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"Smart parts" supply networks as complex adaptive systems: analysis and implications

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Abstract

Purpose – The purpose of this paper is to critically analyze whether supply networks may be validly treated as complex adaptive systems (CAS). Finding this to be true, the paper turns into the latest concerns of complexity science like Pareto distributions to explain well-known phenomena of extreme events in logistics, like the bullwhip effect. It aims to introduce a possible solution to handle these effects.

Design/methodology/approach – The method is a comparative analysis of current literature in the fields of logistics and complexity science. The discussion of CAS in supply networks is updated to include recent complexity research on power laws, non-linear dynamics, extreme events, Pareto distribution, and long tails.

Findings – Based on recent findings of complexity science, the paper concludes that it is valid to call supply networks CAS. It then finds that supply networks are vulnerable to all the nonlinear and extreme dynamics found in CAS within the business world. These possible outcomes have to be considered in supply network management. It is found that the use of a neural network model could work to manage these new challenges.

Practical implications – Since, smart parts are the future of logistics systems, managers need to worry about the combination of human and smart parts, resulting design challenges, the learning effects of interacting smart parts, and possible exacerbation of the bullwhip effect. In doing so, the paper suggests several options concerning the design and management of supply networks.

Originality/value – The novel contribution of this paper lies in its analysis of supply networks from a new theoretical approach: complexity science, which the paper updates. It enhances and reflects on existing attempts in this field to describe supply networks as CAS through the comprehensive theoretical base of complexity science. More specifically, it suggests the likely vulnerability to extreme outcomes as the "parts" in supply networks become smarter. The paper also suggests different ways of using a neural network approach for their management – depending on how smart the logistics parts actually are.

Keywords Supply chain management, Complexity theory, Learning, Neural nets

Paper type Viewpoint

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1. Introduction

The understanding of supply chains as logistics systems has evolved over time from "linear structures" to "complex systems" (Lambert *et al.*, 1998; Bowersox *et al.*, 2002; Hülsmann and Grapp, 2005; Hülsmann *et al.*, 2006) to, most recently, "complex adaptive systems (CAS)" (Choi *et al.*, 2001). But is it really valid to call supply networks CAS? This is the first problem we take on. The term "complex adaptive system" originates in the field of complexity science and is best applied to living systems: Gell-Mann (2002, p. 17) says: "On earth, all CAS seem to have some connection with life." Regarding whether supply networks actually behave like living systems or not, researchers in the field of logistics do not agree – whereas Choi *et al.* (2001) and others (Zhao, 2005) underline the validity of recognizing supply networks as CAS, Surana *et al.* (2005) admit that their understanding of supply networks as CAS is more a postulate than validated reality. The question is critical.

Surana *et al.* (2005) list attributes like complex multi-scales, self-organization, evolutionary processes, complex interactions between the structure and function of a supply network, and consequent high-nonlinearity. In CAS, it is the interactions among intelligent agents[1] capable of learning from each other that create the possibilities of nonlinear behavior. Nonlinearity, in turn, gives rise to possibilities of Pareto-distributed extreme events having negative (or positive) consequences. This sets up the second problem: If complex adaptive logistics systems (CALS) exist, what are the implications? As the materials in logistic flows become smarter – i.e. become learning "smart parts" – the possibility of extreme negative outcomes is exacerbated and gives rise to what has long been known in logistics as the "bullwhip effect" (Forrester, 1961; Lee *et al.*, 1997).

Third, if CALS worsens the bullwhip effect, what managerial action is most apt to work? If CALS will, in fact, come to exist, we will need new kinds of management approaches and new designs of supply networks (Gripsrud *et al.*, 2006). We suggest using a neural network model as one method for mitigating extreme negative outcomes in supply networks.

We begin with an introduction into the field of complexity science to generate a general understanding of CAS and the underlying logic (Section 2). Next, we take a closer look at today's supply networks. Can they be considered as CAS? (Section 3). Then, we introduce typical outcomes of CAS and examine what parallels we see to the existing logistics systems literature. We also discuss what additional outcomes could be expected from CALS, given a complexity perspective, that are not considered in current research of supply networks (Section 4). We propose several options to better manage CALS outcomes (Section 5). We finish with a short conclusion about key implications for the ongoing developing process of CALS (Section 6).

2. Background

We begin with a short introduction into CAS and follow this with a brief review of complexity thinking in logistics and supply network literature.

2.1 Introduction into complex adaptive systems

Tracing the roots of complexity science, Maguire *et al.* (2006) identify three phases: European, American, and more recently econophysics.

2.1.1 Stage one. It begins in Europe with the work of Prigogine (1955), Prigogine and Stengers (1997), Haken (1977), Nicolis and Prigogine (1989), Cramer (1993) and Mainzer (1994), among many others. Prigogine (1955) studied the order-creation tension that energy above a specific "critical value" imposes on fluid flow. His research focused on the formation of what he termed "dissipative structures" that serve to speed up entropy production – that is, the newly created forms of order speed up the dissipation of heat or other kinds of energy. More generally, they focus on general principles about circumstances in which mostly physical complex systems autonomously create newly ordered structures when imposing energy forces reach a critical level – the "edge of order;" once over the edge, new order appears.

2.1.2 Stage two. Beginning in America, this stage emphasizes intra-system processes occurring once a system reaches the region of emergent complexity (Cramer, 1993). This region occurs between the edge of order – which Bak (1996) termed "self-organized criticality"[2] – and the "edge of chaos" (Lewin, 1992). Once criticality is reached, a system produces new order to reduce tension; it is here that heterogeneous agents (parts) begin to coevolve toward new order. At the edge of chaos, too much tension brings disorder that overwhelms constructive order creation (Cramer, 1993). Holland (1975, 1995) and Kauffman (1993) use computational models to study agent interactions giving rise to new networks, groupings, and other system processes.

2.1.3 Stage three. Econophysics focuses on how order creation actually unfolds once the forces of emergent order creation by self-organizing agents – such as biomolecules, organisms, people, or social systems – are set in motion. Scalability, fractals (Mandelbrot, 1982; Brock, 2000) and power laws[3] (Newman, 2005; Andriani and McKelvey, 2007), which can be found in natural self-organizing systems, are key elements of this idea. A cauliflower is fractal; cut off a "floret;" cut a smaller floret from the first floret; then an even smaller one; and then even another, and so on. Other than increasingly small size, each performs the same function and has roughly the same shape of the floret above and below it in size. The causal basis of its survival is the same at each level; causality is scale-free – i.e. it has scalability.

2.1.4 Defining CAS. The concept of CAS comes from biology – and pertains to living entities (Gell-Mann, 2002). Holland (1995) describes a CAS as a system that emerges over time into a coherent form, adapting itself without any singular entity deliberately managing or controlling it. Examples of CAS phenomena include all levels of biological analysis from base-pairs, DNA and genes to species in ecologies, memes, languages, networks, cities, organizations, cultures, social and political systems, and so on. CAS are composed of agents. Agents are autonomously acting, coevolving units within a system, trying to reach individual and/or system goals over time. Through coevolving agent interactions, CAS adapt to changing environments via changing networks, subunits, hierarchy, and causal influences (Arthur *et al.*, 1997; Holland, 2002; Lichtenstein and McKelvey, 2007).

2.2 Background: complexity thinking in logistics

As noted at the outset, logistics scholars appear to be shifting from linear to CALS views of supply networks (Warnecke, 1993; Tharumarajah *et al.*, 1996; Choi *et al.*, 2001; Surana *et al.*, 2005; Mason, 2007). Using new communication and information technologies as well as agent-based computational modeling, several researchers aim for more robustness, flexibility, autonomy, and emergence in logistics systems through the development of bionic (Okino, 1993), genetic (Ueda, 1993), holonic (Winkler and Mey, 1994), random (Iwata and Onosato, 1994) and virtual manufacturing (Gunasekaran and Ngai, 2004). In management, the concept of the fractal factory[4] (Warnecke, 1993) is one example how to plan and organize a CALS. In distribution logistics, current research deals with the development of autonomous cooperating processes that integrate new forms of communication and information technologies (like RFID and smart tags) and methods of agent-based modeling to develop a comprehensive new form and design of logistics processes (Scholz-Reiter *et al.*, 2004).

What all these concepts have in common, is the objective of adaptive logistics processes that – in an ideal case – autonomously react to the complex and changing demands of their environment in order to compete profitably in highly competitive, but changing, markets.

3. Are supply networks complex adaptive systems?

In this section, we take on our first problem: are logistics researchers, such as Choi *et al.* (2001) and Surana *et al.* (2005), correct in proceeding under the presumption that the several methods and approaches concerning the design, management and operations of logistics systems such as global supply networks meet generally accepted CAS definitional criteria? We define essential properties of CAS, primarily following Kauffman (1993) and Holland (2002). We first separate elemental properties of a system (heterogeneous agents, interaction, autonomy, and ability to learn) from properties concerning system behavior (self-organization, melting zone, and coevolution). We then show that key CAS properties do indeed match with descriptions of logistics systems in the literature.

3.1 Parallels between supply networks and CAS properties

3.1.1 Heterogeneous agents. Agents can be distinguished by different "rules" defining and/or governing abilities, fitness, goals, patterns of actions, rules of actions, etc. Owing to differences among their governing rules, most agents comprising a CAS are heterogeneous – at least to begin with Holland (2002); homogeneous agents do not behave in the manner of CAS. In complex logistics systems, such as global supply networks higher-level agents may represent firms, such as suppliers, manufacturers, distributors, retailers, customers, and other firms constituting the entire supply network. Lower-level agents may be single physical entities within a firm, such as piece goods, machines, containers, or applicable materials for the production of goods (Surana *et al.*, 2005; Choi *et al.*, 2001). Owing to their different functions within the supply network (distribution and allocation functions), agents may follow individual goals, under different constraints and different action patterns – they are heterogeneous.

3.1.2 Interaction. CAS agents may be highly interactive (Holland, 2002). The form of interaction depends on the nature of the system. For example, with laser light, interaction takes place through the exchange of energy (Haken, 1994); in social systems interaction might be different modes of human communication. As long as agents remain motivated to exchange information and/or resources, a stable degree of interaction is assured. Heterogeneity is one driver that sustains the motivation of interaction between agents: if, for example, all agents possess the same knowledge, they would have no motive to exchange information among themselves. Within logistics systems, individual objectives of agents provide motives to interact in order to match timely, qualitative, quantitative, cost-oriented or flexible-based logistics goals. Interaction takes place within the whole supply network in form of flows of information, resources and/or finances. In this context, Choi *et al.* (2001), in their comparison between supply networks and CAS, talk about a "critical level of connectivity" that exists among companies within a supply network and that is a presumption for a firm to be a part of it. Also, at a lower level of a logistics system, a high degree of interaction between employees and between physical entities may be found. In the case of physical entities, this is possible, if they are enabled to interact directly through communication and information technologies (Scholz-Reiter *et al.*, 2004).

3.1.3 Autonomy. Agents within a CAS act autonomously; meaning that their actions may be self-initiated without any external influence steering or controlling them, though there are usually a few imposing influences (Holland, 1988, 2002; Kauffman, 1993). Autonomous behavior can also be related to logistics agents (Surana *et al.*, 2005). Firms, subunits, and even physical entities (if enabled) are empowered to a certain degree, via delegation and decentralization, to plan, decide and act without direct supervision (Kappler, 1992).

3.1.4 Ability to learn. Owing to their ability to learn, agents are able to adapt by modifying their individual capabilities by changing their rules of action so as to improve their performance as experience accumulates. In doing so, agents search for so-called "building blocks," a set of plausible rules enabling them to interact within a CAS (Holland, 2002). Mostly, current research articles explicitly discussing the treatment of logistics systems as CAS, do not mention learning ability. However, where agents represent higher-level organizational entities within a supply network, organizational learning may be present. In contrast, at lower levels, where agents represent physical entities, we cannot ascertain a general ability of learning at this time. The learning ability of physical entities requires the newest information and communication technologies (e.g. multi-agent-based models, RFID tags, etc.), but their development is still in progress and not completely implemented in general practice (Spekman and Sweeney, 2006).

3.2 Parallels between supply networks and CAS behaviors

3.2.1 Self-organization. Self-organization results from the autonomous interaction of single agents within a system (Mainzer, 1994). Self-organization gives rise to bottom-up (new) order creation by a system itself, as opposed to structure and process imposed on the system by outside entities – what Holland (1988) calls "controllers." Based on the ability of autonomous decision making by the agents comprising a logistics system, processes of self-organization may also occur. Considering the structure of an entire supply network, there is no single firm deliberating or steering it – i.e. no outside "controller." Through the autonomous decisions by any participating firm – to fulfill customer orders – which then impact the decisions of other interrelated firms, an autonomously-created, spontaneously-ordered structure keeps evolving the supply network (Surana *et al.*, 2005; Choi *et al.*, 2001).

3.2.2 Melting zone. What Kauffman (1993) calls the "melting" zone is a region between the "edge of order" defined by the first critical value (Bérnard, 1901; Prigogine, 1955) and the "edge of chaos" defined by the second critical value of energy imposing on a system (Langton, 1989; Lewin, 1992); these "edges" define the "region of emergent complexity" where self-organization and emergent system behavior arise (McKelvey, 1999, 2007). In physical systems, this phase transition occurs at a specific temperature – the "1st critical value." In biological and social systems, the edge of chaos is less precisely defined; but in all cases, once imposed energy rises above the second critical value, functional and/or adaptive emergent order becomes maladaptive chaos. According to Bak (1996), the capability of staying within the melting zone is essential for living systems to survive; that is, CAS maintain themselves in a state of "self-organized criticality." If processes of self-organization take place in a logistics system, we also assume the existence of a melting zone. However, at this time we do not see any parallels in the logistics literature.

3.2.3 Coevolution. Kauffman (1993) emphasizes that CAS react to, but also influence their environment. Positive feedback loops may emerge in two ways:

(1) individual agents may sequentially respond to each other's actions, with the sequential behavioral consequences magnifying; or

(2) a CAS and elements in its environment may sequentially influence each other with positive feedback loops emerging.

Owing to a competition for limited resources among subsystems within a CAS, feedback loops emerge that, in turn, force coevolving adaptive responses by agents within a CAS or between a CAS and its environment. According to Choi *et al.* (2001), coevolutionary processes within logistics systems are initiated and influenced by non-linear state changes, and path dependences in the development of supply networks. Through a high degree of interdependent relationships within a supply network, each individual decision by agents has the possibility of influencing directly or indirectly the rest of the entire supply network. This can result in a coevolving system in which many, if not all, agents are simultaneously adapting to one another (Surana *et al.*, 2005).

3.3 Limitations of the parallels

Although most properties of CAS appear applicable to logistics systems, doubts remain. First, CAS best fits living systems (Gell-Mann, 2002). Supply networks are usually only partly living socio-technical systems. Most still have a living human component managing the non-living logistics elements. Consequently, logistics systems are not yet 100 percent self-organizing – they still rely on human initiative (Knyphausen-Aufseß 1988; Kosiol, 1973) and they still depend on operational frameworks designed by people (Kieser, 1994; Bea and Göbel, 1999). Currently, self-organization in logistics systems is mostly decentralized decision making by people.

New concepts and approaches to logistics systems, such as autonomous logistics processes (Freitag *et al.*, 2004; Scholz-Reiter *et al.*, 2004; Langer *et al.*, 2006), the fractal company (Warnecke, 1993), and holonic manufacturing (Tharumarajah *et al.*, 1996) are beginning to feature intelligent machines and goods – what we are calling smart parts – that rely on new information and communication technologies (such as smart tags and RFID). These systems are capable of developing non-human decision making and problem solving. Self-organized coordination and steering stem from smart parts rather than people. But, the bottom line is that smart-part-based self-organization absent people does not exist.

4. The challenge of extreme events in CALS

In the following section, we first describe implications for the design of supply networks in order to further approximate CALS. Therefore, we introduce current development of smart parts in information and communication technologies. Next, we describe the main CAS outcomes drawn from complexity theory (emergence, adaptation, irreversibility, butterfly effect, multi-levels, and scalability). Then, we examine parallels we already see in the current logistics systems literature, and some additional outcomes that could be expected from fully smart-part CALS systems. We pay special attention to both positive and negative outcomes.

4.1 Implications for logistics development

While there is no validated proof that logistics systems, as yet, will really behave and act as natural CAS, this possibility does not seem far away. Imagine containers from Hong Kong or cars from Japan, each of which has a substantially improved version of the "OnStar" chip now on Cadillacs. The new chip knows where it is supposed to end up, can contact the GPS satellite, can contact truck, train, and ship companies, can locate itself in giant storage yards in LA or New York through RFID tags, etc. With this new technology, containers or cars become "smart parts," each capable of planning their own best path (quick and expensive; slow and cheap) from the factory, to the dealer, to the final customer. Imagine a million of these doing this every month.

If the chips have a low cognition, in terms of ability of learning and processing information, they can just check into a neural network program that constantly keeps up to date on what the best routing plans are. An artificial neural net (ANN) is a mathematical or computational model based on biological neural networks. It can vary its degree of complexity and consists of densely interconnected adaptive processing units (Hassoun, 1995). In most cases, an ANN is an adaptive system that changes its structure based on external or internal information that flows through the network during its learning phase. If the chips have more learning capability and can contact other smart part chips they begin to behave like semi-autonomous heterogeneous agents. Now, there is the possibility that they can learn from each other; for example, what the best routes are. However, there is also the down side of an extreme outcome; for example, where all the smart chips simultaneously aim for the same ship, only to find out that the ship is full and most parts, then, are left on the dock.

We see that self-organizing systems of smart parts that have learning capability could more rapidly respond to changing environmental conditions like strikes, storms, or political disturbances, than a neural net or even human operators. But with smart-part learning capability there is also the risk of extreme negative events, as noted above. Once, smart parts are self-organizing we have to be mindful of all aspects of their emergent behavior (Klimecki, 1995). Therefore, we now draw parallels between CAS outcome behaviors and possible smart-part logistic systems.

4.2 Outcomes of CAS for understanding supply networks as CALS

4.2.1 Emergence. As noted earlier, via processes of interaction and self-organization new characteristics of a system arise, i.e. new kinds of orders evolve, referred to as emergence (Holland, 2002). Emergence is a phenomenon where the behavior of the whole is greater than the sum of its parts. This means the outcome of emergence is not related to individual system components, but results from the synergistic effects of interacting elements (Haken, 1977). Emergence occurs between the edges of order and chaos. Complexity scientists identify several more specific outcomes indicating emergence, which we detail below.

4.2.2 Adaptation. Adaptation includes structural, physiological and/or behavioral processes of systemic change that increase the expected long-term success of a system. It can apply to changes stimulated by environmental demands over a long time span (i.e. across generations) or a process of development within a shorter time period (such as a life time). Through processes of adaptation CAS are able to cope with environmental changes they are interrelated to. In the case that systems are not adequately adapted to their environment they will either have to move out of the habitat or die off. The essentials of adaptation are captured in Holland's (1975) genetic algorithm.

4.2.3 Nonlinearity; irreversibility. Emergent CAS behavior is non-linear; agents interact in non-additive ways (Holland, 1988, 2002); the near total autonomy of each agent fosters heterogeneous actions. Since, subsequent actions are not necessarily pre-determined, the entire system behavior of a CAS is unpredictable (Haken, 1977). In parallel, Prigogine and Stengers (1984) argue that irreversibility is a typical system behavior characteristic of self-organizing systems tipped across the edge of order by tension imposition. Irreversibility describes thermodynamic processes and other order-creation outcomes that cannot be undone, revoked or reversed – self-organized systems cannot return to the initial nature of their parts. Prigogine's emergent "dissipative structures" are new systems designed to speed up the production of entropy; that is, they emerge to speed up reduction (dissipation) of the imposing energic tension that tipped the system over the edge of order in the first place (Prigogine, 1962).

4.2.4 Butterfly effects. One outcome of CAS is known as the "Butterfly Effect," introduced by Lorenz (1963, 1972), with the question: "Does the flap of a butterfly's wings in Brazil set off a tornado in Texas?" More generally, the idea is that insignificant initiating events can trigger remarkably different system dynamics. These tiny initiating events are the bifurcation points in chaos theory (Gleick, 1987). Butterfly-events of chaotic histories are never repeated, are not predictable, and can produce significant nonlinear outcomes, specifically, extreme events. By this means, the degree of complexity resulting from dynamic interaction (e.g. high degree of inter-dependencies, non-linear interactions, short-range interactions and positive and negative feedback loops of interactions (Cilliers, 1998)) can reach an enormous level. Holland (2002) talks about "butterfly levers" to capture the idea that small initiating events are levers for thwarting negative follow-on events – possibly extreme ones – or for furthering positive events.

4.2.5 Multi-levels. CAS produce multi-level (hierarchical) structures in which "an emergent whole at one level is merely a component of an emergent system at the next higher level" (Heylighen, 1989, p. 2). According to Simon (1962), the adaptation of a system is enhanced if subunits are "nearly decomposable" – meaning nearly autonomous with only the most essential connections and interactions with other units remaining. In this way, a system can use less adaptive energy for intra-system connections, thereby saving more energy to adapt to a changing environment or competitors. Small assemblies of autonomous agents or subunits form stable, but adaptive, modules; these may be combined to create more adaptive higher level modules (Holland, 2002).

4.2.6 Scalability. There is a growing view that CAS causal dynamics can often be self-similar (fractal) across levels; what Mandelbrot (1961, 1982) terms "fractal geometry" – meaning that the same kind of dynamics work at multiple levels (Kaye, 1989; Schroeder, 1991; Peitgen *et al.*, 1992). Scalability occurs in physical, biological, social, and organizational systems (Gell-Mann, 2002). Fractal structure is explained by scale-free theories applying at multiple levels – Andriani and McKelvey (n.d.) list 15 of them.

4.3 Applying CAS to supply networks outcomes

4.3.1 Emergence in logistics systems. Some logistics observers do see emergent phenomena in supply networks. Choi *et al.* (2001, p. 358) state:

> Although it is true that individual firms may obey the deterministic selection process (Choi and Hartley, 1996), the organization of the overall SN emerges through the natural process of order and spontaneity.

Surana *et al.* (2005, p. 4239) also describe logistics systems as emergent:

> In most circumstances, order and control in the network are emergent, as opposed to predetermined. Control is generated through nonlinear though simple behavioral rules that operate based on local information.

These authors point to non-linear interactions among autonomous agents comprising a supply network; each agent experiences the supply network as self-organizing. Though details of the entire system may be unknown, agents at multiple levels participate by making decisions about selecting suppliers and striving for timely deliveries to customers. If today's supply networks really are totally CALS, we should see emergent behavior at all levels (e.g. the management level, the information level, and the operational level). This means CALS, virtually by definition, have to have smart parts at the bottom levels.

Real-world smart parts supply networks do not yet exist, but Scholz-Reiter *et al.* (2004) observe that there is an ongoing paradigm shift from centralized control of "non-intelligent" items in supply networks towards decentralized operations by "intelligent" items (smart parts) in logistic structures – so-called "autonomous cooperating processes." These smart parts could be raw materials, components or products as well as transit equipment (e.g. pallets or packages) or transportation systems (e.g. conveyors and/or, trucks).

The main characteristic of smart parts is their ability to control themselves, which means that they can make autonomous planning and production choices. Reichl and Wolf (2001) describe such intelligent items as "things that think." Windt and Hülsmann (2007) define autonomous cooperation as decentralized decision-making processes within logistics structures, that is, interacting parts possess the ability to render decisions independently. The objective of effective CALS is the achievement robust and effective emergent behaviors that are efficaciously adaptive in the face of uncertain, changing, and frequently non-linear environments.

4.3.2 Adaptation. Logistics systems such as supply networks adapt to their environment by adapting their structures by adding or deleting relations between agents (e.g. connecting with new suppliers, serving new customers, etc.), changing their physical abilities (e.g. implementing new technologies) and adapting their behavioral processes, i.e. shifts in strategies. In doing so, a supply network reacts to environmental demands and at the same time creates a new environment for its competitors (Choi *et al.*, 2001). Processes of adaptation take place in different levels of the supply network at different times and different dimensions. The more supply networks approximate to "well-behaving" CALS, the more the frequency and size of negative (and positive) outcomes will follow Bak's (1996) "self-organized criticality."

Our logic rests on the following sequence. If supply networks consist of learning and interacting agents and, thus, are vulnerable to nonlinearities, we may presume that they will also be subject to the "self-organized criticality" discovered by Bak and Chen (1991) and Bak (1996). Given this, logical design and delivery solutions by a CALS, then, will display the non-linear dynamics of Bak's sandpiles; i.e. the logistic flow outcomes of collective smart-part decisions will display the power law signature – every once and a while there will be an extreme event of the kind where all the parts aim for a particular ship, say, only to find out that most of them are left sitting on the wharf. Criticality has, in fact, already been shown to be the case in a computational-model demonstration of supply-network dynamics by Scheinkman and Woodford (1994). A dilemma results: On the one hand, absent the power law signature there is no evidence that a CALS exists; on the other, if a CALS exists then there is the follow-on problem of how to anticipate, prevent, or otherwise deal with extreme negative events – such as thousands of parts left on a wharf in Hong Kong after the ship leaves for the USA It follows that CALS will also exhibit efficacious adaptation as a power law signature.

4.3.3 Butterfly effect as "bullwhip effect". As noted earlier, the CAS butterfly effect has already been observed in logistics systems and named the "bullwhip effect," which stems from Forrester's (1961) *Industrial Dynamics* and was coined by Lee *et al.* (1997). It is typically observed in forecast-driven distribution channels. Like butterfly effects, the bullwhip effect describes how tiny initial shifts (in customer demand in order quantity) can result in chaotic and extreme events along the supply network via dynamical (non-linear) processes. Owing to strong interdependencies among the actors of a supply network, e.g. regarding stocks, each decision and action by an individual agent will affect the others. Since, customer demands are not stable, firms have to forecast demand in order to adequately store products and stocks. These forecast calculations are based on statistics. However, errors in forecasts and informational asymmetries lead companies to keep a "safety stock" (Svensson, 2003). Moving up the supply network from end-user to raw-materials supplier, each participant has its own forecast about needed stocks. If each participant adds a safety stock, there is some risk that the sequential building of safety stocks will result in far more stock than needed. Consequences of the bullwhip effect are overfilled warehouses or periods of shortness of needed resources and products (Towill, 2005). In contrast to natural systems, where the butterfly effect occurs from low-cognitive agents (e.g. a falling tree sets of a large avalanche of snow; the failure of one sub-station causes spreading power failures throughout the entire North East of the USA; one infected mosquito can initiate of West Nile Virus, etc.), the bullwhip effect takes place in human systems (logistics), where "intelligent" actors can worsen it through their conscious decisions of action and behavior (Dejonckheere *et al.*, 2003). According to Lee *et al.* (1997), there are four major causes of the bullwhip effect: demand forecast updating, bulk purchases (e.g. encouraged through quantity discounts), price fluctuations, and shortage gaming (e.g. regarding veridical customers demands), which could be understood as Holland's "butterfly levers." Dejonckheere *et al.* (2003) state that, the bullwhip effect cannot be totally avoided with today's planning methods. We also assume that self-organizing smart parts could smooth the risk of the bullwhip effect, through their self-regulating "natural" dynamics.

4.3.4 Multiple-levels. Simon's (1962) nearly decomposable subunits combine the novel-search advantages of autonomous subunits with the lowered cost of minimized subunit connectivity, thereby enhancing adaptive efficacy. Agents in a logistics system connect via interaction and interdependency. In doing so, they create a variety of interactive subsystems. Conceptualized vertically, a supply network is by definition multi-level: supplier, manufacturer, distributor, retailer, and customer. Sufficiently stable subsystems will survive likely form long-lasting contracts. Weak subsystems fall apart, which could mean cancelling existing contracts with customers or suppliers. Small assemblies of agents can form stable modules like cooperating suppliers, which can then be combined in higher-level modules, as for example the in the stage of production where suppliers and the manufacturer build one cooperating system. As smart parts are added to the supply network, we see additional levels forming.

4.3.5 Scalability. CAS theory suggests the same causal dynamics may work at multiple levels. If today's supply networks are really CAS, then the same kind of dynamics might be present across different levels of a supply network. As described above, a supply-network network is a multi-level hierarchical and heterogeneous network where, at a higher level, each agent represents a supplier, manufacturer, distributor, retailer or customer. Owing to strong interdependent relationships, Surana *et al.* (2005) assume correlations between agents within one supply network over long distance and timescales; these indicate scalability in supply networks. The concerns at each level are essentially the same: lower product and storage costs, improve quality, and speed up deliveries. Within each of the forgoing levels – suppliers to retailers – we see one or more levels of physical entities – eventually smart parts – that also add layers of multi-level system behavior. Since, agents have the same concerns about adaptation at multiple levels there is some evidence in the literature of scalability in multilevel supply networks (Surana *et al.*, 2005).

5. Suggestions for reducing smart parts extreme outcomes

The CAS literature makes it very clear that CAS result in non-linear behavior with some probability of butterfly events spiraling into positive and negative extremes. It follows that CALS comprised of smart parts will show butterfly events and extremes. Holland's (2002) butterfly "levers" become the tools by which managers can foster positive extremes or turn off the negative ones. CALS, thus, become two edged swords. On the one hand, they are capable of more quickly and efficiently responding to adaptive tensions from non-linear events in changing CALS environments. On the other, they are prone to extreme events. What is disturbing to us is that the current logistics literature appears to be moving toward CALS without realizing the potentially devastating downside extremes. We know from the modeling done by Scheinkman and Woodford (1994) – over ten years ago – that CALS will produce such dynamics. Also in practice companies, such as Proctor & Gamble or Hewlett-Packard, detected this phenomenon by discovering significant degrees of variability in distributor's orders as well as in material supplier's orders (Lee *et al.*, 1997). But now, we see articles like those by Svensson (2003, 2005), Towill (2005), Catalan and Kotzab (2003) and Paik and Bagchi (2007) that reflect on the current relevance of this topic.

If managers enable supply networks comprised of both human and smart-part agents to become CALS, then, they have to have solutions in place for managing severe negative outcomes, or better yet, preventing them in the first place. If nothing is done, it is inevitable that at one time or another, too many "smart automobiles" will simultaneously head for the same ship, with the result that thousands could be left sitting on the wharf. In what follows, we list several possible options to reduce the risk of extreme events from a complexity theoretic perspective, but further research is needed:

(1) One solution is to stay with low-cognition parts. They could keep checking in with a neural network program. The neural net would monitor all possible shipping options – trucks, trains, ships – and give up-to-date information about the fast/expensive or slow/cheap choices. In this case, we would be still far away from true autonomous self-organizing agents and CALS, and thus we could not take advantage of emergent system behavior and fast reacting logistics processes.

(2) Given truly smart parts, one option is to zero in on treating Holland's tiny initiating events as "butterfly levers" by which to derail negative extremes. In all of the analyses of disasters such as the Bay of Pigs, Challenger, Pioneer, 9/11, Enron, Airbus, or Parmalat, all sorts of small events were evident after the fact analyses, but missed before hand:

   - One option is to use a monitoring system of the smart parts logistic dynamics so as to forestall the tipping point where a system appears headed toward an extreme outcome – unless of course, it appears to be a positive one.
   - A second option is to use a neural net instead of human monitors. The neural net would monitor all "parts" decisions, analyze what system dynamics their collective decisions are apt to produce at any given time. Then the neural net would alert human operators, or even better, inform the parts to try other options.
   - A third option is to keep smart parts but also give them the option of checking with the neural net "monitor" so the parts, themselves, can keep checking so as to avoid the tipping point.
   - One of the things we learn from LeBaron's (2001) model of the stock market is that crashes occur when agents lose their heterogeneity – they all end up with the same "buy-sell" rule. A fourth option, then, is to constantly monitor (via neural net or humans) the heterogeneity of smart parts choices. As they lose their choice heterogeneity, at some point they become treated like "dumb" parts and the system reverts to option one above.
   - A fifth option resulting from LeBaron's model is that smart parts could mix in routing options constantly produced by the neural net with options they learn about from other parts.

6. Conclusion

Over the past decade or so concepts of supply networks have shifted from a linear structure to a "complex adaptive system" CAS that is presumed capable of autonomously adapting in timely fashion to environmental changes. But do today's supply networks truly meet the criteria of living systems – so-called CAS? If so, what implications are there for managers; How to manage nonlinear systems?

To answer the first question – Is it really valid to call supply networks CAS? – we look for parallels between CAS theory (Kauffman, 1993; Holland, 2002) and supply networks. The logistics literature points to several common properties: heterogeneous agents, interaction, autonomy, ability to learn, self-organization, melting zone, and coevolution. Consequently, we validate earlier logistics papers –Choi *et al.* (2001), Surana *et al.* (2005) and Zhao (2005) to reaffirm that supply networks at their current status can be fully defined as CAS. However, there is still potential to raise the sophistication of their performance to the point they perform as CALS through the development and implementation of smart parts, for example.

The second question is: If CALS exist, what are the implications? To answer this question, we draw on the most recent – third phase – of complexity science thinking. We note the wide spread discovery of Pareto distributions, butterfly effects, fractals, power laws, and extreme events in organizational phenomena (Andriani and McKelvey, 2007). These effects appear as "bullwhip effects" in supply networks (Lee *et al.*, 1997; Svensson, 2003, 2005; Towill, 2005; Catalan and Kotzab, 2003) From this we see that, besides positive effects of CALS, such as a higher adaptivity, emergence, and flexibility, we also find that supply networks are vulnerable to all the non-linear extreme dynamics found by complexity scientists.

The probability of extremes has to be considered in supply network management, especially when facing the new trend of implementing intelligent autonomous "smart" parts in logistics. To answer the third question – What managerial action is most apt to work? – we suggest integrating neural network models with smart parts autonomous supply networks (Scholz-Reiter *et al.*, 2004; Hülsmann and Grapp, 2005; Hülsmann *et al.*, 2006). We outline a variety of managerial design options, depending on how "smart" the parts are and how much autonomy they are given.

Consider that smart parts will be engaged in arranging their transportation from one continent to another, trips in which cost and speed of transport are critical. Smart decisions about speed versus costs are embedded in a network of transportation options that become available only at some costs. These costs, in term, are a function of a contract market that could be in a constant state of flux. The market pricing system is, itself, a complex adaptive system. Further detailed research is needed, however, in testing the neural network approach for managing extreme events in the foregoing kind of complex international transportation market.

Notes

1. "Agents" may be biomolecules, genes, organelles, cells, organs, organisms, and species. At the human level of analysis, "agents" may be cognitive elements, people, groups, firms, and societies, etc. (Holland, 1995).
2. "Self-organized criticality" is the phrase Bak (1996) used to describe the steepest slope a sandpile can achieve. As grains of sand continue to fall, the sandpile continues piling up till the critical slope is reached. At this point the slope maintains its criticality via the slippage of many tiny movements of one or a few grains of sand or, oppositely, by infrequent large avalanches involving many grains.
3. Power laws often take the form of rank/frequency expressions such as $F \sim N^{-\beta}$, where F is frequency, N is rank in size (the variable) and β, the exponent, is constant. In exponential functions the exponent is the variable and N is constant (Newman, 2005). The inverse slope signifying a power law typically results when a well-formed Pareto distribution is plotted using log-scaled X and Y axes.

4. The concept of the "Fractal Factory" introduced by Warnecke represents a production model based on natural systems. The structure of a factory is decentralized and consists of autonomous subsystems, which highly interact with each other. These are fractal structures showing similar causal dynamics at multiple levels. They participate in processes of their own development, mutation and disintegration while orienting to the general company goals (Warnecke, 1993).

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