving at A&E will depend on the number of doctors in A&E and the patients in A&E. If the policy function implies the use of another piece of information by a different manager in another A&E, then the model will need to be updated since policy functions do not intend to be normative (e.g. rationalistic, optimizing behavior) but descriptive (bounded rational behavior). In some cases, the policy function is not a simple equation but a nonlinear function. Nonlinear functions require to specific shape and value of the nonlinear relationships (Sterman 2000). Sources for nonlinear functions are interviews, statistical studies, physical/biological laws and not necessarily large sets of data. The basic guidelines to develop nonlinear functions are: normalization of the inputs and outputs, identification of reference points related to events recognized by the decision makers, benchmarking with similar functions in other situations, evaluation of extreme conditions on the function, discussion of different shapes of the function with decision makers, checking the model behavior with respect to historical data in terms of approximating historical patterns and testing the sensitivity of the model to different values (Sterman 2000).

Another perspective in SD modeling involves the extensive use of data to estimate model parameters (Rahmandad, Oliva, and Osgood 2015). Under this perspective, it is assumed the SD model captures the structural component of the variations in observed data but there is a random component, which is not included in the model, that needs to be calculated and acknowledged in the model (Rahmandad, Oliva, and Osgood 2015). In this perspective, modelers tend to use methods related to econometrics and statistics such as maximum likelihood, method of simulated moments, Markov chain Monte Carlo and Kalman filtering (Rahmandad, Oliva, and Osgood 2015). The purpose of statistical estimation is to be able to minimize the discrepancy between simulated data and observed data with the objective to develop models which are grounded in extensive use of data and with uncertainties quantified (Rahmandad, Oliva, and Osgood 2015).

To summarize, Forrester (1992) suggests three sources of information for SD modeling: mental, written and numerical databases. He also claims the content of the available information is larger in the mental database (observation and experience) and declines substantially moving from mental to other databases, especially in terms of structure of a system and policies applied. For example, Kunc and Kazakov (2013) found healthcare information for their SD model was not available in a long established pharmaceutical database but in the mental models of patients and doctors. Kunc and Morecroft (2007) also found that the existence of diverse conceptualizations of the system among participants (only discovered through interviews) implied different responses to similar numerical data affecting the representation of policy functions. Thus, the role of mental databases is critical when SD is used as a behavioral simulation method even if big data has become widely available to analyze behavior (Kunc 2014).

3 APPLICATIONS OF SYSTEM DYNAMICS AS A BEHAVIORAL RESEARCH METHOD

After the brief review of the tools in SD, we can observe the importance of behavior in the design and use of SD models. The interest in behavior is not a new trend but it reflects an integration of ideas from other subjects in the modeling process in order to address behavioral issues (White, Malpass, and Kunc 2016). For example, there is increasing integration of insights from psychology in the conceptualization of behavior in models and the evaluation of changes in behavior after using models (White, Malpass, and Kunc 2016). SD can not only benefit from this interest in behavioral issues but also contribute substantially to address behavioral issues in three ways to be discussed next.

3.1 Laboratory Experiments of Individual Behavioral Decision Making

Research in the area of decision making under dynamic complexity has focused on identifying and documenting systematic misperceptions of feedback in decision making processes across multiple industries and environmental conditions (Gary et al. 2008, Gonçalves and Villa 2016). Experimental studies exploring decision making and performance employ management flight simulators or microworlds (Gary et al. 2008). Management flight simulators are SD models with a user-friendly interface in terms of inputs (slide bars) and outputs (graphics reflecting time series). To study decision making experimentally, some feedback loops are cut in the SD model behind simulators and individual subjects make decisions each time period based on the information available in the user interface. Some of the most well-known management flight simulators (not an exhaustive list) are People Express represents a low cost airline star-up (Sterman 1988), Fish Banks models the problem of managing fisheries (Meadows, Fiddaman, and Shannon 2001) and Salt Seller portrays dynamic competition in the salt industry (Sterman 2014).

Experiments using management flight simulators that incorporate feedback, delays, and nonlinearities intend to approximate the decision-making environments of executives (Gary et al. 2008). SD researchers suggest factors affecting subjects' poor performance in complex systems: significant feedback delays (Sterman 1989), feedback complexity (Sterman 1989) and changing conditions (Gonçalves and Villa 2016). Typically findings from this research suggest that dysfunctional organizational behavior can be caused by systematic misperceptions of feedback at the individual level (Gary et al. 2008). Most of this research has primarily been published within the field of judgment and behavioral decision making.

Another dimension of individual experimental work examines how differences in mental model accuracy and decision rules lead to differences in the performance of simulated firms (Gary and Wood 2011). Mental model accuracy is related to the identification of feedback loops in the simulation model behind a management flight simulator and the performance of participants with respect to a benchmark solution. The findings indicate there is substantial variation in mental model accuracy and participants with more accurate mental models achieved higher performance levels (Gary and Wood 2011). Moreover, results also indicate considerable variation in participants' decision rules (Gary and Wood 2011).

An interesting area of behavioral research using SD is the understanding of the bullwhip effect. Forrester (1961) identified the existence of amplifications in the supply chain using a SD model. In recent years, researchers have created experimental studies using the Beer Distribution game to evaluate the role of knowledge of the supply chain structure on behaviors leading to hoarding and phantom ordering (Gonçalves and Villa, 2016).

To summarize, SD can be employed to perform laboratory experiments on individual decision making processes in dynamic environments by developing ad hoc (or using existing and already tested) models and embed them in management flight simulators.

3.2 Field Experiments of Behavioral Group Decision Making

Research into decision making must also be embedded in broader organizational, competitive and institutional contexts. For example, experimental study can explore the role of team decision making in a competitive context. Kunc and Morecroft (2007) employed Fish Banks (Meadows, Fiddaman, and Shannon 2001) to study decision making and rivalry among competing teams when they have to manage a fishery. The "tragedy of the commons" behavioral pattern was observed systematically but the results show substantial heterogeneity in group performance. Performance varied as a function of the team's own decisions as well as the decisions of other teams. The competitive context determined when a given decision rule resulted in positive or negative performance. Aggressive teams blinded by short term performance were successful in fisheries where other teams sold their fleets, but they failed when more teams followed similar decision rules. Kunc and Morecroft (2010) also employed Fish Banks to demonstrate the value of context on strategic behavior responsible for developing resources in competitive industries.

Another avenue for research using SD models is in-depth exploratory study of organizational processes using behavioral experimentation by the use of a simulation model which is subject to before-after control (Kazakov and Kunc 2016). This approach can also be linked with a participatory action research perspective since it provides the solution to a real organizational problem in a collaborative mode and reflects a continuous process of research and action (Kazakov and Kunc 2016). Kazakov and Kunc (2016) employed this approach in a strategic planning process conducted by a team of senior managers of a pharmaceutical company. The data collection process was split in two parts. First, the team defined the strategy for the product market without a SD model (pre-treatment or before modeling). In the following meeting managers performed the strategic planning process employing a SD model and simulating interactively their strategies (treatment or after modeling). The data collection process recorded and compared managers' selection process of alternative strategies as well as their collective understanding of the strategic problem by measuring the number of feedback loops, variables employed before and after using the SD model and differences in performance.

There is wide research in the area of model conceptualization in groups; see Rouwette et al (2011). The result of this process can be a qualitative or quantitative SD model. While the research is related to experiences on practice of group model building, some of the research can be categorized as field experiments. Rouwette (2016) performed a review of the four research phases of group model building. Firstly, researchers intended to assess the effects on communication, learning, consensus and commitment. The second phase was focused on the perspective of the receiver of the group model building exercise. The research measured the changes in mental models and understand the impact of group model building in terms of persuasion and attitudes. The third phase intended to evaluate the information existing within the participants and how to facilitate sharing it during group model building. Finally, research intended to observe the use of the model as a boundary object so the model becomes a tangible representation of the participants' objectives and other dimensions (Rouwette 2016).

To summarize, field experiments using SD can involve two modes. First, an experiment before and after using a SD model to support an organizational process. The data collection must involve measures related to changes in the behavior of the participants during the field experiment. Second, the evaluation of the impact of practice on participants involved in modeling stages, mostly the conceptualization stage. In this case, data collection attempts to use frameworks from diverse subjects, e.g. psychology, to measure the changes in the participants in terms of commitment to action as it was documented by Rouwette (2016).

3.3 Modeling Theories-in-use

Argyris (1976) propose human action is based on theories of action, which can be differentiated between espoused theories of action and theories-in-use. Argyris (1976) defines espoused theories as theories reported to be the basis of actions but theories-in-use are those deduced from the actual behavior. In many cases, there are differences between both theories. Argyris (1976) suggest a model of theories-in-use should reflect satisficing solutions (actions) consistent with governing values.

SD research performed in organizations tend to uncover theories-in-use using qualitative research methods before transforming the findings into quantitative models depicting the theories employed by the decision makers. For example, Atkinson and Gary (2016) performed an analysis of the behavior involved in M&A integration projects. To develop the analysis, they interviewed more than 20 professionals related to integration projects with extensive experience in the area. The interviews originated a set of causal links between actions, results and feedback defining typical theories-in-use to manage integration in a M&A project. The structure of the model consisted of four sectors: cost and revenue synergies; integration management office; employee attitudes; and total staff and skill level. The links between and inside each sector were modeled and a set of workshops showing performance over time were presented. As a result of the SD model analysis, four typical behaviors in M&A integration projects were observed: exceeding expectations, below estimates, decline in cooperation and terminal decline. Another example is Repenning and Sterman (2002) who evaluated the failure of organizations to adopt and exploit administrative innovations, e.g. TQM. They addressed the problems at two levels: individual and group. Individuals tend to be biased in terms of perceptions and cognition with respect to the systems in which they are embedded and time horizon (short vs. long). The situation is defined as ‘capability trap’. At the group level, there are important consequences on the interaction between managers and workers during administrative innovations. Managers tend to look for feedback that confirms or reinforces their initial attributions rather than correct them, a process called self-confirming attribution errors.

To summarize, SD can be employed to structure qualitative research in terms of theories-in-use by members of organizations. The results of the data collection are transformed into SD models which are employed to discover new theories or test existing theories in behavioral or organizational science. In this case, SD acts as a behavioral theory development tool.

4 CONCLUSIONS

Modeling behavior has become an important area for research and practice in recent years. Increasing use of behavioral sciences, psychology and economics has paved the way for more integration between behavioral issues and simulation leading to the development of behavioral models. By behavioral model, I mean the representation of bounded rationality and theories-in-use rather than normative, rational behavior or passive, predictable entities, as implied in other tools, e.g. optimization and discrete event simulation respectively. Modeling behavior is not without challenges. Kunc (2016) list a series of suggestions to address them:

- Since the level of knowledge of the person needs to be matched with respect to the task or the focus of the decision, modeling decision making needs to consider the initial level of knowledge and how fast the person builds/changes their knowledge, e.g. students may not be good subjects to capture certain behavioral decision making processes.

- It is physically impossible to update knowledge before evidence is presented since it is updated as evidence is captured through the five senses. Decision making accuracy improves over time once the decision maker is able to interpret the evidence presented. Consequently, decision making processes improve over time and they need to be updated accordingly, e.g. misperceptions of feedback can decline over time.
- Behavioral modeling of decision making must consider the diversity in the perception processes of environmental stimuli among subjects. Therefore, perceptions of the same event can be very different due to structural differences. It is important to consider the diversity of human behavior in behavioral models, e.g. is the diversity at individual or group level?
- Modelers need to consider the complexity as well as ambiguity in the environment. Subjective perceptions take time to calibrate in order to obtain a reasonable representation of the environment. This situation can affect substantially the representation of ad hoc or unique events, e.g. modeling behavior of ad hoc events can involve more errors than recurrent events.

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