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Looking Across the Fence: Comparing Findings From SD Modeling Efforts With those of Other Modeling Techniques

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The two prominent nonlinear modeling schools of System Dynamics and Agent-based modeling have studied numerous problems as they occur in complex human and natural systems. Areas of applications range from economics, ecology, and biology, over anthropology, psychology, and sociology, to traffic simulation, the military, and model testing. However, the two disciplines have rarely compared their results let alone each other's research designs. This study compares the findings from both streams of research as well as those from recent traditional research on the so-called bullwhip phenomenon. The bullwhip effect has become well known to a wider audience through the beer distribution game. As this study shows, despite differences in methodology and other areas the findings of all three research streams converge in significant areas. Further cross study seems to be a promising undertaking. Integrated research designs may have a high potential for result triangulation adding to model validity and result robustness.

Keywords

Agent-based modeling, accelerator-multiplier effect, bullwhip effect, beer game, supply chain management, mental models, information distortion, cross study

Introduction

Numerous natural and human-made systems can be described as nonlinear or complex. Such systems often escape the straight cause-effect and linear modeling patterns which traditional science has successfully used over centuries. Nonlinear modeling techniques became feasible and more popular with the advent of the digital computer some fifty years ago.

Two prominent approaches to the modeling of such dynamics are system dynamics (SD) and agent-based modeling (ABM). The principles of SD were developed at MIT in the 1950s. SD modeling rests on the idea of feedback, or circular causality, inherent in nonlinear systems. The observer/SD modeler attempts to capture causal relationships between elements of a given system by describing its feedback structure with a multiplicity of positive and negative feedback loops. Carefully formulated models are able to simulate the behavior of a complex real system at an aggregate level. Identifying leverage points and applying structural changes to such SD models help pre-testing real system changes and implementing new policies.

In contrast, agent-based modeling (which resulted as a discipline from work at the Santa Fe Institute) focuses on the interaction of rule-based individual agents. The power and intelligence of real life system, for example, is mimicked in the laboratory populated by agents that act in the model space exactly according to rules observed in real life. Rather than trying to compute the solution to models, the agent-based model lets a solution emerge. This modeling approach has been adapted to a wide range of applications.

Remarkably, or for some scholars, annoyingly, the two modeling disciplines have rarely looked across the borders of their own respective field in terms of comparing the results and the insights garnered by the other modeling technique. This paper makes a contribution in bringing forward the process of cross study between the two disciplines.

In the next section, it briefly summarizes early attempts of cross study and joint research. In the three following sections then, it discusses and compares research in the SD, more recent economist/management science, and finally agent-based modeling literature in the area of supply chain management such as the "bullwhip effect," which has been known to and researched by SD modelers for decades under the title of the classic "beer distribution game." The paper then concludes that employing both techniques to the same problem can derive both joint and complementary insights about the nature of a given nonlinear system. Moreover, this not only helps deepen the understanding of the phenomenon at hand but also has the potential for triangulation, thus, leading to higher confidence in the conclusions drawn. Further research is charted out (e.g., comparing results in areas such as the tragedy of the commons, deer management, and predator and prey) where both fields have accumulated a rich body of literature.

Some Proposals for Bridging the Gap

One of the earlier acknowledgements of the "correspondence between complexity and systems theory" notably came from Phelan (Phelan, 1999) who analyzed from the perspective of a complexity scientist the contributions which were mainly made by System Dynamics. Even though Phelan does not sharply distinguish between "Systems Theory, General Systems Theory, and Systems Dynamics" cf. (Richardson, 1991), he gives a comprehensive account of differences and commonalities between the two disciplines. He honestly confessed his emotions when he came across the (mainly) System Dynamics literature: "As a complexity scientist, I was both surprised and embarrassed to find such an extensive body of literature virtually unacknowledged in the complexity literature" (p. 237).

According to Phelan, the definitions and usage of terms such as system, dynamic, nonlinear, adaptive, hierarchy, and emergence seem virtually identical between the disciplines as well as the fundamental understanding "that there are universal principles underlying the behavior of all systems" (p.238). Phelan assesses that "system theory's" (a term which he uses sort of interchangeably with System Dynamics) main focus is on confirmatory analysis and problem solving.

Major areas of departure between the disciplines - as he sees them - are the tendency in complexity theory (1) to engage in exploratory research (rather than confirmatory and problem solving), (2) to rely on modeling individual agents (rather than system inherent feedback structures) and (3) to see simple rules which govern the agents' interactions as the central source for system behavior and target for intervention (rather than leverage points in an SD system model).

Phelan also discusses epistemological similarities between the two disciplines, and concludes that both are gradually moving away from a "hard" systems science perspective as proposed by a pure positivist epistemology.

He summarizes that both theories "capture some of the essence of the conceptual categories of complexity and emergence" (p. 244) and maintains that despite some frictions (e.g., holism - as in SD - versus emphasizing the importance of events and individual interaction -as in ABM) there is good reason for rapprochement between the two disciplines.

In his call for cross study and joint research between the two disciplines, Scholl (Scholl, 2001) responds to Phelan's proposal "from the other side." Though he takes a critical perspective regarding Phelan's account of "systems theory" as opposed to a more precise treatment of System Dynamics as opposed to Systems Thinking, or more importantly, General System Theory, Scholl gives further evidence for some of Phelan's assessments. He discusses that the major point of departure between the two disciplines lies in the concept of emergence (much from little) while SD models try to capture system behavior from an aggregate level. Emergent properties become visible over time at an aggregate level. Thus, a major difference is that the SD approach is deductive in nature while the

ABM approach is inductive. He argues that besides understanding the general similarities and differences it is worthwhile to study each others approaches in more detail and particularly compare results and insights when approaching such commonly known research problems as supply chain management or predator and prey. He also discusses in some detail one modeling example for each discipline ("boids" for ABM and the Lorenz weather equations presented as a SD model the latter of which raised the attention of some complexity scientists).

Scholl also points at the potential for practical collaboration when it comes to testing model sensitivity and validity. John Miller's Active Nonlinear Tests (ANTs) serves as an example. Miller (Miller, 1998) demonstrates that world3, one of the best-known and best-tested SD models, exhibits a major sensitivity to changes to two parameter values. The model still maintains its behavior over time (which is the good news), however, the results (e.g., what the maxima for population growth are, when population growth slows, when decline sets in etc.) can differ by orders of magnitude from the originally assumed limits. Miller proposes to routinely use ANTs for model testing. ANTs are agents that automatically generate and run "solutions" (that is, parameter settings etc.). Each solution requires s single model run. Miller incorporates a combination of hill-climbing and genetic algorithms into ANTS in order to generate new test solutions. Thus, ANTs can cover extremely wide test spaces. Analysis of multivariate sensitivity (regarding groups of parameters), model breaking conditions, extreme case conditions, and the discovery of policy options are typical fields of testing models with ANTs. Miller concludes, "ANTs can be used to discover worst (or best) case scenarios and therein give the user an idea about which parameters should either be altered (if possible) or most closely monitored" (p. 829)

There are clear indications that both sides begin to develop interest in each other's approaches, methods, and findings. However, as to this author's knowledge, today there is no study which incorporates the two modeling techniques in an integrated research method fashion.

The SD Literature on the Bullwhip Effect

Almost half a century ago, SD scholars and teachers began using the famous "beer distribution game" (cf. (Hines, 1996; Hines, 2000; Repenning, 2000; Rockart, 2000; Senge, 1990; Sterman, 1989b; Sterman, 1992; Sterman, 1996)) to demonstrate what economists now use to call the "bullwhip" effect. Playing the game is part of every "SD 101" ever since. The experimental game mimicks a multi-echelon supply chain of beer distribution in which each player takes on the role of one layer in the chain (e.g. retail, wholesale etc.) Players are asked to minimize overall costs (e.g., inventory carrying costs versus stock-out penalties). The game starts with the supply chain in equilibrium. Consumer orders taken by the retailers (generated as external input) are kept constant for a while. Then they are suddenly disturbed by a step increase of 100 percent. After this sudden increase in demand consumer orders stay flat at the higher level for the remainder of the game. In almost every case, however, this one-time step increase in demand leads to tremendous oscillations in orders for the whole duration of the game along the entire supply chain (the bullwhip effect).

The game is intended to expose the participants to playing a role in a system over which they have obviously no control. It further lets them experience how system structure produces behavior. In particular, SD teachers try to demonstrate that regardless of individual quantitative differences in orders posted, the qualitative patterns of behavior are the same for every individual player. Moreover, they want to make clear, that it is the internal system structure (not a system-external event) which was capable of generating the observed fluctuating behavior (cf. http://www.sol-ne.org/pra/tool/outline.html).

The first systematic treatment of the phenomenon in the SD literature dates back to Forrester's 1958 Harvard Business Review article on *Industrial Dynamics* (Forrester, 1975). Forrester demonstrated that a multi-echelon production-distribution system "by virtue of its policies, organization, and delays" is "naturally oscillatory" (p. 12), and, that minute perturbations suffice to unveil this oscillatory nature. He also showed how non-seasonal demand patterns were mistakenly regarded as seasonal when pushed through such a system. This, in turn, reinforces further seasonal impulses (e.g., by advertising and employment policies). Forrester proposed several remedies to contain the bullwhip effect: (1) faster order handling, (2) better information along the chain regarding actual consumer demand, and (3) modest and gradual inventory adjustments.

In two papers published in 1989, Sterman underpins and expands Forrester's results (Sterman, 1989a; Sterman, 1989b). The two papers report on two related experiments, one of which shows how subjects play the classical beer distribution game, while the other one simulates an economy in which subjects have to match supply and demand over time. While subjects in the beer game have limited (local) or no information on overall demand and suffer from an external disturbance in demand during the early phase of the experiment, subjects in the latter experiment have perfect and complete (global) information on the structure and variable values of the simulated economy and do not encounter any external disturbance. Interestingly, Sterman records strong oscillations in both experiments, in other words, with or without perfect information, with or without external disturbance, the pattern of behavior produced by the subjects in the system remained the same. In the beer game experiment, he systematically finds subjects producing the accelerator-multiplier effect (an earlier term for the bullwhip effect) and its three characteristics of oscillation, amplification, and phase lag. He reports that subjects place their orders with the purpose to narrow gaps between demand and supply but then seem to "promptly forget that these units had been ordered" (Sterman, 1989a, 316) Sterman, as did Simon before (Simon, 1979), therefore, casts doubts on the notion of an entirely rational basis for managerial decision-making. Sterman attributes the flawed decision making and, hence, the bullwhip effect to - what he calls - misperceptions of feedback.

He defines these as "a failure on the part of the decision maker to assess correctly the nature and significance of the causal structure of the system, particularly the linkages between their decisions and the environment" (p. 324). One variant of such misperceptions of feedback is the misperception of time delays. Subjects over-aggressively try to correct discrepancies, or, they completely ignore the delay between the initiation and the resulting effect of their action. The other variant of misperception of feedback is to confuse endogenous with exogenous feedback,, for example, demand for capital in the capital market. Sterman concedes that it may be difficult "for experience alone to overcome misperceptions of feedback structure and produce a robust ordering heuristic" (p. 330). He also suggests that it "is the subjects' dynamically deficient mental models themselves which hinder learning by focusing attention on inappropriate variables and relationships. Thus misperceptions of feedback may be self-perpetuating" (ibid.). And consequently, "outcome feedback is not sufficient" (Sterman, 1989b, 338) to overcome the dilemma. Sterman, therefore, emphasizes the importance of action feedback which links the decision-makers' actions to changes in the environment which condition further decisions.

Peter Senge (Senge, 1990), finally, has made the beer distribution game known far beyond SD or economist circles. He also shows the solution to the problem to be embarrassingly simple: "every player would simply place new orders equal to the orders he received" (p. 47). If every player follows this "no strategy", simplistic rule, the instabilities and oscillations die out after only seven weeks. He concludes that players are less prisoners of "the system" rather than prisoners of their own thinking.

Recent Economics and Management Science Literature on the Bullwhip Effect

As Sterman points out, in the economics and also in the management science literature the bullwhip effect was described at least as early as the 1920s and 1930s. It seems, though, that the recently increased interest in the subject matter has two sources: (1) the practical management challenge along ever more computerized and networked supply chains as it appeared in the last decade of the 20th century, and (2) the widely risen public attention and the explanatory impact produced by the SD literature.

Lee et al. (Lee, Padmanabhan, & Whang, 1997a) characterize the bullwhip effect as the consequence of distorted information transmitted up a supply chain. They quote examples from Procter & Gamble in its diaper and Hewlett-Packard in its printer business where despite predictably stable consumer demand, forecasts received from downstream supply chain member, and particularly, from resellers, were so poor that this resulted in excessive inventory stocking and production capacity allocations. Their study confirms the SD insight that coordination and planning along the chain can control the bullwhip effect.

However, as opposed to Sterman's and others conclusions, they attribute the effect to the "players' rational behavior within the supply chain's infrastructure" (p. 95). Unlike Forrester, Sterman and Senge who suggest to work on the mental models of decision-makers in order to change their behavior within a given system Lee et al. propose modifications to the system itself, that is, the supply chain's infrastructure. The authors identify four distinct causes for the phenomenon: (1) demand forecast updating/ demand signaling, (2) order batching, (3) price fluctuation, and finally, (4) rationing and shortage gaming.

They consider demand signaling a major contributor to the bullwhip effect. They argue if exponential smoothing techniques for updating forecasts and safety stocks are used at every link of the chain, then variability and swing necessarily increase along the chain. And even more so, when lead time for replenishment become longer.

Periodic ordering and push ordering also cause and amplify the effect. "If all customers' order cycles were spread out evenly throughout the week, the bullwhip effect would be minimal" (p. 96). Particularly, when batched orders overlap, even higher peaks are generated and the effect amplified.

Price fluctuations may lead to "forward buying". Once higher inventory carrying costs are offset by promotional low prices, a buyer may opt for purchasing beyond actual demand, seizing the low-cost situation in anticipation of future demand. Such fluctuations can be very costly for the whole supply chain, since they directly generate the bullwhip effect. As Lee et al. remark "The irony is that these variations are induced by price fluctuations that the manufactures and the distributors set up themselves" (p. 97).

Manufacturers' rationing and shortage gaming upon short supply directly leads to exaggerated ordering from downstream, particularly, if downstream players lack information on future availability, which again, generates the bullwhip effect. This scenario is very common upon introduction of "hot" new products.

The authors recommend three remedies that tame the bullwhip effect: (1) information sharing, (2) channel alignment, and (3) improved operational efficiency. Once market demand data as collected by the downstream end of the supply chain is made available along the chain, but, especially, to the upstream end, the artificial amplification of demand is eliminated. Meanwhile some manufacturers demand such raw data from their downstream partners (Apple, HP, IBM). More radical approaches (VMI) let vendors manage inventories at downstream sites (WalMart and Procter & Gamble). Inventory reductions result along with less fluctuations.

Lee et al. further recommend to break up order batches, for example, by computer-assisted ordering (CAO) techniques eliminating paperwork. They also give examples how the full-truckload (FTL) problem can be addressed by order assortments and bundlings, or, even by using third party logistics. They also propose to significantly cut down, and most preferably eliminate price discounting and campaigning. Using everyday low price (EDLP) and everyday low cost (ELDC) contracting along the supply chain further containing any fluctuation. Finally, they propose to eliminate shortage gaming by allocating proportionally to past sales records rather than actual orders when it comes to supply shortages. They also propose to penalize order canceling and implement less generous return policies at the same time. Furthermore, they argue if upstream capacity and inventory information is made available, downstream anxiety levels may be reduced.

In another paper on which the above study relies, Lee et al. (Lee, Padmanabhan, & Whang, 1997b) give the subject an in-depth theoretical treatment. They describe the causes of the bullwhip effect by means of mathematical models with which they demonstrate that the phenomenon results from "*strategic interactions* among *rational* supply chain members" (p. 548). The authors explicitly question the interpretations of the bullwhip effect as presented by Forrester ("industrial dynamics and time varying behaviors of industrial organizations") and Sterman ("misperceptions of feedback"). Consequently, they see the opportunities for reducing the bullwhip effect in countermeasures affecting the system structure itself rather than "through modifications in behavioral practice (Forrester) and / or individual education (Sterman)" (ibid.). In a related paper Lee and Whang (Lee & Whang, 1999) further develop the idea of interest and information alignment in a multi-echelon supply chain as they are also found within decentralized organization.

Chen (Chen, 1997) also analyzes supply chains comprised of divisions of the same firm where inventory information is local. As in external supply chains, information is transmitted from downstream to upstream causing information lead times, while in the opposite direction, the flow of material is also accompanied by delays. There are costs for inventory carrying and penalties for stock-outs However, in this internal scenario, the firm's overall objective is to minimize system-wide costs over the long run. Chen shows in two scenarios that the optimal decision rule throughout the supply chain is "to follow an installation base-stock policy" (p. 1077), that is, keeping the installation stock constant. Installation stock is defined as on-hand inventory minus backlogged downstream orders plus outstanding upstream orders. It only involves local information and eliminates the bullwhip effect. Chen discusses two scenarios which he calls the team solution and the cost center solution. In the former the local managers cooperate towards the system-wide goal. Chen finds that information lead-times play the same role as production-distribution lead-times when determining optimal replenishment strategies. However, production/distribution lead-times tend to be much costlier. As a remedy for the information lag, he numerically demonstrates the benefits of making downstream information available upstream soon. Interestingly, the cost center approach also produces near-optimal results as long as the performance measurements are based on inventory levels and incentives are kept compatible along the chain. Chen also studies the effects of irrational behavior in supply chain management. In particular, he analyses the mistake when managers try to maintain their *net inventory* (inventory on-hand minus backlogged customer orders) constant, forgetting outstanding upstream orders, rather than keeping installation stock constant. He confirms Sterman's findings that such behavior is costly to the firm. Furthermore, the farther downstream this mistake is made the more costly it becomes.

Carlsen and Fuller (Carlson & Fuller, 2001) propose to use a fuzzy-logic controller (FLC) to control the bullwhip effect. In their paper, the authors re-discuss Lee's et al. theorem on demand signaling and demonstrate in this particular case how the application of an FLC to order data over time can gradually contain the bullwhip effect.

Recent Agent-based Modeling Literature on the Bullwhip Effect

Kimbrough et al. (Kimbrough, Wu, & Zhong, 2001) give the first full account of an agent-based study on the bullwhip effect. In particular, they implement the MIT beer distribution game as an agent-based model incorporating the asymmetric cost function (different values for inventory carrying cost and stock-out penalty). For every agent player the weekly values for inventory position, cost (see above), inventory on-hand, downstream demand, and shipments from upstream are calculated. At the end of a game the total costs for all players over the duration of the game are computed. The algorithm to search for the optimal order policy contains seven steps:

> "1) Initialization. A certain number of rules are randomly generated to form generation 0. 2) Pick the first rule from the current generation. 3) Agents play the beer game according to their current rules. 4) Repeat step 3, until the game period (say 35 weeks) is finished. 5) Calculate the total average cost for the whole team and assign fitness value to the current rule. 6) Pick the next rule from the current generation and repeat step 2, 3, and 4 until the performance of all the rules in the current generation have been evaluated. 7) Use genetic algorithms to generate a new generation of rules and repeat steps 2 to 6 until the maximum number of generations is reached" (p. 3).

Kimbrough et al. conduct several experiments with varying parameters the first of which mimicks the classroom MIT beer distribution game. Each agent (retailer, wholesaler, distributor, brewery) independently finds and converges to the simplistic "no strategy", "pass-order", or "one-for-one" ordering rule. In a further step the authors give evidence that the one-for-one rule establishes a Nash equilibrium, that is, no agent can benefit by changing her strategy/rule while the other agents keep their strategies/rules unmodified. Upon increasing the number of agents, the convergence times, however, also increase substantially.

In the second experiment, the authors, change the input parameter from stationary to stochastic demand and find the "interesting and surprising discovery … that, when using artificial agents to play the Beer Game, in all test cases, there is no bullwhip effect, even under stochastic customer demand" (p. 6). Also in this experiment the Nash equilibrium is confirmed. Surprisingly, the agents also find rules that outperform the pass-order rule.

In the third experiment, production-distribution lead-time is no longer fixed but can take on a stochastic value between 0 and 4. With now two stochastic inputs the agents still find better rules than one-for-one within 30 generations. These experiments, when applied to the so-called Columbia beer game, produce consistent results.

In their summary, Kimbrough et al. state that artificial agents may be capable of managing supply chains. They play the beer game effectively, tracking demand, eliminating the bullwhip effect, and also find "the optimal policies (where they are known) and … good policies under complex scenarios where analytical solutions are not available." The agents are obviously capable of coping with dynamic environments and find superior rules to rules so far known as optimal even though the function spaces they operate in are relatively simple. The authors are particularly cautious regarding generalizing their results for extended time horizons.

In two papers, or, actually, one split paper, Wu and Sun (Wu & Sun, 2001a; Wu & Sun, 2001b) study how artificial agents bid and contract in a non-storable goods market, and how trust in such a multi-agent bidding scenario may evolve. Even though, these two papers do not directly refer to the bullwhip phenomenon, they nevertheless address an area of supply chain management which according to Lee et al. has a direct impact on the effect. Wu and Sun also see a potential for artificial agents when it comes to strategy discovery in such vaster functional spaces. In their experiments, the agents seem to find equilibrium bidding/contracting solutions, if existent, rather quickly. They also find better-than-known strategies in more complex and non-equilibrium environments. The agent-based experiments further confirm game-theoretical findings, that is, tit-for-tat strategies induce cooperation and trust, while good will not necessarily does.

Areas of Agreement and Departure

Looking at what the three fields identify as the causes of the bullwhip effect we find some clear points of departure between the SD literature and the recent economics/management science (E/MS) literature. The SD literature unveils (1) the potentially oscillatory nature of the underlying system and (2) the human interactions with this system (where the human interactions are based on misperception about this system's nature) as the two intertwined "causes" of the bullwhip effect. In contrast, the E/MS literatures maintains that four distinct causes, namely (1) demand signaling, (2) order batching, (3) price fluctuations, and (4) shortage gaming, are responsible for the phenomenon. These four causes (in the E/MS view) are structural parts of the supply chain system each leading to the oscillatory system behavior when players in the chain make their locally rational decisions based on distorted information.

The major point of departure here lies in the disagreement whether or not the decision-making rests on rationality. As March and Simon (March & Simon, 1958, 138-140) point out the claim for rationality in decision-making

> makes three exceedingly important demands upon the choice-making mechanism. It assumes (1) that all alternatives of choice are “given”; (2) that all the consequences attached to each alternative are known (in one of the three senses corresponding to certainty, risk, and uncertainty

> respectively; (3) that the rational man has a complete utility-ordering (or cardinal function) for all possible sets of consequences…the notion of objective rationality assumes there is some objective reality in which the 'real' alternatives … exist…we can only speak of rationality relative to a frame of reference, and this frame of reference will be determined by the limitations on the rational man's knowledge.

Lee et al do not clarify their definition of rationality. So one may speculate that they claim this latter relative or limited rationality in some form. This is indicated by their emphasis on "local" decision-making. From a local perspective, however, some decisions may well appear rational which - in a non-local perspective - are not. In a recent experimental study Moxnes gives disturbing evidence for experts' limitations in terms of rational decision-making even when given perfect information and full control over the environment (Moxnes, 1998). Demand signaling, for example, which Lee et al. consider a major contributor to the bullwhip effect can also be interpreted as a misperception (from both a non-local or local viewpoint)..

Lee et al., however, confirm Forrester's point that the possibility of demand inflation results in order amplification along the supply chain. There seems to be little disagreement regarding the other three causes which Lee et al. present from a SD perspective. These phenomena have been also covered in the SD literature and known for their oscillatory potential.

As opposed to Lee et al. Chen explicitly acknowledges and confirms Sterman's findings on misperceptions of feedback in the beer game.

The agent-based literature is relatively silent (and, maybe even uninterested) regarding the causes of the bullwhip effect. However, when following Kimbrough et al. comparison of humans' and artificial agents' performance in the beer game, one rather finds a strong confirmation of Sterman's finding of human misperception regarding the system feedbacks. As opposed to Lee et al. the ABM authors mentioned above maintain a system-wide perspective.

Agreements between all three literatures seem to prevail when it comes to recommending remedies for the bullwhip effect: from the SD perspective it has been proposed to (1) increase operational efficiency (for example, cutting lead-times by faster order handling), (2) improved and timely information on actual consumer demand data, (3) non-aggressive and gradual inventory adjustments, (4) change in behavior through development of superior mental models based on understanding the endogenous forces at work, and (5) "no strategy" or "pass-order" policy.

From the E/MS literature the recommendations comprise (1) improved organizational efficiency, (2) information sharing and channel alignment, (3) no order batching, no shortage gaming (4) no discounting, and (5) maintaining the installation stock constant.

The ABM literature confirms the benefits of the "pass-order" strategy but sets out to discover even better strategies which for limited time horizons can be found. Agents, it is claimed (and demonstrated through some experiments), do not fall victim to misperceptions and can outperform human decision-makers consistently never generating the bullwhip effect.

It is obvious and remarkable that all three literatures settle on the same practical rule of "one-for-one" or "pass-order" despite differences in many respects from identifying the causes of the phenomenon over methodologies employed for analysis until assumed positions in an epistemological and philosophy-of-science context. Interestingly, the recommended remedies from both the SD and E/MS literature are almost identical except that there is no change in behavior etc. requested by the E/MS literature.

It is noteworthy that bi-directional information-sharing along the supply chain as well as cutting lead-times mark an intervention at a leverage point, a policy change, and create a different system (feedback) structure which leads to modified system behavior (actually, eliminating the bullwhip effect for the most part). Or, in other words, both the SD and E/MS literatures propose interventions at the system level which reduce the oscillatory nature of this very system. As opposed to the E/MS literature the SD authors also emphasize the benefit of educating decision-makers about the counter-intuitive patterns of behavior of complex systems hoping to sufficiently arm them for such situations.

Concluding Remarks and Future Research

This paper intends to encourage further cross study between the non-linear modeling disciplines of System Dynamics and Agent-based Modeling. This may (as in this case) or may not include traditional research approaches to complete the picture when analyzing the problem at hand. In this paper it has been demonstrated how the bullwhip effect is explained when various research and modeling techniques are applied. Despite methodological differences (among others), the results are confirmatory (at least in major portions) for all three approaches. Or said another way, at least, for the remedies, the results are robust.

Each research method has its unique strengths and weaknesses. Upon, for example, modeling aggregate systems one may miss out on subtleties in the underlying structure of individual interactions. This may result in not identifying some properties that only emerge when the full range of interactions of individual agents is accounted for. However, this can also happen the other way around. Holland, for example, also suggests "interdisciplinary comparisons {which - insertion mine} allow us to differentiate the incidental from the essential. When we look for the same phenomena in different contexts, we can separate features that are always present from features that are tied to context" (Holland, 1999, 242). When we apply research tools of complementary capacities, we may be able to triangulate gained insights leading to increased confidence regarding the robustness of the conclusions. We may understand a problem much better when we view from different angles. The above discussion of the bullwhip phenomenon is a case in point. So far, the two disciplines walked their ways rather unconnectedly. This may be as the cross study in this paper demonstrates a mistake, or, at least, a great opportunity missed.

Even, if results are not confirmatory, or perhaps, particularly in case the findings do not overlap when studying the same problem at hand, it may be insightful to compare each other's results which can define the starting point and direction for further research.

In the discussion of the bullwhip effect it became obvious that Phelan's claim, SD modeling is more confirmatory and problem-solving in nature while ABM is more exploratory, does not hold in this case. This is not to say that Kimbrough's et al. agents failed in discovering new and better rules in the beer game. In fact, as we saw they did so in a remarkable fashion. But their study had a strong confirmatory part. Regarding the new rules they were able to demonstrate a remarkable problem-solving capacity. By the same token, the SD literature (especially Sterman's contributions) had predominantly exploratory character. In other words, we may be well advised to wait until more cross study has been performed before we attach these labels.

Once we have compared more results from different studies of the same problems we may not only better understand each research method's strengths and weaknesses and how they can help seeing the same problem through two distinct lenses but also learn how to design integrated research projects. One possible outcome can also be that we find a relation between the SD model leverage points (where policy changes are most effective) and rules that agents discover.

In future research other problems well-known and well-researched by both disciplines will be cross-studied such as deer management, predator-and-prey, and the tragedy of the commons which we hope will produce further insights along those lines discussed before.

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