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# Designing an electronic auction market for complex 'smart parts' logistics: Options based on LeBaron's computational stock market

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ABSTRACT

Modern technologies, such as RFID, offer never-before seen learning abilities to parts moving in supply chains. Logistics systems may be understood as complex adaptive *logistics* systems (CALS). They also may be conceived as electronic auction markets as 'smart parts' bid for the best routing and pricing from transportation firms. To ensure the world-wide functionality and efficiency of CALS transportation markets, we suggest the utility of an agent-based computational market design based on Blake LeBaron's stock-market model. Given that parts may be more or less smart, markets more or less complex, and self-organizing CALS systems probabilistically subject to the bullwhip effect, we suggest nine different computational CALS market-design options, offering more adaptivity to unexpected environmental contingencies.



## 1. Introduction

Modern technologies, such as RFIDs, GPS; sensor networks, and low-power microcontrollers, make it possible for logistics networks to automate and optimize their function (Bollinger, 1998). Logistics goods, such as cars and containers containing transponder technologies like RFIDs, are enabled to self-organize their transportation routing across oceans and continents to their destination point. They become what we term 'smart parts'. The vision of *complex adaptive logistics systems* (CALS) (Choi et al., 2001; Surana et al., 2005; Pathak et al., 2007; Wycisk et al., 2008) is partially realized in that smart parts become agents in a worldwide computer-based logistics network and then self-manage the planning and routing process of their transportation via different shipping companies—the *sellers* of transportation space.

But transportation is not for free. Car and container *shippers* have to buy space on trucks, trains, and ships. For smart parts, then, to self-organize their routing, they must play the role of individual entities trading in a *world-wide transportation-space market*. Depending on their technical capabilities logistics goods, as agents, may be guided by humans or they may become intelligent, learning 'smart parts' that self-organize their transportation in a '*complex adaptive system*' (CAS) (Holland, 1995, 2002) within electronic auction markets (Anandalingam et al., 2005). Moyaux et al. (2007) talk about supply chains as a network of auctions.

Facing these trends in supply chain management, the question arises: How may CALS be appropriately designed as markets to assure the most efficient transportation? The efficient functioning of a specific logistic system

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depends on supporting and sustaining timely responses to changing environmental demands (Hicks and Gullet, 1975). Efficient processing within a CALS means the constant reduction of frictions at interfaces within the multi-dimensional structure of CALS processes by constantly reducing resource usage to a minimum (Krystek, 1987; Hülsmann and Grapp, 2007b).

Due to the inherent complexity of CALS network dynamics, model design requires as many details as possible about the real-world logistics application (Pedahzur and Schmelkin, 1991). Because CALS are characterized by their ability to adapt a system's profiles to changing environmental demands (Wycisk et al., 2008), the designing of a CALS also has to cope with its dynamic learning features (i.e., those based on transponders, sensors, micro-controllers, etc.). Thus, engineers planning the design of a CALS have to worry about not only the complexity of CALS, but also its agents' learning ability pertaining to required adaptive responses. The planning and design of CALS then, like international supply networks (Hülsmann et al., 2008) or global service supply chains (Hülsmann and Grapp, 2007a) calls for modelling a market-based CALS comprised of agents having varying amounts of 'smartness'.

Crainic and Gendreau (2004) state that intelligent transportation systems have been up to now largely hardware driven and have led to the introduction of many sophisticated technologies in the transportation area. However, the development of the *software component* of intelligent transportation systems, models and decision support systems in particular, is dramatically lagging behind. Agreeing with this opinion, the primary objective of our paper is to outline an agent-based computational approach for modelling CALS logistic markets to contribute to this lack of software-based solutions for realizing CALS. In doing so, we experimentally design an expeditiously adaptive smart-part logistics supply network. We draw on LeBaron's (2001a–c) agent-based computational model to deduce and describe alternative design possibilities for CALS markets differing in their learning capabilities.

LeBaron's stock-market model is already operational; its baseline simulation is well validated against the S&P stock market over the past 50 years. From this stock-market-based calibration, we can redesign it to support a smart-parts computational logistics market. LeBaron's model allows us to design an agent-based logistics market in which the agents have varying amounts of decentralized sensing, intelligence, and learning ability that self-organize so as to give the entire CALS an adaptive learning capability. This feature is not yet seen in any but a very few world-wide logistics systems.

We begin by defining and presenting the current vision of CALS, which includes reviewing current applications of complexity theory to further the understanding of the properties and learning outcomes of complex logistics networks (Section 2). Next, in Section 3, we first introduce and define the essential features of electronic auction markets. Then, we show that CALS possess a structure not unlike that of a stock market; they can then be understood as 'international "smart parts" logistics markets'. Third, we describe the essentials of a world-wide smart-parts 'bid/offer' electronic auction market as part of our logistics market model. Fourth, basic features of LeBaron's stock-market model as a basic scheme for modelling smart-parts choices embedded within electronic logistics auction markets are described in detail. In Section 4 we outline nine logistics market choices in addition to the baseline simulation of a market operated only by humans. Section 5 discusses contributions of these design options to the logistics goals to reduce cost and to gain adaptivity. Finally, a short conclusion suggests further learning implications for the ongoing developing process of CALS.

## 2. Characteristics of complex adaptive logistics systems

We set the stage by reviewing the current state of CALS theory and the development of complexity science, complex adaptive systems and emergence theory. Then we define key elements of CALS, their emergent properties, and emergent outcomes.

### 2.1. Defining complex adaptive logistics systems

As noted at the outset, logistics scholars appear to be shifting from linear to complex views of supply chains (Warnecke, 1993; Tharumarajah et al., 1996; Choi et al., 2001; Surana et al., 2005; Mason, 2007; Wycisk et al., 2008). This leads to the question, are there additional contributions from complexity science for understanding supply systems and networks? To answer this question we primarily follow Kauffman (1993) and Holland (2002).

#### 2.1.1. Defining complex adaptive systems (CAS)

The concept of CAS comes from biology—and pertains mostly to living entities (Gell-Mann, 2002). Holland (1995) describes CAS as systems that emerge over time into a coherent form, adapting without any singular entity deliberately managing or controlling them. Examples of CAS phenomena include all levels of biological analysis from base-pairs, DNA words and protean–protean interaction networks, 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 (Holland, 1995, 2002; Arthur et al., 1997; Lichtenstein and McKelvey, 2004). This leads to an understanding of supply networks as CALS (Choi et al., 2001).

#### 2.1.2. Defining CALS

This tendency to a more complexity-based perspective in logistics is forced by the usage of new communication and information technologies as well as agent-based computational models, with researchers aiming for more robustness, flexibility, autonomy, and emergence in logistics systems (Roy, 1998; Terzi and Cavalieri, 2004). Approaches to establish new logistics concepts are bionic

(Okino, 1993), genetic (Ueda, 1993), holonic (Winkler and Mey, 1994), random (Iwata and Onosato, 1994), and virtual manufacturing in concept (Gunasekaran and Ngai, 2004). In the context of production and logistics, one example is the concept of the fractal factory[1] (Warnecke, 1993); it 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 modelling to develop a comprehensive new form and design of logistics processes (Scholz-Reiter et al., 2004).

There are four characteristics all of these complexity-based logistics concepts have in common: *First*, they are all based on adaptive processes; this means that the logistics systems may adopt the larger system's profiles (e.g., the structure, resources, business processes characterizing the firm). *Second*, a there is a topology of interconnectivity among multiple supply chains. *Third*, these processes may run autonomously. This means that without any external means and/or instructions, logistics systems may alter their structure and actions as a function of their own resources, considerations, decisions, etc. *Fourth*, these processes are initiated by changing environmental constraints; they embody reactions to changing external requirements. Each of these constitutive attributes within a CALS can maintain several properties regarding the entity, the topology, the system and the environment that describe the state of a CALS at a point in time or over a finite span of time: capacity, service level (entity), path length, redundancy, and clustering (topology); efficiency and flexibility (system); and demand, dynamism, and risk (environment) (Pathak et al., 2007).

### *2.2. The vision of complex adaptive logistics systems*

In logistics research an ongoing paradigm shift can be observed, going from centralized control of *non-intelligent* elements in *hierarchical* structures towards decentralized control of *intelligent* elements in *heterarchical* structures. The understanding of logistics systems has evolved over time from 'linear structures' to 'complex systems' (Lambert et al., 1998; Bowersox et al., 2002) to CALSs most recently (Choi et al., 2001; Surana et al., 2005; Pathak et al., 2007; Wycisk et al., 2008). CALS comprise various logistic entities from raw materials, components or products to transit equipment (e.g., pallets, packages) or transportation systems (e.g., conveyors, trucks) (Scholz-Reiter et al., 2004). A key feature of CALS is that they consist of smart parts. The term 'smart parts' describes logistics entities, which possess the capabilities of interaction and autonomous decision-making through the usage of modern communication and information technologies, such as RFID, GPS, sensor networks and electronic markets (EMs). Smart parts can be all kinds of the before-listed logistic entities. Their 'smartness' lies in the ability of the parts to autonomously decide about their optimum behaviour regarding their given individual goals (e.g., time, quality, costs).

While there is no validated proof that logistics systems, as yet, will act as natural CAS, this possibility does not seem far away. Researchers are working on the development of de-centralized adaptive logistic processes that possess the ability of autonomous local cooperation (Scholz-Reiter et al., 2004; Wycisk et al., 2008). Autonomous cooperation describes processes of decentralized decision-making in heterarchical structures. It requires that interacting elements in non-predictable systems possess the capability and the possibility of making decisions independently. The implementation of autonomous cooperation aims at increased robustness and positive emergence of the complete system through distributed and flexible coping with dynamics as well as complexity (Windt and Hülsmann, 2007).

The objective of our research is the self-producing self-delivering product. This *intelligent* product can initiate its own production according to customers' requirements, autonomously plan and find its most efficient way to the customer, and flexibly react to changes or hurdles affecting its progress. Imagine containers from Hong Kong or cars from Japan, each of which has a vastly improved version of the 'OnStar' chip now in Cadillacs. This 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 Amsterdam via RFID tags, etc. With this new technology, containers or cars become '*smart parts*', each capable of planning their own best path (quick/expensive; slow/cheap) from the factory, to the dealer, and then to the final customer. Imagine a million of these doing this every month worldwide.

The literature on complexity theory makes it very clear that CAS result in nonlinear behaviour with some probability of *butterfly-events*[2] spiralling into positive and negative extremes (Bak, 1996; Brock, 2000; Gell-Mann, 2002; Holland, 2002). It follows that CALS comprised of smart parts will also show butterfly-events and extremes (Wycisk et al., 2008). An exact or even heuristics-based solution for global optimization in the logistics system becomes impossible. Holland's (2002) *butterfly-levers* become the tools by which managers can enable 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 nonlinear events in

[1] The concept of the 'fractal factory' introduced by Warnecke (1993) 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.

[2] We will use 'butterfly-events' to refer to the 'tiny initiating events' (Lorenz, 1963) that may spiral up into extreme events and frozen accidents (Gell-Mann, 2002); we use 'butterfly-levers' (Holland, 2002) to refer to the use of small events to 'lever' a system up toward a positive extreme or stop a negative extreme from happening. The term 'butterfly' comes from Lorenz's (1972) paper.

changing CALS environments. On the other, they are prone to Pareto distributions, long tails, and extreme events (Wycisk et al., 2008).

### 2.3. Properties of complex adaptive logistics systems

Besides the four overarching common characteristics mentioned just above, there are several characteristics that reflect a more detailed description of CALS—on an individual, intra-systemic, and inter-systemic level.

#### 2.3.1. Individual level

Natural CAS consist of a number of constituent entities that are called agents. *Agents* may be distinguished by different attributes such as goals, patterns of actions, rules of actions, etc. Due to their individual idiosyncratic features, most agents of a CAS are in general *heterogeneous* (Holland, 1988). 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 chain (Choi et al., 2001; Surana et al., 2005). Due to their different functions within the supply chain, agents may follow individual goals, under different constraints, and with different action patterns. This both creates, and results from, their heterogeneity (Wycisk et al., 2008). According to Holland (2002) agents in a CAS also may be highly *interactive*. Within supply networks, individual objectives of agents provide motives to interact in order to match timely, qualitative, quantitative, cost-oriented or flexible logistics goals (Hülsmann et al., 2006). Interaction takes place within the whole supply network in the form of flows of information, resources and/or finances (Sun and Wu, 2005; Göpfert, 2005). Due to their *ability to learn*, agents are able to adapt by modifying their rules of action and improve their performance as experience accumulates (Holland, 2002). Furthermore, where agents represent higher-level organizational entities within a supply chain, organizational learning may be present. In contrast, at lower levels, where agents represent physical entities, we cannot ascertain a general ability of learning yet in existing logistics systems (Wycisk et al., 2008).

#### 2.3.2. Intra-systemic level

From a complexity perspective, agent actions may be self-initiated without any external influence steering or controlling them—they are *autonomous* (Holland, 1988, 2002; Kauffman, 1993). Surana et al. (2005) state, that autonomous behaviour or autonomy can also be related to logistics agents. Firms, subunits, and also physical entities (if enabled) are empowered to a certain degree, via delegation and decentralization, to plan, decide and act without direct supervision (Kappler, 1992). *Self-organization* results from the autonomous interaction of single agents within a CAS (Mainzer, 1994). It gives rise to bottom-up (new) order creation by a system itself, as opposed to structure and process imposed on the system by outside (or higher-level) entities. From an intra-systemic perspective, self-organizing processes result from the interaction of individual agents (e.g., employees, physical entities) within a logistics *system*, e.g., a company. What Kauffman (1993) calls the '*melting*' zone is a region between the 'edge of order' defined by the first critical value of energy imposing on a system and the 'edge of chaos' defined by the second; these 'edges' define the 'region of emergent complexity' where self-organization and emergent system behaviours arise (McKelvey, 1999, 2008). If processes of self-organization take place in a logistics system, Wycisk et al. (2008) also assume the existence of a melting zone. 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 technological or market environment or competitors. Agents in a logistics system connect via interaction and interdependency. Conceptualized vertically, a supply chain is by definition *multi-level*: supplier, manufacturer, distributor, retailer, and customer.

#### 2.3.3. Inter-systemic level

*Self-organization* takes place on the next higher aggregation level of organizational interaction between independent systems, e.g., between supply network firms. Considering the structure of an entire supply chain, there is no single firm steering it. Through the autonomous decisions by any participating firm, an autonomously created structure keeps evolving the supply chain (Choi et al., 2001; Surana et al., 2005). Kauffman (1993) emphasizes *coevolution***,** in which positive feedback loops may emerge as agents sequentially respond to each other's actions. Due 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 nonlinear state changes, and path dependences in the development of supply networks. Emergent CAS behaviour is *nonlinear*; agents interact in non-additive ways (Holland, 1988, 2002). Since subsequent actions are not necessarily predetermined, the behaviour of a CAS is unpredictable (Prigogine and Stengers, 1984). Choi et al. (2001) as well as Surana et al. (2005) point to nonlinear interactions among autonomous agents comprising a complex 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, which reflect the process of adaptation.

### 2.4. Outcomes of complex adaptive logistics systems

Adaptive processes of interaction and self-organization give rise to new system attributes—i.e., new kinds of order (Kauffman, 1993; McKelvey, 2004)—referred to as *emergence* (Holland, 1988). Emergence is a phenomenon where the behaviour of the whole is greater than the sum of its parts. This means the emergent structure and process outcomes are not related to individual system components, but result from complex, nonlinear agent interactions. Emergent phenomena are now seen by logistics observers of supply chains. Choi et al. state: ‘Although it is true that individual firms may obey the deterministic selection process (i.e., Choi and Hartley, 1996), the organization of the overall supply network emerges through the natural process of order and spontaneity’ (2001, p. 358). Surana et al. also describe supply networks as emergent: ‘In most circumstances, order and control in the network are emergent, as opposed to predetermined. Control is generated through nonlinear though simple behavioural rules that operate based on local information’ (2005, p. 4239).

Within CAS, *butterfly-effects* already have been observed in forecast-driven distribution channels and named the ‘*bullwhip effect*’; this finding dates back to Forrester’s (1961) *Industrial Dynamics*. Like butterfly-effects, bullwhip effects in CALS occur when insignificant initiating events—e.g., shifts in customer demand in order quantity—grow by compounding positive feedback effects to produce extreme events along the supply chain. These are especially likely as systems become more complex and self-organizing, with resulting dynamical (nonlinear) processes. Due to strong interdependencies among the actors of a supply chain trying to adapt to each others demands, each decision and action by an individual agent will affect the others. Consequences of the bullwhip effect are overfilled warehouses alternating with periods of resource and product shortages (Lee et al., 1997).

Hülsmann and Grapp (2005) assume that self-organizing networks (like international supply networks have a certain *capability to learn*. Within a network structure, the intelligence of a system may be located in its smart parts (RFID transponders, smart tags etc.)—*and their connectivity*. This ‘distributed intelligence’[3] manages, for example, the disposition of material flow, instead of traditional centralized planning and control units. This learning feature of CALS is a necessary basis for increasing a logistic system’s robustness and the adaptively efficacious coevolutionary processes within its supply network as well as amongst its connections to the environment (Wycisk et al., 2008).

Well-working CAS have a high degree of *robustness*—i.e., they are relatively insensitive to perturbations or errors, and have a strong capacity to restore themselves (Heylighen, 2003; Sun and Wu, 2005). Carlson and Doyle (2000, p. 2529) define robust systems as ‘…systems designed for high performance in an uncertain environment and operated at densities well above a standard critical point’. A robust (resilient) system has an ability to cope with external dynamics without either being unstable nor becoming a ‘locked’ organization (Hülsmann et al., 2007)—what Arthur (1989) terms ‘lock-in’. Heylighen (2003) discusses *three main reasons for robustness* in CAS: redundancy, randomness, and feedback loops. *First*, the redundant, distributed-organizing form of these systems allows non-damaged regions to overcome the loss of the damaged ones. Thus, in CALS there is typically more than one company fulfilling the same or a similar task. If one supplier is out of stock for example, the producing company can easily ask another one. Transaction costs may be higher in this case, but the supply network is not interrupted. *Second*, self-organization thrives on randomness, fluctuations or ‘noise’. CAS have initial random movements that can lead to newly ordered structure. A certain amount of random perturbations facilitates rather than hinders self-organization. Within CALS these random perturbations can take the form of changing companies involved in the supply network—e.g., a production company can change or add new supply or retail firms. This action cannot be predicted and may appear random. *Third*, robustness also results from the stabilizing effect of feedback loops in CAS. From building up and changing the supply network, new connections will appear that may result in completely new system dynamics or a new kind of ordered structuring of the supply chain.

Sun and Wu (2005) state that CAS causal dynamics may often be self-similar (fractal) across levels; what Mandelbrot (1982) terms fractal geometry—meaning that the same kind of dynamics works at multiple levels (Peitgen and Richter, 1986; Kaye, 1989; Schroeder, 1991; Andriani and McKelvey, 2009). *Scalability* occurs in physical, biological, social and organizational systems (Mandelbrot, 1982; Gell-Mann, 2002). The presumption of supply networks as CALS, then, strongly implies that scale-free causes and consequent dynamics may occur at multiple levels of supply networks—the individual, the intra-systemic and the inter-systemic level. If today’s supply networks are, in fact, truly CALS, we should see scale-free emergent behaviour at multiple levels. Once smart parts are added in at the bottom levels of logistics networks, there is the possibility that fractal structures will emerge because of scale-free causes at the smart-parts levels of an automated supply chain. Sun and Wu (2005) successfully analyse the growth of supply distribution networks on the basis of scale-free theories. This means that in well functioning CALS, fractal dynamics among smart-parts supply networks at the bottom can very well affect the behaviour of the logistics systems at various higher levels as well (McKelvey et al., 2009).

## 3. Toward an electronic auction market based on LeBaron’s stock-market model

This section moves from our use of complexity science to better *understand* supply networks as CALS towards how to *design* them. In a logistic market sellers offer transportation space and manufacturers (buyers) buy space to ship goods (e.g., containers or cars) from the place of manufacture to dealers and ultimately to customers. We begin with a short review of electronic auction markets and the management science emphasis on agent intermediation based on computationally

[3] Intelligence in brains rests entirely on the production of emergent networks among neurons—intelligence ‘*is* the network’ (Fuster, 1995, p. 11).

complex optimization algorithms. Then we progress toward smart-parts electronic auction markets.

### 3.1. Some basic elements of electronic auction markets

#### 3.1.1. History

While financial electronic marketplaces date back to the founding of NASDAQ in 1971, supply-chain EMs did not materialize until later (e.g., Peer, 1976; Sporleder, 1980; Bell et al., 1983; Henderson, 1984; Malone et al., 1987). Only after 1990 do we see research and commentary on electronic supply-chain auction markets beginning to emerge (Schmid et al., 1991; Neo, 1992; Borman et al., 1993; Schmid, 1993; Lee, 1996; Gudmundsson and Walczuck, 1999; Wenninger, 1999; Kaplan and Sawhney, 2000; Van Hoek, 2001). Even so, in his review of electronic supply-chain research, Grieger (2003, p. 280) says: 'The supply chain dimension of an EM is largely neglected and poorly managed…'. Now we see evidence of a more pervasive interest in managing supply-chain EMs (Goldsby and Eckert, 2003; Anandalingam et al., 2005; Nair, 2005; Nault and Dexter, 2006; Agrali et al., 2008).

#### 3.1.2. Bundling

EMs range from simple ones such as the eBay C2C (consumer to consumer) market (one seller, one item, simple bid rules), to those that are what Anandalingam et al. (2005) call computationally complex—i.e., 'NP-Hard'.[4] What produces NP-Hard? Typically, these are B2B (business to business) EMs in which products are:

- *Substitutable*: the trade items are exchangeable—e.g., it does not matter to the carrier which ones are put on a truck going from one city to another;
- *Complementary*: the trade items are worth more as a package—e.g., one truck can deliver them sequentially on one trip; and
- *Bundled*: when items are worth more as a package, the 'bundle' presents a much more complex auction problem that leads to 'combinatorial auctions' (Anandalingam et al., 2005).

Most of the attention in management science is put into the creation of sophisticated '*combinatorial optimization methodologies*' for bundled shipments (Crainic and Gendreau, 2004). These are the subject of most of the articles in the special issue of *Management Science* edited by Anandalingam et al. (2005). Bundling is what produces NP-Hard integer programming (IP) challenges. Examples are auctions concerning *shipping lanes* (Ledyard et al., 2002), *airport take-off and landing slots* (Ball et al., 2006), *electricity markets* (O'Neill et al., 2005), *goods and services* (Wu and Kleindorfer, 2005), and *supply-chain auctions* in general (Chen et al., 2005). Besides complexity, a problem mentioned in the EM literature pertains to the likelihood that EMs are subject to the typical human perversions that lead to collusive bidding (Goldsby and Eckert, 2003; Anandalingam et al., 2005; Nair, 2005).

[4] For a definition of NP-Hard, see http://en.wikipedia.org/wiki/NP-hard.

#### 3.1.3. NP-Hard

Central to management science approaches to solving the NP-Hard challenges is the emergence of an independent 'agent' that serves as the intermediary in '*agent-intermediated*' markets (Nault and Dexter, 2006). The management science approach generally presumes agent-intermediated auctions with the agents using the most sophisticated IP methods available (e.g., Anandalingam et al., 2005, and all the other articles in their special issue). The state-of-the-art in current EM research focuses exclusively on human agent-intermediated auctions and combinatorial optimization methods. These are all well and good, but they are also vulnerable to unexpected changes—an obvious example being the disruption of IP solutions because of snow-storms at Chicago's O'Hare International Airport. When this happens the FAA switches to an agent-based computational program to decide which flights are cancelled, told to circle before landing, or told to wait on ground.[5]

#### 3.1.4. Smart-part EMs

Ten years ago, Roy (1998, p. 31) set forth the argument for 'replacing central, global optimization with a distributed, self-organizing market approach'. He notes that:

- centralized IP methods should be replaced with true market behaviour;
- the idea '…is to break up the sophisticated logic in [IP] algorithms and distribute it in agents across the supply web…';
- decentralized agent-based self-organization '…adjusts in real time to breakdowns, supply shortages, or fluctuating customer demand;
- in changing circumstances IP methods cannot produce optimal arrivals of the six million parts going into a 747, for example;
- even though Malone and Rockart (1991) argued early on for a free electronic market, the academic response in management science has largely been to substitute 'free' with centralized IP optimization methods; and
- Dick Morley, who invented a bidding system at General Motors, says:

> The job changes from building trucks to allowing parts to 'flock' together to form one'; GM lets paint booths bid on which truck to paint next.

In Wycisk et al. (2008) we pick up on the idea of a truly 'free' agent-based electronic market based on 'parts' like cars and containers being smart enough to 'freely' decide and then bid on what their optimal routing from source to destination should be.

[5] Based on statements by FAA computational modellers at the *New England Complexity Science Institute Conference*, Boston, MA, March 1999.

*3.1.5. Risk*

We are well aware, however, as discussed in Wycisk et al. (2008), that 'free' markets can have a downside. Despite Mandelbrot's 45 years devoted to how to better analyse stock market volatility (Mandelbrot and Hudson, 2004) risk management in free markets is invariably subject to fractal dynamics, Pareto distributions, and scale-free causes (Peters, 1994; Sornette, 2003; Baldovin and Stella, 2007). Wycisk et al. observe that truly 'free' agent-based supply-chain markets are equally vulnerable to Pareto-distribution dynamics that may be accompanied by significant down-side risk.

*3.1.6. Summary*

In light of the foregoing discussion about EMs, we stress the following:

- a 'free-market' agent-based self-organization approach based on ideas from complexity science;
- the soon-to-be availability of 'smart parts' with RFID chips capable of bidding and planning optimal routing strategies in real-time, real-world, and around-the-world circumstances;
- use of LeBaron's stock-market model as the platform from which we develop our 'free-agent' electronic auction market;
- LeBaron's model reflects both equilibrium and volatility dynamics of the S&P stock market;
- the vulnerability of 'free' smart-parts electronic markets to be subject to volatility events, fractal dynamics, Pareto distributions of a negative nature; and
- the use of a neural network (NN) programming approach that introduces the idea of an electronic agent-based agent-intermediated EM.

*3.2. First steps toward a 'free' smart-parts auction market*

Our preliminary concept of a truly free 'market-making' electronic auction process draws on the description of a smart-parts auction market that was experimentally put in place in a Daimler–Chrysler factory a few years ago ('P2000') (Schild and Bussmann, 2007). An auction can be generally defined as '… a mechanism of information submission, together with rules for assigning items and payments to participants based on this submitted information' (Anandalingam et al., 2005, p. 317). Building from this, our proposed smart-parts (e.g., cars, containers) buyers/sellers-of-space auction market looks roughly as follows:

1. To begin, a smart-part '*buyer* of transportation space' chip has to get information from its destination customer (perhaps via a dealer), thereby gaining 'knowledge' about the customer's timing and cost preferences (e.g., fast/expensive vs. slow/cheap); for illustrative purposes, we select a part preferring a slow/cheap routing.
2. This part creates a shipping scenario and asks for bids from trucking, rail, shipping, and storage lot companies. It expects bids from competing companies for each shipping stage. A quick *Google* search shows that smart parts can easily find local within-city/country bids and cross-oceanic bids. Electronic bid-processing *agents* are already readily available on the Internet for all sorts of shipping needs.[6] We assume special sites would emerge for smart parts and that some initial pricing would be set between large parts shippers and space sellers.
3. The computers of the sellers of shipping space (we assume humans only for drastic interventions) that have available space respond with bids; these computers keep track of their bids and the amount of available space; if they have no transportation or storage space they do not bid.
4. The part could have access to hi-volume prices already contracted for in advance by its manufacturer or it could delay its decisions so as to take advantage of low-cost space coming available just before a ship leaves the harbour, for example—just as some people wait to buy really cheap unsold airplane seats the day before departure (and same with hotel rooms).
5. To avoid paying for interim storage space, the part accepts a bid to get itself transported from manufacturer's storage space to the storage space at the ultimate destination; it is possible, however, that sometimes the part may find that paying for some interim storage space lowers the cost of the entire trip because it can wait for last-minute space-available auctions—as noted just above.
6. It is also possible that sellers of transportation space will include interim storage space in their bid price. Parts could then take this into account in their bid-acceptance decisions.
7. Once buyer/seller contracts are agreed to, parts signal their manufacturers to pay whatever up-front portion of the total price that is contracted for. And then the trip begins….

The foregoing bullets illustrate the essence of the kind of basic buyer/seller-of-space electronic auction market we are proposing. But it is quite an electronic stretch to go from parts making bids on a closed assembly line to a world-wide electronic market with many buyers and sellers ranging from giant firms to individual cars and containers. In Section 3.3, we complexify the foregoing auction market by drawing on LeBaron's agent-based computational stock-market model. In doing so we find that there are a number of design options firms could buy into in designing a smart-parts electronic auction market; these are outlined in Section 3.4.

[6] For example click on for a URL listing after clicking into Google 'automobile shipping Europe prices' and you get: http://www.google.com/search?hl=en&q=automobile+shipping+europe+prices&btnG=Search. For example 'agent' go to: http://www.m3carshipping.com/?s=g1&p=s&g=1. It is easy to see that we are very close to a fully electronic auction market for smart parts since any '*electronic agent*' available via Google could easily become available to smart part bidding and/or bidding by the LeBaron process we detail later on.

### *3.3. Basic features of Le Baron's stock-market model*

We justify our use of LeBaron's (2001a–c, 2003, 2006) agent-based computational model as follows. While smart parts are real things like containers and cars that exist in the real world, their smartness is embodied as sensors in electronic chips. The containers, cars, and chips—the smart parts—are, in turn, embedded in a world-wide electronic network of local chip sensors, GPS connections, and computer connections. This network, then, is embedded within two additional entities: (1) the one or more computers to which all of the chips are electronically connected and (2) the real-world electronic auction market created by *product buyers* who need to buy transportation space to get their products to market and *space sellers* who make money by selling transportation space to the buyers of space. The ability of smart parts to move from manufacturer to final destination is a function of (1) how well the parts function within the computational EM and (2) how well the computational EM itself behaves.

We choose LeBaron's model because, right now, it is the best agent-based computational model of a stock market available. We draw on its design in two ways:

1. Since it replicates 50+ years of the S&P stock market index very well (LeBaron, 2003), we use it to frame our design of the various smart-parts market options.
2. Given the various options, we then propose to use a variant of LeBaron's model to create an artificial computational-market platform with which to conduct experiments so as to determine which of the various design alternatives may be the best and under which circumstances.

In what follows, we take LeBaron's well-validated market model and then elaborate it into various options available to manufacturers shipping parts around the globe. LeBaron's agent-based computational model of the stock market consists of three parts:

1. His model creates an operating electronic market which is well validated against real stock-market behaviour.
2. It consists of traders who learn via a *genetic algorithm* (GA) (Holland, 1975).
3. A *neural network* (NN) model (Mehrotra et al., 1997) that 'watches' the market and keeps updating six investment strategies based on standard criteria used by market investors.

We briefly describe these elements next.

#### *3.3.1. Electronic market*

LeBaron's stock-market model is what he calls a 'partial equilibrium model'. This means that it contains some pressures toward equilibrium; but it also mirrors the volatility features of the S&P as well. Investors can buy from an infinite supply of risk-free assets (bonds) that pay a constant interest rate, or they can buy from a fixed supply of risky securities paying a random dividend. The risky dividend is calibrated so as to correspond to actual dividend properties in the US. Traders, thus, have two kinds of income: that from risk-free bonds and from purchases and sales of stocks (equities). When traders buy from the stock market (which is of fixed size) the price goes up and when they sell it goes down. A trader's objective is to maximize $E_t$ as according to the following function:

$$\mathrm{Max}\, E_t \log[1 + \alpha_j r_{t+1} + r_f(1 - \alpha_j)]$$

where $E_t$ is expected return at time $t$; $\alpha_j$ is one of the 250 rules; $r_t$ the return on a risky security at time $t$; and $r_f$ the risk-free rate of return.

A trader's investment is relatively 'myopic', as LeBaron puts it, for two reasons: (1) traders cannot invest on the basis of presumed long-run expectations about the future; they are only interested in finding an investment rule that maximizes returns in the next time period—i.e., they see one time-period ahead and (2) since, for any given time period, traders are myopic because they can never know what all of the other traders have done or will do in this particular time period. For further market performance details, please consult LeBaron's articles; we avoid presenting most of formulas he describes.

His model contains 1000 traders whose buy/sell decisions are based on a portfolio of up to 250 investment rules. In his 'calibration' paper, LeBaron (2003) provides results showing how two versions of his model ('all memory' and 'long memory') compare with the S&P stock market index across three databases (1947–2000; 1928–2000; and sometimes 1871–2001). After conducting many kinds of comparative analyses, LeBaron concludes:

> 'The agent-based model is capable of quantitatively replicating many features of actual financial markets. Comparisons show favourable results for returns and volatility and their persistence. The data also replicates the well known feature of excess kurtosis in the returns series' (2003, p. 18).

There are some comparative tests that are not so strong. The model, needless to say, is a much simplified replication of a real market. Even so, the fact that it shows partial equilibrium along with replications of skew, kurtosis, ARCH, and the effects of long- and short-memory trader-knowledge effects is impressive.

#### *3.3.2. Adaptive traders*

Traders have a pool of up to 250 investment rules they can use to decide how to take advantage of the six sources of relevant investment information (supplied by the neural network model which we discuss next). Each rule has several elements that may be weighted differently by a particular trader. LeBaron (2001b, c) uses a genetic algorithm as a means for traders to learn about and keep updating across time periods to create their best possible investment strategy. In GA terms, the 250 rules play the role of genes in one or more chromosome strings and the weights define the genes. In any given time-period 50% of the traders may update their investment strategy. Investment rules not used over the last ten periods are deleted.

In any given time period several of a trader's rules may be replaced or altered. In LeBaron's GA this happens in three ways (each has equal probability):

1. *Mutation*: a randomly selected rule has one of its *existing* weights randomly altered by adding an increment drawn from a uniform distribution ranging from −0.25 to +0.25.
2. *New weight*: a *new* weight is added to a randomly selected rule; the new weight is randomly assigned a new value using the same uniform distribution as is used in the initial start-up; this distribution ranges from −1 to +1.
3. *Crossover*: randomly select two traders who have shown success in improving their investment portfolio via trading; replace all the weights connected to a specific 'information input' in a selected rule used by one trader with the comparable weights used by the other trader. As LeBaron says, 'this is equivalent to chopping off a branch of the network from [trader] one, and replacing it with a branch from [trader] two' (2001b, p. 445).

Once a new rule emerges, it is right away given an initializing investment record by evaluating its performance based on past market behaviour. This way traders know right away whether to use it or not. Note than in a computational GA there is no 'sex' nor 'offspring'. Instead a computational trader morphs from a trader using old rules to a partially altered trader using newer rules as time periods progress—the trader keeps going forward in time but its genetic rule-base keeps changing.

By the foregoing methods a given trader's learning and use of investment rules is continuously updated as the market progresses. Traders can, and do, eventually learn the same investment strategy—the same buy/sell rules—such that LeBaron's computational market can crash as do real-world markets (the market crash related to the failure of LTCM being a good recent example of traders evolving toward the same buy/sell rule (Lowenstein, 2000). The investment rule 'chromosome string' is provided by the NN, as follows.

### 3.3.3. Neural net model

The best way to understand LeBaron's use of the NN is to think of it 'as being separate from the actual agents [traders]. The best analogy is to that of an investment advisor or mutual fund'—as he puts it (2001, p. 443). The NN sits off to the side, so to speak, updating its six sources of investment information; traders may create up to 250 trading rules by weighting information elements from the NN (and/or other traders) differently. We illustrate this in Fig. 1.

Fig. 1 shows six sources of information on the left; shows a hidden layer in the middle comprised of six weights, one for each source; and on the right-hand side shows a few of the rules plus weights $\omega_n$ being connected to the hidden layer. The sources of information are 'predictors that are commonly used in real markets' (2001, p. 444) that are continuously updated: information about current returns, past returns, price-dividend ratios, and technical trading rules based on exponential moving averages. For any given time period, then, a trader can select from a large range of different weightings of the basic information set.

In Table 1 (and later in Tables 3 and 4) we summarize key elements of LeBaron's 'stock trading' formalizations to show how we alter them to fit our 'shipping-space' model.

In the following, we consider four categories: our baseline simulation of human space trading with nine possible alternatives in addition to the existing—human only—logistics market system. This is a way to properly

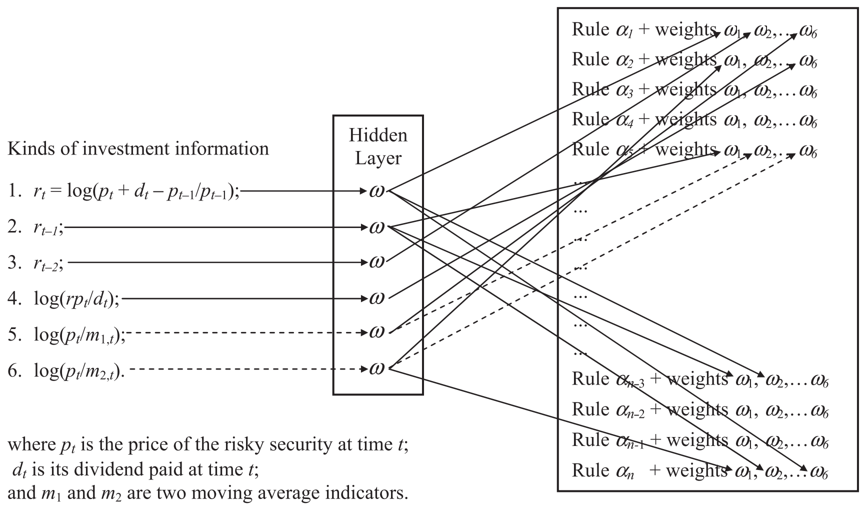


**Fig. 1.** Neural net schematic: from six information sources to 250 rules plus weights. Each information source gets a weight $\omega$ in the hidden layer. Each rule $\alpha_j$ has additional weightings of the six rules. In principle, each rule $\alpha_j$ could have 6! weight combinations. Clearly, LeBaron's model does not use all of these. Note that the NN keeps updating the investment information and the rules and their weights. Traders, then, keep trying to find the best investment rule at the time of their investment in the risky security.

**Table 1**
Human stock trading formula translated to human space buying/selling[a].

| Stock formula | Space formula |
|---|---|
| $T = \sum_{i=0}^{I} s_j$ | $1 = \sum_{i=0}^{I} s_j$ |
| $s_i$ = total share holdings of trader $i$<br>$I$ = total number of traders<br>$T$ = total # of shares times # of traders; this number does not change | $s$ = set of all $i$ buyers and sellers of space on trucks, trains, and ships. Fixed supply of space, $s$, at any given time |
| Market has two securities, bond with fixed interest rate and risky stocks | Market is electronic, like Nasdaq. Agents buy and sell transportation space on trucks, trains, ships. Large agents (car makers, transporters) buy/sell large amounts of space<br>$\max_{aj} E_t \log[1 + a_j r_{t+1} + (1 - a_j) r_f]$ |
| $\min_{aj} E_t \log[a_j r_{t+1}]$ | |
| $a_j$ = set of all trading rules | $a_j$ = set of all rules for buying/selling all kinds of transportation space available |
| $r_t$ = total risky asset return at time $t$ | $r_t$ = total cost of all spaces at $t$ |
| $r_f$ = is the risk-free rate of return on bonds<br>Traders try to find trading rules maximizing returns<br>LeBaron's equation includes returns from risk-free bonds as well as risky stocks | Buyers/sellers try to find rules that minimize the cost of transporting a car from factory to dealer at the specified rate of transportation time preferred by the customer |

[a] Other stock trading details from LeBaron's model (2001) are omitted for relevance and space reasons.

represent the interaction among the several transportation design options and their costs, profits, and speed of delivery. The starting point—what we call the 'baseline' model—is the current system of human manufacturers (shippers) and human transportation companies (sellers) negotiating the price and speed at which cars, containers, and whatever other goods needing transport are routed to customers.

Our *Category One* represents the typical existing logistics approach—i.e., without any modern information and communication technology. In modelling it we suggest a baseline simulation of human space trading activities, along with Option 1, which builds space speculation into the baseline simulation. *Category Two* describes design options of a supply consisting an optimized decision-making capability via the usage of a neural network model. *Category Three* contains the most advanced options, which give electronic *agents* [(materials, components, products) or (packages, pallets, containers) or (trucks, trains, ships)]—our '*smart parts*'—many of the learning abilities of humans trading on a stock market. We discuss each in turn, the level of realizing a completely autonomous CALS rises with each option. An overview of our nine options appears in Table 2.

### *3.4. Category I: traditional logistics*

Our baseline simulation is based on the existing view of a logistics system, that is, the traditional concept of

**Table 2**
Design alternatives for CALS.

| Level of realization | Design alternative for CALS |
|---|---|
| − | *Category* I:<br>• Baseline model<br>1. Speculative reserve space |
| | *Category* II:<br>2. Neural net<br>3. Neural net auction based<br>4. Neural net and less-dump parts |
| | *Category* III:<br>5. Smart parts learning from the neural net<br>6. Smart parts learning from the neural net and from each other<br>7. Smart parts with grouping capability<br>8. Smart parts having full choice<br>9. Speculating |
| + | |

supply-chain management. From a systems perspective, a logistics system consists of a set of nodes and a collection of links that connect pairs of nodes through transfers of goods, capital or information (Daganzo, 2005). In this graph-theoretic perspective, our nodes are agents—i.e., raw materials, components, products, transit equipment (e.g., pallets, packages) or transportation systems (e.g., conveyors, trucks)—that are directed and steered by employees—there is no communication between non-human elements nor artificial intelligence. In this case, information about orders is the only data firms exchange within the supply chain; for example, when suppliers only observe their retailers' orders (Cachon and Fisher, 2000). Daganzo (2005, p. 1) describes traditional logistics problem solving as '…gathering as much detailed information as possible about the problem, formulating a mathematical program including as input data all the information that *might* possibly be relevant, identifying solutions in detail by means of numerous decision variables, and then using the computer to sort through this numerical maze'.

Our first task, then, is to see if we can design a model more or less like LeBaron's model that *simulates* an existing real-world logistics system of human buyers and sellers of transportation space. In this 'baseline' system the smartness is all in the people; parts are totally dumb. Obviously a transportation-space market is not exactly like the S&P or any other stock market. But it is a market, just not as risky or uncertain at stock markets. Instead of 1000 traders, the model could have, perhaps, less than 100. Some space buyers could appear like institutional investors on the stock market—they buy large amounts of space, say, space for 50,000 containers or cars per year. Other buyers, especially in the container market may be buying one container at a time, sort of like 'odd-lot' players on the stock market. This aspect of the market will behave more like the market for last-minute space on airplanes or in hotels—people wait and then get low prices but not much choice at the last minute.

#### *3.4.1. Human speculative reserve space*

After the baseline simulation of human buying/selling, the first option is to simulate a beginning level of human space-cost speculation. When a ship is empty sellers sell space more cheaply. As the ship fills up they raise the price. But as departure time gets closer, sellers lower the price to make sure the ship fills up before departing. To begin, then, sellers sell considerable, but not all space to larger shippers. But, they can choose to keep some space in reserve to sell later at a hoped-for higher price. This space could be sold to large firms or to individual smart parts. It could also be made available to the NN acting as an eBay-style auction house (discussed next). Knowing this, buyers could buy less space up front with the expectation of fire-sales by shippers as the time approaches for their truck, train, or ship to depart.

### *3.5. Category II: neural net involved*

#### *3.5.1. Neural net*

In LeBaron's model, the NN is simply used to keep updating the six investment strategies. It is a very simple design; it views the changing market in terms of the typical means by which traders estimate whether the market is going to move up or down—using current returns, past returns, price-dividend ratios, and technical trading rules. These are the inputs to the NN. It has only one hidden layer (our brains have many). It has six outcomes in the form of investment strategies based on a few just mentioned investment information variables. As noted earlier, the NN behaves like an investment advisory firm that traders can turn to get the best current investment strategies, given what the market is doing at the time. Our first two NN options presume 'dumb' and 'slightly less dumb' parts.

In this, first, NN involved option, the NN is installed to watch the shipper/seller market on a timely basis—possibly minute-by-minute at some times for some parts. LeBaron's market model does weekly updates. Thus, when parts are in the middle of a three-week trip across a body of water NN check-in can be sporadic. As the parts get to a transition point from truck to train or from storage yard to truck on its way to a dealer, NN check-in would have to be much faster.

The 'dumb' parts are constantly connected to the NN. They have no choice. It simply '*tells*' parts the best available transportation strategy at any given time—in the manner of LeBaron's NN—quickest, cheapest, safest routes, etc., according to chip designation; the best route for different kinds of perishable goods depending on their rate of ripening, and so on. In this option, parts do not have choices. The NN keeps track of their progress and, as needed, routes them to the next most relevant transportation space seller. They are always connected with the NN and it organizes them so as to move according to the best strategy available.

This may, in fact, be the *best option* given the possibility that smart parts have some susceptibility to an extreme event where too many of them would simultaneously aim at the same truck, train, or ship, with the result that many of them would be left behind. In actually running a model of the electronic smart-parts transportation-decision system, a key question is whether learning smart parts can arrange their transportation more effectively than the NN can. In this option the NN simply substitutes for human decision making about routes.

An additional question is how many different choices does the NN give to dumb parts. For example, the NN could have an overall package from manufacturer to dealer, or it could *sequentially* (1) offer a trucking route; then, (2) based on updates it would offer the best rail routing; and then when the time comes, (3) the best ship and ship route, and so on. For cars going from Japan to NYC, the NN could develop (1) fast and slow ship strategies, (2) straight to LA and then by train to NYC (fast and expensive), or (3) via the Panama Canal, or (4) around Cape Horn and then up to NYC (slowest but cheapest)—all based on routing designations in the chip.

As you can see, in this design option the NN plays the role of the agent intermediary that is essential to the management science approach to electronic auction markets. The NN could be given all of the best IP-based optimization models that management scientists advocate. It could be given choices about which IP models to use. It could also be closely monitored by human operators who could offer advice to the NN as to which IP model to use at one time or another. This option essentially mirrors current management science thinking about EMs, except that the NN acts as the primary—electronic—agent.

#### *3.5.2. Neural net auction-based*

As sellers and shippers get used to living in a virtual world of parts transportation planning, they will come to realize that they can set up their own electronic, eBay-style '*auction house*'. Sellers of space make it available to the NN auction house at various prices, depending on volume, cost of transportation, speed of transportation, and so on. Shippers then go to the NN auction house to buy space as desired. Later on, we show that smart parts can also take advantage of the auction house. Like humans buying last-minute space on airplanes and in hotels, smart parts may play the same game. Shippers may do this as well.

The following sections introduce various levels of *smarter-part* options.

#### *3.5.3. Neural net and less dumb parts*

In this option the NN does not just 'tell' parts what to do. Rather, they check in to the NN as appropriate to find the best transportation strategies available. They are just smart enough to check in with the NN, but not with other parts. They use only space already bought by their manufacturer. Shippers can buy or re-sell space as desired. Sellers make space available as desired. It is sort of a one-stop-shop. Parts check in; the NN tells them the best choices available at the time. Parts can keep checking in and can update their strategy, but only according to what the NN tells them at the time. This allows parts to monitor the transportation situation; become aware of weather, equipment, labour, and other possible disruptions calling for different routing. The NN would always be up-to-date on this.

With Option 2, the parts are totally dumb and passive; the NN does all of the watching of the market and keeps track of when it needs to change a part's strategy, shift if from truck to train or to ship, and so on. The NN speeds up its check-in rate depending on whether the part is in the middle of an ocean or about to switch from truck to train. In Option 4, however, the parts are in contact with GPS, know where they are and then know when they are reaching a transition point and, *then*, parts check in to the NN. Here, the parts are smart enough to know where they are and when to check in with the NN, but, they have no learning ability.

In this option parts can check with the NN at every routing choice-point so as to get the NN's latest IP optimization about the best routing strategy. Instead of being given one optimal strategy by a human agent at the outset, parts check in frequently and, thus, have constantly updated optimization algorithms to take advantage of. This appears as an ideal compromise between the IP advantages offered by management scientists while at the same time taking advantage of the NN's ability to keep up with changing conditions.

### 3.6. Category III: neural net and computational agents

In the options below, parts become fully 'smart' *computational agents*. They can learn from humans, the NN, and from other parts. The autonomous cooperation of every single logistic object—our smart parts—may be represented by a computational agent. These agents can either be raw materials, components or products as well as transit equipment (e.g., packages, pallets, containers) or transportation systems (e.g., trucks, trains, ships). They are able to act together as a loosely coupled network via the exchange and storage of information, autonomous decision-making, and learning capacities (Scholz-Reiter et al., 2004).

A key characteristic of an intelligent computational agent is its capability to control itself, which means that these agents act autonomously in their planning and production processes. Probst (1987) describes autonomy in general as the capability of a system, process or an agent to design its input-, throughput- and output-profiles as an anticipative or reactive response to changing constraints of environmental parameters. A second specific criterion of autonomous processes and smart parts—as computational agents—is that they make decisions by themselves on the basis of parameters that can lead to different but, in principal, predetermined process or order fulfilment steps (Windt and Hülsmann, 2007).

In order to fulfil their individual orders in an information-rich environment, agents are able to communicate with the environment and learn from its offered data. For example, this could be information about suppliers, prices, ways of transportation, etc. Depending on the technology used, and the desired manifestation of autonomous cooperating logistics agents, there could be several choices of communication-learning structures, such as single-loop, or double loop learning (Argyris and Schön, 1996). And, as we note earlier, they can get IP updates about the EM from the NN anytime they choose.

#### 3.6.1. Smart parts learning from the neural net

In this option, parts can take advantage of various transportation choices made available by the NN. They begin acting like traders in LeBaron's market model. But, they only have choices of what and when to learn from the NN, which is constantly watching the market. As we note in our earlier paper (Wycisk et al., 2008), smart parts face some possibility of extreme events in the form of too many parts buying space on a ship, then arriving at the dock to find the ship full and, thus, are left stranded on the dock.

The difference here, in comparison with dumb parts checking in with the NN is that, as in LeBaron's model, the NN supplies various transportation strategies and parts, like LeBaron's stock traders, can, then, choose their preferred one. For example, the NN could offer truck and train strategies in Japan, ship options across the Pacific to LA, and then train options cross-country to the Midwest and East Coast of the US, or via ship through Panama Canal, or around Cape Horn, or even the Northwest Passage. All of these choices would be constantly updated by the NN as to speed and cost; smart parts could check with the NN in timely fashion as much as necessary—the NN (with or without human help) would be offering constantly updated IP optimizations about routing options. In short, smart parts could choose from various IP options at any given time as their circumstances change. Each part could develop its own 'IP-updated' routing package of how it gets itself, say, from Japan to the US West and East Coasts or Europe, and then, finally to its originating dealer—and change it as needed.

At this stage, the parts know where they are; they check in with the NN in timely fashion to get the best IP routing options available. But, they are not yet 'learning' smart parts.

#### 3.6.2. Smart parts learning from the neural net and from each other

Take all of the strategies offered by the prior option and now *let smart parts also learn from other smart parts* in addition to learning from the NN. Again, following LeBaron's model, smart-part agents, like LeBaron's traders, can take elements of strategies that appear to be working from other smart-part agents, and also take advantage of strategies offered by the NN. For example, they could take (1) a trucking strategy from some other smart part, (2) a train strategy from another, and then (3) a ship strategy to LA. Or, learning from the NN, a smart part could (1) land in LA and then take a train across the US to New York, or (2) take get to NYC via the Panama Canal or (3) by Cape Horn, or (4) via the Northwest Passage. A learning smart part could take IP-based routing strategies from other smart parts who have apparently benefited from them, or directly from the NN. Smart parts could, thus, compare choice preferences learned by other smart parts with those offered by the NN. Each part could then create its own unique transportation strategy.

Since it is an electronic market, space availability at a given price could change minute by minute; the market could be in constant flux. Some parts could gain advantage by locking in good strategies found earlier by other smart parts. Other parts could wait for last-minute space choices available at very cheap rates. Parts could start by wanting a cheap route strategy, but if possible delay is too much of an issue, they could change toward a faster, more expensive, and more guaranteed routing strategy. Parts might have to check in with their manufacturer and final destination parties before deciding on a final strategy. Needless to say, all of this is going on in 'electronic' time in the computer and via its connections to the various other relevant parties.

As you can see, what is optimal for a smart part may not be optimal for IP-based 'bundling' strategies of transportation space sellers. In fact, a part may want to opt out of its manufacturer's bundling strategy to jump into a quick or cheap option coming available to it unexpectedly—e.g., it is waiting in some storage yard for a 'bundling' strategy to materialize when a last-minute spot on a just-about-to-depart ship opens up. Here is where what is good from an overall bundling perspective jostles with what works best for a choiceful smart part.

#### 3.6.3. *Smart parts with grouping capability*

In general, shipping firms have the advantage of buying in advance and in volume, and thereby getting cut-rates. They also have EM bundling options. Parts trying to buy space individually have no such advantage. Yes, parts do have the advantage of taking the 'long tail' approach (Anderson, 2006) of looking for micro-niche (idiosyncratic) advantage. This is what people do when they search for cheap airplane seats and hotel rooms at the last moment—because the space is about to go unused and the particular individual has the flexibility to make unique last-minute schedule changes. Smart parts can also try to take advantage of this.

But, they could also have the option of self-organizing into emergent groups by checking preferred transportation strategies with each other. They could 'bundle' and play the bundling game just as the buyers and sellers do. Those with the same strategy could group together to generate increased bargaining power and thereby get a cheaper shipping rate and perhaps even on a faster transportation route. The NN could be brought into play here for both grouping and bundling advantage-seeking. It could constantly search for similar strategy preferences by parts and then suggest group packaging and bundling strategies, identify shippers, suggest possible price objectives, and so forth.

#### 3.6.4. *Smart parts with full choice*

Smart parts now have choices to learn from the environment, from each other, and to check in with the NN and/or with people. This is the fully-designed smart parts model—all choices are available to them to use or not use. Both parts and NN may benefit by human guidance at various times. It is possible that humans can offer better IP-based optimization choices than can the NN. But note that the full-choice option is a two-edged sword.

While we do not wish to discount the role of human intervention at various stages, human monitoring of millions of parts at any given time is not possible. In the event of a major typhoon, earthquake, political upheaval, or whatever, some human advice into the system may be relevant. With smart parts learning from each other and running the risk of a negative extreme (see Wycisk et al., 2008), it may take human intervention now and then to watch and learn from these and then re-work the programming of parts and NN.

Furthermore, at this point, no one in the literature has suggested that smart parts can read newspapers. For some time to come, then, it seems likely that people will have to read the newspapers and then inform the NN and smart parts of announced strikes, reported effects of floods and storms, political upheavals, possible typhoons and hurricanes, and so on. Quite possibly this could take the form of humans coding newspaper information in to forms usable via the NN.[7] Human intervention offers the best means to prevent smart parts running afoul of expected transportation stoppages.

#### 3.6.5. *Speculation*

In LeBaron's model there are only traders who use weightings of six kinds of market information to make their investments. There is no allowance for 'anticipating' or 'guessing' or 'hoping' *in a more speculative nature* about whether the market will go up or down. Suppose we allow speculation. According to Pagh and Cooper, (1998) the so-called 'full speculation strategy' is traditionally the one most often used by firms. In logistics, full speculation of all manufacturing and logistics operations is based on inventory forecasts. This view of speculation holds that decisions pertaining to the form and movement of goods should be made at the earliest possible time to reduce supply-chain costs. The order-point of retailers or customers is positioned at the lowest level downstream in the supply chain. All manufacturing operations are performed prior to the product and are differentiated by location. Through a decentralized distribution system, the product is stocked close to customers, and distributed. Speculation makes it possible to gain economies of scale in manufacturing and logistics operations, and limit the number of stock outs.

In the case of CALS, it is a question of just how 'human' smart parts are going to be allowed (i.e., programmed) to get. Shippers can speculate in the form of reserving more space than they need and then re-selling it at a higher price. Obviously there is risk in this. Shippers could also speculate by withholding space in the hope that it would drive the price up. We actually start with this in Option 1.

We pretty much have to assume that if there is not an explicit means of preventing speculation, shippers, sellers

[7] We already see shades of this in the form of people paid by the information 'bit' actually competing to constantly update Internet-based sites, blogs, games, and so on. Firms could easily pay a few people on various continents to constantly translate incoming radio and newspaper information into a form usable by the NN.

and smart parts could get into the speculation game. The use of an eBay-type NN auction house by shippers and sellers could easily have a speculative component embedded. However, smart parts—no matter how smart they are—are not smart enough to beat humans at the speculation game.

The Federal Reserve Bank in the US is generally averse to attempts at 'managing' stock markets—though the Fed did intervene during the LTCM crash (Lowenstein, 2000) and there is considerable discussion about the advisability of Fed intervention during the subprime meltdown of Summer of 2007 (e.g., see Elder, 2007; Gray, 2008; Landler, 2008; Grynbaum and Stout, 2008). The smart-parts market more likely would be more of a 'contrived' market that key users could collaborate in designing. Presumably, the primary design feature is to improve efficiency in parts transportation as opposed to the money-making feature of stock markets. Whether shippers benefit by fostering smart part speculation could be tested by computational modelling before the 'real' parts market is put in play. While smart parts could be smart enough to speculate, designing this out of the smart-parts market seems like a desirable design objective. But of course, this may be impossible!

In Table 3 we summarize LeBaron's use of the NN model in terms of his formalizations. It serves as the basic source of information for the traders. We then show a comparison set that represents how we would apply the NN model. In the Table we make no changes from LeBaron's usage. But, as you can see from the foregoing discussion, we offer some options that enlarge the role of the NN model.

Finally, in Table 4, we first show (left side) LeBaron's equations defining the total wealth of a particular trader as it accumulates. On the right-hand side we show our simplifications as we translate the 'wealth' formalizations into 'space costs' as buyers and sellers of space buy and sell it. The focus here is on how LeBaron uses a GA to allow traders to adapt to changing circumstances as they continually seek to accumulate wealth. We also compare LeBaron's use of the GA with how we propose to use it for space traders.

**Table 3**
Neural net model usage translated from stock trading to space buying/selling.

| Stock formula | Space formula |
|---|---|
| $a(z_t; w_j)$<br>$z$ consists of all available information at time $t$; (not shown are the six kinds of market information LeBaron has the NN updating at each time period) | $a(z_t; w_j)$<br>$z$ consists of all available information at time, $t$, about the cost and availability of truck, train, and ship space, + travel-time from beginning to end of each leg of a truck/train/ship journey |
| $w$ represents the number of weighting parameters preferred by a trader with respect to elements of each specific buy/sell rule, $j$ | $w$ represents some number of weighting parameters preferred by a space buyer/seller with respect to elements of each rule, $j$ |
| Each rule, $j$, in the set, $a_j$, is kept up to date by the NN with respect to the best information about the market: | Each space-buying rule, $j$, in the set, $a_j$, is kept up to date by the NN with respect to the best information available about the 'space market' |
| $h_k = g_1(w_{1,k}z_{t,k} + w_{0,k})$<br>$h_k$ = represents one hidden layer, with $k$ connections to the equations in information-set $z_t$; While NN models may have multiple hidden layers, LeBaron uses only 1 hidden layer consisting of 6 elements; each information equation updated by the NN model is made available to all traders, but may be differentially weighted by each trader | $h_k = g_1(w_{1,k}z_{t,k} + w_{0,k})$<br>To begin, we keep the NN model simple, as does LeBaron; we specify only one hidden layer, $h_k$ Our information set, $z_{t,k}$ would include information equations for:<br>a) Choice, timing, speed of trucks<br>b) Choice, timing, speed of trains<br>c) Choice, timing, speed of ships |
| With NN, $w$ represents weights attached to NN network connections any given trader may use to create a rule | With NN, $w$ represents weights attached to NN network connections comprising the rule(s) any given trader may use to create a rule; $w$ fully describes the rules (and weights of elements of rules) comprising the dynamic trading strategy of each buyer or seller of space.<br>While Table 1 mirrors the situation where human buyers/sellers of transportation space buy/sell large amounts, starting with Option 4.2, we add individual cars (or containers) as buy/sell agents in addition to the human buyer/sellers of large chunks of space |

- In Option 2, the NN watches the space market and 'tells' 'dumb' smart-part space buyers where the best seller prices and timings are–parts are dumb and passive
- In Option 3, we allow for the possibility that buyers/sellers will enter into an eBay-style auction market
- In Option 4, smart parts, like human traders can chose to check with the NN model at times they select, rather than being 'told' what to do by the NN
- As noted in the text, smart parts learn as they progress across time periods in the manner of agents in a genetic algorithm

## 4. Contributions of the design options to logistics goals

Central goals of logistics can be traditionally described integrated into two main goals: reducing costs, raising adaptivity of the logistics system (Bowersox et al., 2002). In the following, we are going to discuss the concept of CALS regarding its contribution to each logistics goal.

### 4.1. Reducing costs

#### 4.1.1. Technology-based reductions

From a financial point of view, investing in, and implementing, modern technologies has to be connected with a positive cost-benefit analysis. This gains even more relevance, given that logistics managers have to face the reality that their decisions are always made in the context of the key data and management ratios upon which their firm places most value (Bowersox et al., 2000, 2002). Since the main anticipated benefit from creating a CALS lies in its adaptivity, a simple cost-benefit analysis might miss important strategic value aspects of CALS like flexibility to

**Table 4**
Translating the 'wealth' formalizations into 'space costs' for CALS.

| | |
|---|---|
| $\hat{w}_{i,t} = (p_t + d_t)s_{i,t-1} + (1 + r_f)\, b_{i,t-1}$<br>$s_{i,t}(p_t) = a_j(p_t; I_t)\, \beta \hat{w}_{i,t}$<br>where $\hat{w}_{t,i}$ is total wealth of a trader; $\beta$ = time discount rate; $p_t$ = market clearing price of a stock and $d_t$ = dividend price | $c_{i,t} = (p_t + d_t)\, s_{i,t-1}$<br>$s_{i,t}(p_t) = a_j(p_t; I_t)\hat{c}_{i,t}$<br>$\hat{c}_{i,t}$ is total cost of space (including time considerations) purchases by buyers. For buying/selling transportation space, we delete $\beta$ (time discount rate) and $b$ (risk-free bond) from LeBaron's equations |
| $D(p_t) = \sum_{i=1}^{I} s_{i,t} p_t$<br>LeBaron's aggregate demand function is presented above.<br>In LeBaron's model, setting $D(p_t) = 1$ finds the total market equilibrium price $p_t$<br>Since there is no analytical way because of the many nonlinearities, it is done computationally—this because each trader can alter its rules at any time | $D(p_t) = \sum_{i=1}^{I} s_{i,t} p_t$<br>$s_{i,t}$ = clearing price in the buyer/seller of space market<br>$D$ remains as the aggregate space-demand function; $p_t$ is the total market equilibrium price |
| *LeBaron's traders*: traders evolve via a GA. As time periods progress, the NN network weightings, $w_j$, comprising their rules are altered in three ways: | *Buyers/sellers of space*: our time periods are defined as decision points: (a) in humans buying space on a means of transportation; or (b) smart parts changing from truck to train to ship, as necessary. There is no logic for mutation or new weight. We have: |
| 1. *Mutation*: a rule weighting is randomly selected and altered by an amount between [−.25, .25]<br>2. *New weight*: a new rule weight is randomly drawn to replace one existing weight<br><br>*Crossover*: two traders randomly selected; an NN branch of one trader replaces the equivalent branch in the other. LeBaron's crossover partners are chosen randomly, but one could allow one to choose the other based on the latter's fitness, i.e., total wealth, $\hat{w}$ | 1. *Human learning processes*: learning based on current industry methods<br>2. *NN learning processes*: which can include insertion of human-created optimization algorithms<br>3. *Smart part learning processes*: as our Options progress toward 'learning' smart parts, they have options to learn from the NN as needed, and/or learn from each other (i.e., crossover), or learn from humans<br>4. *Smart part crossover*: smart parts can learn transportation strategies by cost and/or time; they can learn segment by segment (e.g., truck, train, or ship schedules and costs), or comprehensive routings, and/or decided priority given to NN vs. other smart parts or humans |

- In Option 5, smart parts can check in with the NN to select routing and cost strategies and choice points (changing transportation modes), when and where, as necessary
- In Option 6, smart parts can learn from each other (our version of crossover) or the NN
- In Option 7, smart parts can learn to group together to make volume buys, lower cost, get special routing timings, etc
- In Options 8, 9 smart parts have full choice to apply the LeBaron agent-based computational modeling approach to learn from whatever sources prove valuable for minimizing $\hat{c}_{i,t}$.

respond to changing competitive conditions and/or changing corporate strategies. Therefore, beside the examination of strategic electronic auction-market options resulting for CALS, one major task for future research lies in defining their relative economic value for a particular company involved in a smart-part CALS.

On the one hand, we have the hardware costs of implementing smart parts into logistics systems, such as costs of:

- RFID tags; chips with more or less memory and intelligence capabilities; one-time-only or reusable chips;
- servers located in various places; centralized (super) computers; owned or rented; software development;
- associated with one-time equipment implementation; employee training; and
- communication between chips and computers; costs of private transmission stations (e.g., like private cell-phone towers).

Hardware costs have sunk dramatically within the past few years. Especially the costs for RFID tags as a substitute for the traditional bar code are nowadays more and more established in logistics. The realization of CALS in any fashion seems not far away.

On the other hand, we have many kinds of cost savings through implementing the idea of CALS, as for example, reduced costs of:

- salaries, coordination, interaction time among human traders; human scheduling, observation, management;
- being too slow, or not being not able to, adapt to unexpected changes in transportation environments; reduction of delays; reduced costs of customer complaints, loss of customers;
- more timely and improved routing; better optimization of micro-costs (see below); and
- herding behaviour; the bullwhip effect (see below).

There are additional possibilities of cost savings via the implementation of CALS. These result from different kinds of strategic flexibility, such as the flexibility to switch routes or transportation carriers, or the higher likelihood to stick to arranged delivery periods. *The bottom line within this discussion should be*: does joining a smart-parts self-organizing computational auction market, as we suggest, actually offer cost, speed-of-transportation, and adaptation-to-environmental-contingencies advantages, as compared to existing management science IP-based methods?

### *4.1.2. Micro-pricing*

In real stock markets and in LeBaron's model, trading comes at a cost—traders always sell below and buy above the current market price; there are also broker fees. Should smart-part routing choices have fees attached? Should parts be allowed to make changes at no cost?

The inherent market characteristics of CALS offer the chance to combine the exchange of information between two or more smart-part 'traders' with a *micro-pricing* strategy (Uckelmann et al., 2008). The infrastructure (e.g., RFID chips) as well as the processing (e.g., communication, computing) does cost time and money. It also costs to run the smart-parts electronic auction market and to set up, manage, and update the IP-based strategies supplied by the NN. Today, the information handled between agents in a CALS is for free. No charge is requested for offered information (e.g., regarding status of the stock in a fruit supply chain). The prospective benefit for all agents (information-offering agents as well as information-requesting agents) is based on the expectation of the more profitable and more robust logistic processes that all participants benefit from. But the profit-sharing model lying behind these structures of CALS is asymmetric: For example, food producing companies are forced by the retailers to implement RFID-technology so as to reduce the handling costs for the retailers and to gain more information for managing their supply chains (e.g., decreasing the risk of being out of stock and/or reducing the cost of capital). The food producing companies might have benefits for their logistics management, but they also have to bear the investments and maintenance of the infrastructure without getting any compensation—because the fair share of costs and benefits for the retailers cannot determined properly.

If one combines a smart parts CALS with micro-pricing, then a cost-sharing model can be run, which allows a precise market-based calculation of the costs and benefits to all CALS participants. This micro-pricing is an information-on-demand and pay-per-information driven model guided by the idea that information requested by one agent will be offered by another agent only for a certain micro-price (e.g., 0.001 cent per information bit). Therefore, the benefit resulting from information one agent is demanding for a certain purpose can be shared and induces a minimal cost compensation for the agent that gained by offered this information. With this micro-pricing feature of smart parts, CALS can become real 'markets' because, in addition to the core function of 'logistic' functions (i.e. supply, coordination, and distribution), better pricing is obtained: The agent offering information can calculate its costs and its price for a specific kind of information and the agent receiving the information can also make a similar calculation. In doing so, both agents reflect the market situation regarding the value of information and its driving factors (e.g., competition). With this feature of micro-pricing, CALS would become fully functioning electronic markets with equilibrium micro-pricing.

### 4.2. *Reducing the bullwhip effect*

In our earlier review of the logistics literature, we noted the reality of the bullwhip effect—typically leading to unwanted oversupply or undersupply—this issue is also discussed by Wycisk et al. (2008). The study by Moyaux et al. (2006, 2007) proposes the mechanism of speculation to reduce the bullwhip effect within supply chains. One of the things we learn from LeBaron's (2001c) stock-market model is that crashes occur when agents lose their heterogeneity—they all end up with the same 'buy/sell' rule and market inevitably crashes. This occurs because they connect, communicate, and learn from each other. And, we know that the cheaper and easier it is to connect the more likely crashes, like plagues, will occur. Worse, the digital age of free electronic communications readily exacerbates connectivity.

Our penultimate option, then, is to constantly monitor (via NN or humans) the heterogeneity of smart parts' choices. As they lose their heterogeneity, at some point they are reprogrammed to behave like new parts—that is, the parts' heterogeneity is increased. Specifically, model agents (traders) die off at some rate and are replaced by new agents having their attributes defined by random draw—thereby assuring some re-creation of heterogeneity. There is clearly an issue here about what the ratio between the two rates is:

1. On the one hand, we have a rate of creating agent heterogeneity;
2. And on the other we have a rate at which smart parts learn similar transportation strategies and thereby lose their heterogeneity.

Starting with Option 6, as parts let go of the NN in favour of learning from each other, they run the risk of running into negative extremes. These are a problem; in the worst case scenario, occurring when all the containers (smart parts) wanting transportation aim for the same ship, most could be left on the dock looking for another option. Choices are to let the NN and/or people monitor, or let the parts also take on the job of monitoring, so as to avoid tipping points.

- Perhaps one can assume that self-organizing smart parts can smooth the risk of the bullwhip effect through their own self-regulating dynamics. Thus, parts can keep checking for increased similarities in their strategizing; probably they could do this best by checking in with the NN, which would be better at the overall market-monitoring job.
- Another choice is to give the NN more dominance in using its monitoring system of the smart- parts logistic dynamics so as uncover possible negative tipping points, The NN could then inform parts as to how best to change their routing strategies so as to forestall the tipping point—unless of course it appears to be a positive one.
- Bottom-line: a '*tipping point monitoring system*' has to be designed, whether it is used by parts, NN, or people.

One would have to do some serious computational experimentation with our proposed 'LeBaron-style' model 'in the lab' so to speak, to see whether smart parts on their own, or with the help of the NN can avoid tipping points. Or, is human intervention the only solution?

## 5. Conclusion

Modern technologies, such as RFID chips, GPS, sensor networks, and microcontrollers, offer never-before seen learning abilities to containers, cars, and other parts and work-pieces requiring transportation via logistics networks. After reviewing the current vision of logistics networks, we outline the elements of *complex adaptive systems*, their self-organization processes, and outcomes. We then argue that future international supply networks are best understood as *complex adaptive logistics systems* (CALS) markets between '*smart parts*' and transportation firms. One major characteristic of CALS is their ability to adapt to changing environmental requirements. This ability is based on learning features enabled through the aforementioned technologies.

Interactions between smart parts and transportation firms are best seen as an *electronic auction market* in which buyers and sellers of transportation space move toward their best price in a buyer/seller auction market. To assure the world-wide functionality and efficiency of CALS, as a smart-parts transportation market, we suggest an agent-based computational market design based on LeBaron's (2003, 2006) stock-market model; it is a rich mixture of genetic algorithm, neural network, and other agent-based computational methods. After a short review of electronic auction markets, agent intermediaries, and management science approaches to integer programming-based optimization approaches, we introduce and define the essential features of LeBaron's model as a basic scheme for an agent-based modelling of a world-wide smart-parts electronic auction market.

Given that parts may be more or less smart, markets more or less complex, and self-organizing CALS probabilistically subject to the bullwhip effect, we then outline nine logistics-market options in addition to the baseline simulation of an electronic auction market operated only by humans. Some options call for more smart-part learning and adaptivity to unexpected environmental contingencies than others.

Being aware of these different options of CALS is, however, just the first step in the process of planning and managing them. Questions regarding the inherent systems dynamics, economical costs, strategic advantages or disadvantages, and organizational implications remain. Referring to theories of complexity, Wycisk et al. (2008) point out the downside risks of CALS; due to their inherent complexity, some extreme outcomes of the autonomous acting smart parts within CALS has to be anticipated—both positive and especially, negative.

From a financial point of view, investing and implementing modern technologies has to be connected with a positive cost-benefit analysis. This gains even more relevance, given that logistics managers have to face the reality that their decisions are always made in the context of the key data and management ratios upon which their firm places most value (Bowersox et al., 2000, 2002). Since the main anticipated benefit from creating a CALS lies in its adaptivity, a simple cost-benefit analysis might miss important strategic value aspects of CALS like flexibility to respond to changing competitive conditions and/or changing corporate strategies. Therefore, beside the examination of strategic electronic auction-market options resulting for CALS, one major task for future research lies in defining their relative economic value for a particular company involved in a smart part CALS. *Bottom line*: does joining a smart-parts self-organizing computational auction market, as we suggest, actually offer cost, speed-of-transportation, and adaptation-to-environmental-contingencies advantages, as compared to existing management science IP-based methods?

Another topic of concern lies in the location of smart parts' learning. Are chips in smart parts only sensors—like nerve endings in our fingers? Or, do chips hold some 'brain-like' intelligence? Normally we think of learning as within people, among people, within firms, and among firms. Learning can be both a function of human capital (at the nodes of a network) and social capital (learning in and by the network). In brains, Fuster (1995) tells us that intelligence is in the synaptic links. In firms, intelligence is in both the nodes (people) and in the social capital network (Burt, 1997). As we move to smart part CALS, intelligence and learning can be at the RFID chip level in parts, in the central computer with which they communicate, and in their linkages to other smart parts, the NN, firms, and to humans. The optimal location of the various kinds of learning becomes rather complicated as we move toward the LeBaron style computational modelling of a world-wide CALS with varying choices as to how smart parts are. The strategic-option value of various options can range considerably in cost and complexity.

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