'No one in the driver's seat'

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'No one in the driver's seat': An agent-based modelling approach to decentralised behaviour in supply chain co-ordination.

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Abstract

As decentralised supply chain networks become the norm and vertically integrated firms the exception, there is a need to better understand decentralised co-ordination in such supply chains. However, contemporary research in supply chain management proceeds under the assumption that there is always a dominant actor in the supply chain network who is 'in the driver's seat'. This article describes a study that investigates situations in which effective industrial supply chain co-ordination is achieved by multiple, independent actors where 'no-one is in the driver's seat'. It introduces a formal modelling method to investigate such issues, called agent-based modelling. In this, we build on the notion of complex adaptive systems. The article shows the application of this method in three experiments with an simple supply chain model in one specific agent-based simulation environment. Exploratory findings are discussed and promising areas for further research are indicated.

Keywords: Supply chain management; Network economy; Complexity science; Complex adaptive systems; Agent-based modelling; Simulation; Distributed decision making.

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1 Introduction

The advent of the network economy [1] is triggering profound changes in the scope and impact of supply chain management. In the network economy, the vertically integrated business firm may become the exception and ever changing networks of organisations the rule [c.f. 2, 3, 4]. For many decades, the relevant perspective to maintain in managing a business has been that of the *individual* firm. These days, markets are becoming more transparent, customer demands are being met in a more customised manner and, in general, the rate of change in the business world keeps increasing [5, 6]. More and more, the relevant perspective in thinking about supply chain management seems to be at the level of a *network of independent actors*. While all these individual actors are trying to optimise their own local behaviour, they nevertheless appear to be operating in a seemingly coherent and co-ordinated manner. Obvious analogies here are a school of fish trying to evade a predator, a flock of birds flying Southward or a swarm of bees jointly forming a beehive ecology.

It seems likely that management theory will have to be updated as a result of this. We will need 'new rules for the new economy' [3]. Some of the current debate is on how much of this will be really new and how much is already known to economic science albeit not really at the popularised level [7, 8]. Nevertheless, the management books and journals are filled with suggested bits of management theory or guidelines for managing in this Internet age [e.g. 9, 10, 11, 12, 13].

In the field of supply chain management we are also beginning to see a similar shift in focus of current research. Charles Fine of the Massachusetts Institute of Technology formulates this new perspective on supply chains most clearly: “You may think of your company as a solitary, stand-alone entity served by subsidiary organisations, the collection of which is conveniently called the supply chain. That view, however, underestimates the importance of the chain as a whole and fails to capture its true essence. (...) Properly viewed, the company and its supply chain are joined at the hip, a single organic unit engaged in a joint enterprise.” [4, p.13]. So the new emphasis in supply chain management is on how operations could be co-ordinated between organisational entities that are not under unified control and where power and value can migrate up and down the chain quite quickly.

Regardless of their popular appeal, the underlying evidence for the new theories is often flimsy and anecdotal. This contrasts starkly with the scientific base for the management theory that has been accumulated in the past decades on how best to manage a single firm. This is certainly true in the field of supply chain management, where there exists a strong body of cumulative research, both empirical and formal modelling-based, that can explain why certain management actions are better than others – when operating from the perspective of the individual firm [e.g. 14, 15]. Arguably, the bulk of these formal models operate implicitly from the world view of the single firm, and it is a characteristic of the new business models that they operate at the level of the network of multiple actors, rather than at the level of the individual actor.

Interestingly, many of the theories on managing in the new economy, e.g. ‘business ecosystems’ [16] and ‘swarm-like business processes’ [3], are grounded in biological metaphors and concepts from complexity science [e.g. 17]. One particular scientific field of inquiry where the relevant perspective has long be that of many interconnected actors is ecology. Ecology as a science has its own set of well-established rules [e.g. 18] and also its own body of underlying empirical and formal modelling-based research. The formal models being used here all employ an implicit world view of multiple, independent actors where ‘no-one is in the driver's seat’. As such, organisation and co-ordination emerges from the interaction between the actors, rather than on the basis of an integral model for the network as a whole. Such networks are also called complex adaptive systems [19] and are often based on concepts from complexity science [17]. Here, decentralised computer modelling environments have been developed to study these concepts.

In this article, we suggest to consider the use of agent-based modelling, which is one family of formal modelling techniques often used for studying multiple-actor research questions in biology, for research on supply chain management in a networked business environment. We introduce to the field of production research the concept of swarm-like behaviour in supply chain networks; complex adaptive systems consisting of many interacting, independent actors. In this, we apply agent-based modelling techniques in particular and concepts from complexity science in general. We include an exploratory simulation experiment with a simple supply chain network in an agent-based simulation-modelling environment.

Our argumentation in this article is structured as follows. First, we will examine the current state of research on co-ordination in decentralised supply chains. Then we will discuss complexity science and agent-based modelling approaches to complex adaptive systems in general. After we have highlighted the exploratory, theory-building nature of our research in this article we will introduce and describe the agent-based simulation model developed to test the applicability of agent-based modelling to the field of supply chain management. We have conducted three experiments with this model which we will describe and explain. In the discussion we will reflect on the merits and shortcomings of these experiments and will present opportunities for further research.

2 Co-ordination in decentralised supply chains

In this section we explore the state-of-the-art in research on decentralised co-ordination in supply chains, conceptually, empirically and formal modelling-driven. The literature on these topics is vast. We will not suggest to be exhaustive in our discussion, but will attempt to pinpoint key developments and underlying trends.

2.1 Conceptual work on decentralised supply chains

The conceptual textbook theory on co-ordination in supply chains has been clear for several decades: the question of co-ordination is to be studied from an *integral* and *optimisation*-oriented perspective. This has long been in line with the practice in industrial firms, which used to be highly vertically integrated. In the European literature of the 1980s, Hoekstra and Romme [20] describe supply chain management (or integral logistics management as it was called at that time and place) for an electronics conglomerate that not only sells TVs and medical equipment but also produces the components and subassemblies for these, even up to the manufacturing equipment required for production. All these operations are to be controlled from the perspective of the entire chain, in their view. In this view, buffer echelon stocks could be centred in one single decoupling point across the entire chain, thus securing the entire chain against unforeseen developments internal and external to this chain. US textbooks [e.g. 21] carry similar messages. 'Decentralised control considered harmful' seems implicitly written all over these pages.

These days, the notion of decentralised supply chain networks is rapidly receiving increasing amounts of attention in the conceptual supply chain management literature. This is at least partly a reflection of the changed business reality in the 1990s. In the past decade, companies have eagerly split up in separately controlled business units, have outsourced non-strategic parts of production and distribution, have unbundled mega-corporations into more nimble market players and this trend continues to increase. Indeed, Fine [4] goes so far as to label the current era as 'the age of temporary advantage' and stresses the dynamic nature of supply chains, as continuously changing configurations of different firms performing different tasks. He emphasises that, as the business environment changes, supply chain *design* as opposed to supply chain *co-ordination* is becoming a core competitive advantage, i.e. the ability to continuously evaluate what activities to perform in-house and pick the right partners for work to be outsourced.

It is important to note that authors like Fine still operate from the assumption that somebody has to be 'in the driver's seat'. That actor can change, like supply chain power can go from Compaq to Microsoft or to Intel, but still the implicit assumption remains that 'somebody has to be in charge'. Anderson and Lee [22] appear to go beyond this when they discuss an old ideal in a new format, i.e. the synchronised supply chain. Old (but not outdated) may be their notion that integration (or synchronisation, as it is now called) is the ideal to strive for. But new is their emphasis on partnerships between equals, on collaborative planning and even collaborative product design.

Authors inspired by complexity theory go even further by depicting situations in which effective industrial supply chain co-ordination is achieved by a large number of independent actors, where organisation and co-ordination emerges from the interaction between the actors, rather than on the basis of an integral model for the network as a whole. Roy [23] advocated the use of a self-organising market approach in supply chain management to replace central, global optimisation. He suggests to have exchanges of goods and services in a supply chain network to behave like a market, rather than being tracked and managed centrally. "New products, services, buyers and sellers meet every day; information and feedback are constantly at play; and the prices for goods and services change hour to hour or even minute to minute" [23, p.32]. There could be dozens of linked internal markets in such a supply chain network and in each one, the decision-making entity could be constructed to follow the same logic that is used today to co-ordinate buy-sell transactions.

2.2 Empirical research on decentralised supply chain networks

The empirical literature on supply chain management is again vast. For the purpose of this article, we will focus on empirical research that investigates real-world supply chains from a complexity science perspective. Most of this research is very new, as the popularisation of chaos theory and complexity science is something of the early 1990s. One early example, but unwittingly so, may be Dyer [24], who found in the automobile industry that, the more specialised suppliers in a supplier network were, the better the performance of the entire network was. For a student of complexity science, this fits well with the observation that, in the fundamental trade-off between exploration and exploitation, ecosystems where species become very adroit at exploiting stable local circumstances tend to outperform species that focus on exploration instead. In an unstable, turbulent environment, this principle works the other way round [25].

Other authors explicitly study supply chain phenomena from a complexity science perspective. Holmström and Hameri [26] show that supply chain demand at different levels in the supply chain of a consumer goods wholesaler can be reconstructed as exhibiting behaviour typical for complex adaptive systems. Jayanti and Sinha [27] obtained similar findings for internal operations in a wafer fabrication plant in a semiconductor supply chain. They base their analysis on earlier work by Wilding [28], who, in a similar fashion (but then based on a simulated generic supply chain) showed how easily such a supply chain could exhibit the behavioural characteristics of a chaotic system.

2.3 Formal modelling of decentralised supply chain networks

As for the bulk of the conceptual work on decentralised supply chain co-ordination, the textbook theory on formal modelling of decentralised supply chain has been clear-cut for a long time. Supply chains should be modelled *integrally*, i.e. from the perspective of a single decision-making unit for the entire chain, and co-ordination should be based upon *optimisation* of integral supply chain performance. Sarmiento and Nagi [29] present in a recent literature review 44 references of integral analysis research where the implicit assumptions are that integration is desirable and optimisation is possible. One other literature review observes that "the majority of strategic [supply chain] planning models is mixed integer programming based" [30].

Again, the assumption that supply chains should be controlled integrally and from an optimisation perspective is strongly at odds with present-day business reality. Clearly, this is an anomaly [31]. According to the standard theory, it is obvious that local optimisation of the constituent elements of the chain will lead to sub-optimal behaviour for the chain as a whole [c.f. 32], yet the reality is that this is precisely what the vast majority of firms continues to be doing. As Kuhn [31] has indicated, it often happens when a strong theory is at odds with the data, the data are taken into question or made seem irrelevant. Some examples of this are for instance Lee and Whang [33], who recognise deviations from centralised supply chain control models but stipulate these problems as due to mismatches between the delegating party and the delegates of the centralised control unit and the local agents. This indicates a train of thought that ignores autonomous decision-making at the decentralised level. Another recent example is Gavirneni et al, [34], where again multi-party supply chains are considered, in this case regarding the effects of various forms of information sharing. Again, the underlying assumption is that there can be no workable, optimal situation in a non-integrated supply chain. There are some notable exceptions to this centralised view. One example is the field of hierarchical or distributed decision making where it is recognised that, in the real world, prediction decisions are usually made by multiple local actors [35]. In this article we highlight (1) system dynamics, (2) game theory and (3) agent-based modelling.

1, *System dynamics*. Some of the earliest work on decentralised simulation modelling is Forrester's [36] groundbreaking work on industrial dynamics. In this seminal book he modelled a supply chain with four independent agents who make independent decisions and adapt to their environment: the factory, the factory warehouse, the wholesaler and the retailer. This line of research has continued quietly with Meadows's work on the hog cycle, where multiple independent producers, processors, distributors and consumers were modelled [37]. Morecroft and van der Heijden [38] modelled an oil market considering of different types of producers who operated according to different policies depending on market circumstances. On the specific research area of decentralised supply chain co-ordination, Hafeez et al have used system dynamics modelling to study this topic from various perspectives [39, 40]. Recent research in an other area conducted by Sterman and Wittenberg [41] shows that system dynamics models are quite suited to represent complex adaptive agent networks.

2. *Game theory*. This is a second formal modelling approach not based upon optimisation by linear programming that has had some applications in supply chain co-ordination. Das and Tyagi use game theory to understand better selection and negotiation between buyers and sellers in wholesale distribution environments [42]. Rational behaviour, time-step decision making and full information disclosure is assumed. Cachon [32] also recognises that supply chains are usually operated by independent agents with individual preferences and uses game theory to evaluate different co-ordination techniques such as buy-back and quantity discount contracts.

3. *Agent-based modelling*. In the remainder of this article we will focus on agent-based modelling techniques as a formal modelling approach to analyse co-ordination in decentralised supply chains. The literature on this specific sub-field is still very thin indeed. In fact, the only reference we could identify is work done by Strader et al [43], who use the agent-based modelling tool SWARM [44] to simulate order fulfilment processes in a generic supply chain network. Interestingly, although their simulation environment is clearly designed to represent complex adaptive systems behaviour, their model remains fairly conventional from a conceptual point of view. Roy's [23] self-organising market approach truly operates from a perspective of decentralised co-ordination. Instead, Strader et al [43] evaluate the effects of different degrees of information sharing on make-to-order, assembly-to-order and make-to-stock co-ordination concepts, all three fairly conventional integral control methods.

3 Complexity science and an agent-based modelling approach to complex adaptive systems

In this section we will briefly explore the emergence of a science of complexity and complex adaptive systems as a specific area of interest therein. Further we will introduce the concept of agent-based modelling.

3.1 A science of complexity

The domain of complexity science is, albeit fairly new, relevant because it enables us to seek out hidden order in seemingly chaotic systems so we can better understand their emergent behaviour. Insights on such phenomena has seen increased attention in and derives from research in areas as the social science [45], computer science [46], biology [47, 48], physics [49] and economics [50]. Complexity can be described as being in a state of dynamic dis-equilibrium. Complexity science deals with the nature of emergence [51], innovation, learning and adaptation and tries to galvanise the often hidden order, the simple deterministic rules that seem to guide systems that show complex structures in time and space. Complex systems evolve as integrated entities and yet are too rich and varied for us to understand in simple, mechanistic, linear ways. We can know, but we can not predict; we can understand many parts of a system but the larger and more intricately related phenomena can only be understood by principles and patterns, not in detail.

The 'grandfathers' of complexity science might very well be Hofstadter [52], whose 'Aunt Hillary' analogy would appear to be 'avant-la-lettre' to the emergence of a science of complexity and Axelrod [45], whose computerised iterated prisoners dilemma tournaments continues to enlighten the scientific community. There is nowadays increased exposure in science and literature to complexity, both at a high abstraction level [46] and laymen level [53, 5], both with an advocate view [47] as well as a more critical view [54].

3.2 Complex adaptive systems

A complex adaptive system is a system "...in which complex behaviour of the system as a whole emerges from the interaction of large numbers of simple components, and in which the system is able to adapt - that is, to automatically improve its performance (according to some measure) over time in response to what has been encountered previously" [55, p.1]. Complex adaptive systems are complex for the large amount of independent agents that interact in a large variety of ways. In this whirlpool of interactions, the system displays spontaneous self-organisation and a form of consistency in effect and direction that could not have been foreseen by or contained in the individual agents: the whole is more than the sum of its parts. In the context of this article we tend to follow the notion that agents are systems trying to fulfil a set of goals in a complex and dynamic, turbulent environment [56]. This indicates that the agents in complex adaptive system are diverse both in form and capabilities.

Besides being self-organising, complex systems are adaptive in that they actively seek to make the best out of whatever happens, both intra-system as well as inter-system. In being adaptive, complex systems show evolutionary behaviour. A such, complex systems have the ability to bring order and chaos in balance, displaying responses that are neither chaotic nor rigid but something in between.

In this area of complexity science, insight is gained on the mechanics of complex adaptive systems. Anderson [57] summarises the key elements of complex adaptive systems as made out of agents with internal schemata, as self-organising networks sustained by importing energy, as displaying co-evolution to the edge of chaos and as showing recombination and system evolution effects. Holland [19, 51] has distilled seven major characteristics of complex adaptive systems, subdivided into four properties (e.g. aggregation) and three mechanisms (e.g. tagging). Further, these characteristics are used in describing a common representation of the agents in complex adaptive systems in a framework of three major components, namely (1) a performance system, (2) credit assignment and (3) rule discovery.

1, *a performance system*, denotes the capabilities of agents at a point in time without attention for change by adaptation in order for agents to react (i.e. the reaction ability).

2, *credit assignment*, denotes the usage of failure or success to assign credit to parts of the performance system in order for agents to adapt (i.e. the adaptation ability).

3, *rule discovery*, denotes the changes made to the capabilities of agents replacing low credit parts of the performance system with new options in order for agents to evolve (i.e. the ability to evolve).

This framework can be viewed as a hierarchy, where each component adds a level of sophistication to and hence possibilities for emergent behaviour [c.f. 51] in complex adaptive systems. In this article we limit our model to a performance system only, albeit that we do introduce some form of credit assignment that however does not enable the agents in this article's model to adapt.

3.3 Agent-based modelling

In this article we articulate our argumentation using agent-based modelling in computer simulation. The body of literature on computer simulation [e.g. 58, 59, 60] and the object-oriented software it requires in the light of this article's themes [e.g. 61, 62] is extensive and beyond the scope of this article.

Agent-based modelling in computer simulations is a primary research tool in the study of complexity. The possibilities are apparent when considering such areas of interest as Genetic Algorithms [46, 63] and Artificial Life [64, 65]. Axelrod [66] even argues that the emergent behaviour displayed by large numbers of interacting agents often gets too difficult for deductive mathematical tools for reasons of non-linearity. There are a number of tools available to the scientific community for agent-based modelling. Best known are probably the SWARM and the STARLOGO simulation environment. SWARM was developed at the Santa Fe Institute as an attempt to create a standardised agent-based modelling environment that is flexible enough to allow for different research issues and well as different computer systems. SWARM consists of a number of software libraries of reusable components and is based on Objective-C, an object-oriented superset of the C programming language [44]. STARLOGO was developed at the Media Laboratory of the Massachusetts Institute of Technology and grew out of the idea to introduce programming capacities to LEGO building bricks. STARLOGO is an extension of the Logo programming language [67, 68]. A third example is ECHO, a simulation tool also developed at the Santa Fe Institute on the basis of the initial theoretical work done by Holland [69, 19].

We built the model described in this article using the STARLOGO simulation environment on an Apple Macintosh® computer. For the purposes of this article, SWARM would have been too sophisticated an environment. STARLOGO, on the other hand, is a much simpler simulation environment, is easy to learn and allows for a representation of the complex adaptive system elements that fit the purpose of this article.

4 Research method

In this section we discuss some key methodical aspects of the research reported here. Relatively uncommon about our research design is that it (1) has been exploratory and theory-building rather than theory-testing, (2) uses simulation for these purposes and (3) is presented here as an experiential learning approach, rather than a reconstructed logic after-the-fact.

4.1 Exploratory research in production and operations management

The research reported here is clearly exploratory in nature. Most research on decentralised co-ordination between multiple agents in general, and in supply chain management in particular, is very recent and preliminary. This obviously also holds for our research. Nevertheless, exploratory research remains an unusual research approach in the field of production and operations management. In two literature surveys from the early nineties, theory-testing research designs were found in 85% of all articles published [70, 71]. As such, theory-building remains a step in the research process which has been lamented as sorely missing in production and operations management [70, 71, 72]. Our research here should make a modest and explorative contribution to theory-building on supply chain management issues.

4.2 Simulation as a research method for theory-building

Our research design employs simulation to look for new knowledge, to *build* new theory. This is again unusual. Simulation experiments are normally seen as a suitable research design for theory-*testing* [73, 70], for finding out if a theory will work or to what extent it will work if experiments in reality are expensive, time-consuming, dangerous or impossible [58]. And yet, if a simulation is no better than the assumptions built into it, how can it generate new knowledge? A most eloquent reply to this valid question has been written by Herbert Simon, who states:

"even when we have correct premises, it may be very difficult to discover what they imply. All correct reasoning is a grand system of tautologies, but only God can make direct use of that fact. The rest of us must painstakingly and fallibly tease out the consequences of our assumptions." [74, p.19]. Axelrod, one of the contemporary experts on agent-based modelling, reaffirms this for his field of expertise: "Although the assumptions may be simple, the consequences may not at all be obvious. The large-scale effects of locally interacting agents are called 'emergent properties' of the system. Emergent properties are often surprising because it can be hard to anticipate the full consequences of even simple forms of interaction." [66, p.4].

4.3 Experiential learning with computer simulation

Since this has been exploratory research, we have presented our research findings in very much the order that our exploration has taken us. That is, we have chosen not to present our findings in this article as some kind of 'reconstructed logic' in the form of hypotheses to be tested (which would suggest ours was theory-testing research, which it wasn't). Rather, three consecutive simulation experiments are described, each starting with a specification of the result the authors expected *prior* to the simulation. Next comes a description of the model used and of the actual result of the simulation runs, followed by a comparison of expectation with realisation and concluded by an analysis of explanations for any differences between the two. This approach resembles the generic experiential learning cycle described by Kolb [75].

5 The model

In this section we present a generic discrete, spatially explicit mobile model that can be used to evaluate the performance of two supply chain concepts under equal environment conditions.

5.1 Model structure

Our model represents a 'world' in which two supply chain concepts can act. Next to the grid, five agent types are represented. The model further incorporates a market turbulence concept. The grid has the following characteristics:

Γ Grid. The grid Γ consists of a two-dimensional environment of finite size. The grid Γ wraps around at the edges, making it in effect border-less. All five agent types can move around in this world, according to their various speed settings. The grid Γ does not interact in any way with the agents moving over it. As such the grid Γ is a simplification as in real life various factors of grid-agent interaction can expected. However, as we want to focus this research effort on the two supply chain concepts rather than grid-agent interaction, we have chosen not to incorporate such factors in this model.

The five agent types are described as follows:

σ Suppliers of goods. The (1-n) σ-agents are uniform and have $\propto$ supply. The σ-agents are initially placed randomly on the grid Γ. Obviously this is a clear simplification of a supplier that in real life will be pluriform. However, in our view it is of more importance to investigate the performance of the supply chain concepts rather than an accurate real-world representation of a supplier. The σ-agents have a speed $\tau_{(\sigma)}$ to move on the grid Γ. Further, σ-agents have a number of internal variables, e.g. a boolean variable that denotes whether it has been allocated or not.

ρ Receivers of goods. The (1-o) ρ-agents are uniform and have $\propto$ demand. The ρ-agents are initially placed randomly on the grid Γ. Again, this is a simplification of a receiver that in real life will be pluriform, but again our focus is on the comparison of the supply chain concepts rather than a more accurate representation of a receiver of goods. The ρ-agents have a speed $\tau_{(\rho)}$ to move on the grid Γ. Further, ρ-agents have a number of internal variables, e.g. a boolean variable that denotes whether it has been allocated or not.

δ Agents of the central type. The (1-p) δ-agents receive their instructions from the central concept co-ordinator κ. The δ-agents can have a speed $\varphi_{(\delta)}$ to move on the grid Γ. The δ-agents receive credits π for each delivery made. The δ-agents are initially placed randomly on the grid Γ. Further, δ-agents have a number of internal variables, e.g. a boolean variable that denotes whether it has been assigned or not.

μ Agents of the decentral type. The (1-q) μ-agents do not receive any orders but have the ability to act autonomous on the grid Γ in stead. The μ-agents can have a speed $\varphi_{(\mu)}$ to move on the grid Γ. The μ-agents receive credits π for each delivery made. The μ-agents are initially placed randomly on the grid Γ. Further, μ-agents have a number of internal variables, e.g. a boolean variable that denotes whether it is loaded or not.

κ Centralised concept co-ordinator. There is one (1) κ-agent that co-ordinates the actions of the δ-agents. The κ-agent is placed at the centre on the grid Γ. The κ-agent has a number of internal variables.

Further, a market turbulence concept and two supply chain concepts are incorporated in the model, being

T Market turbulence concept. This is represented by random movements with speed τ of σ-agents and ρ-agents on the grid Γ. The speed τ of these random movements can be varied from a base value $\tau_{(\sigma,\rho)} > 0$ of but is the same for σ-agents and ρ-agents in this simulation. It is clear that this is a simplification of real market turbulence and behaviour. The analogy we would like to stress is that turbulence can be understood as a degree of uncertainty of market behaviour [4]. Although we are aware that there are several ways to simulate such a factor, in our view it is an arbitrary choice. We feel that the random movement at various speeds τ of σ-agents and ρ-agents on the grid Γ suffices in simulation the turbulence factor. The market turbulence factor is thus expressed as follows:

$$\mathrm{T} = t_{(s,r)} \qquad [1]$$

Δ Centralised supply chain concept. This is represented by the actions of the δ-agents. The concept here is that there is a ‘smart’, centralised concept co-ordinator κ that orchestrates the actions of the ‘dumb’ δ-agents. It must be noted that there is no co-ordination between the various δ-agents. The simulation of this concept is set up as follows: in each simulation cycle ι, the κ-agent checks a) if there are any unassigned δ-agents on the grid Γ, b) if so, assigns it by toggling its assigned-variable, c) checks if there are any unallocated σ-agents and ρ-agents on the grid Γ, d) toggles the allocated-variable of the closest σ-agent and ρ-agent relative to itself (effectively shutting them out for selection in a next simulation cycle), e) instils the identifications (IDs) of the allocated σ-agent and ρ-agent in two internal variables of the assigned δ-agent. The δ-agent then f) moves to the allocated σ-agent and ρ-agent. When the δ-agents g) reaches the σ-agent it toggles the σ-agent's allocated-variable (i.e. picks up a good) and h) moves to the allocated ρ-agent. On arrival at the allocated ρ-agent, the δ-agents toggles the ρ-agent's allocated-variable (i.e. delivers a good) and i) gets its credits π increased by one (1). Finally, the δ-agent j) toggles its assigned-variable.

M Decentralised supply chain concept. This is represented by the actions of the μ-agents. The concept here is that there is no central co-ordinator that orchestrates the actions of the μ-agents, but rather that each μ-agents may roam the grid Γ freely as it sees fit. It must be noted that there is no co-ordination between the various μ-agents. The simulation of this concept is set up as follows: in each simulation cycle ι, each μ-agent a) looks which σ-agent is closest to itself if its loaded-variable is false or which ρ-agent is closest to itself if its loaded-variable is true, b) instils the ID of that closest σ-agent or ρ-agent in itself, then c) moves to the respective σ-agent or ρ-agent. On arrival at the σ-agent or ρ-agent the μ-agent d) toggles its loaded-variable (i.e. picks up a good at a σ-agent or delivers a good at a ρ-agent) and e) if at a ρ-agent with a loaded-variable that reads true gets its credits π increased by one (1).

5.2 Model dynamics

A simulation run in our model involves three steps, (1) the setting of a number of variables that determine the simulation run, (2) the initialisation of the 'world' and (3) the actual simulation run.

1 The total number I of cycles ι per simulation run must be set. Further, the number of σ-agents, ρ-agent, δ-agents and μ-agents must be set. It must be noted that we have used a fixed number of cycles ι for each simulation run as well as a fixed and equal number of σ-agents, ρ-agent, δ-agents and μ-agents for all simulations and runs as presented in this article. Next, the value for speed $\tau_{(\sigma,\rho)}$ of the σ-agents and ρ-agents as well as the values for the speeds $\varphi_{(\delta)}$. and $\varphi_{(\mu)}$ of respectively the δ-agents and μ-agents are set.

2 The 'world is initialised by constructing the grid Γ, the random placement of the σ-agents, ρ-agents, δ-agents and μ-agents on the grid Γ and the placement of the κ-agent in the grid Γ's centre. The internal variables of each agent are set to an initial value (e.g. credits $\pi = 0$).

3 The actual simulation makes the σ-agents, ρ-agents, δ-agents, μ-agents and κ-agent perform the actions of the respective market turbulence concept T, centralised supply chain concept Δ and decentralised supply chain concept M per simulation cycle ι until I is reached. It must be noted here that the actions of the agents are not performed

sequential but in parallel, which is a distinct feature of an agent-based modelling environment.

5.3 Performance system

The model described in this article incorporates a performance system analogue to Holland [19] in the form of two factors. The first factor is based on the sum of the credits π of the δ-agents and μ-agents. The performance factor thus is expressed as:

Π Performance factor. For each 'delivery' made, the δ-agent or μ-agent making the delivery gets its credit π increased. At the end of each simulation run, the credits π for all δ-agent and μ-agent are summarised and the run's performance factor is calculated. The formula involved is:

$$\Pi^{I} = \frac{\sum_{i=1}^{i=p} p_{(d,i)}}{\sum_{j=1}^{j=q} p_{(m,j)}} \qquad [2]$$

The second performance system factor involves the relative speeds $\varphi_{(\delta,\mu)}$ of the δ-agents and μ-agents .

Φ Speed factor. In each model run, the speed φ of the δ-agents and μ-agents can be varied. The speed factor is expressed as:

$$\Phi = \frac{j_{(d)}}{j_{(m)}} \qquad [3]$$

Finally, graphs of this data can be constructed, for example based on the performance factor Π and speed factor Φ for a given market turbulence factor T. In doing so, we are basically measuring the performance of the centralised supply chain concept Δ and the decentralised supply chain concept M against each other in a given turbulent environment.

6 Simulation experiments

In this section we shall present the findings of the simulations done using the model described in the previous section. We consider three simulations in this article, a base simulation where the turbulence factor T and speed factor Φ are kept constant, a simulation where the speed factor Φ is varied and a combined simulation where the speed factor Φ and the turbulence factor T are varied in a series of runs.

6.1 Base simulation

In this simulation, we changed neither the turbulence factor T nor the speed factor Φ to derive at a base value for the performance factor Π. Our initial expectation was that there would be a roughly equal performance of the centralised supply chain concept Δ and the decentralised supply chain concept M. To our surprise, the value for the performance factor Π turned out to be 0.29 at the lowest speed factor Φ is 1.00 and the lowest turbulence factor T is 1.

When looking at the actual simulation, a number of things are visible in the behaviour of the agents of the two supply chain concepts. When looking at the behaviour of the δ-agents, it is apparent that they are executing the orders given to them by the centralised concept co-ordinator κ. The δ-agents will move for their assigned σ-agent and ρ-agent insensitive to the environment. This means that one can observe δ-agents that are heading towards their assigned σ-agent, pass other σ-agents but leaving them alone. Respectively, when heading for their assigned ρ-agent, pass other ρ-agents unnoticed. The behaviour of the μ-agents is very different. One can observe the μ-agents moving to whatever σ-agent and ρ-agent that is closest, dependent on the particular state of that μ-agent. In this, μ-agents behave responsive, sensitive to their environment. The particular effect here is that μ-agents cluster around groups of σ-agents and ρ-agents that are relatively close to each other and are hence geared to exploit any local opportunity (or niche) that may arise. This enables the μ-agents to quickly amass credits π, as they do not require to travel the same distances as the δ-agents are forced to due to the changing locations of their assigned σ-agents and ρ-agents.

6.2 Increasing speed

In this simulation, we have run the model at the lowest turbulence factor T is 1, whilst increasing the speed factor Φ from 1.00 to 3.00. Our initial expectation was that the centralised supply chain concept Δ would quickly 'win' over the decentralised supply chain concept M. For this particular simulation, the highest obtained value for the performance factor Π is 0.82 at speed factor Φ is 2.60. Figure 1 shows the data for speed factor Φ versus the performance factor Π for this simulation. It shows that the μ-agents 'beat' the δ-agents, or that the decentralised supply chain concept M easily 'wins' over the centralised supply chain concept Δ.

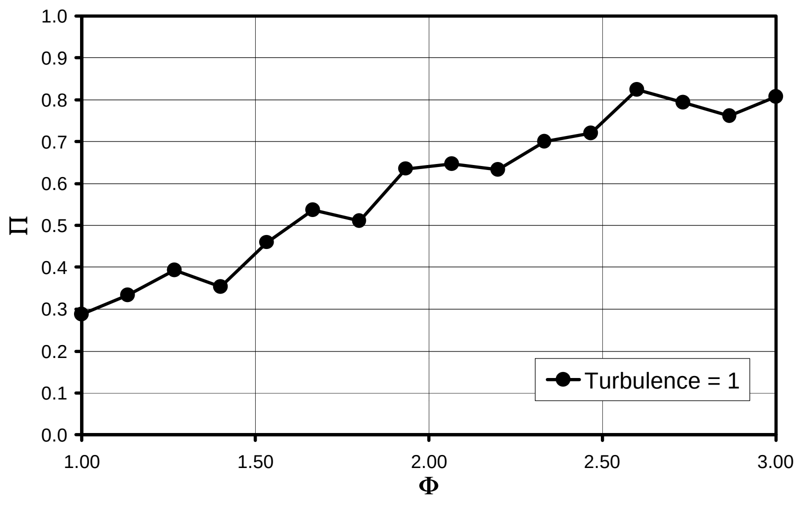

Figure 1: Performance factor Π over speed factor Φ is 1.00 to 3.00 for turbulence factor T is 1.

When looking at the actual simulation, the insensitivity of the δ-agents to the environment is apparent, with the only difference that they move for their assigned σ-agent and ρ-agent faster. The μ-agents remain sensitive to their environment, exploiting the niches as denoted in the base simulation. Apparently, the increased speed $\varphi_{(\delta)}$ of the δ-agents does not do enough to enable the centralised supply chain concept Δ to win over the decentralised supply chain concept M. Figure 2 shows the total values for credits π for both δ-agents and μ-agents. As can be seen, the performance of the μ-agents, although somewhat erratic, remains roughly stable, whereas the performance of the δ-agents shows a steady increase due to their increased speed $\varphi_{(\delta)}$.

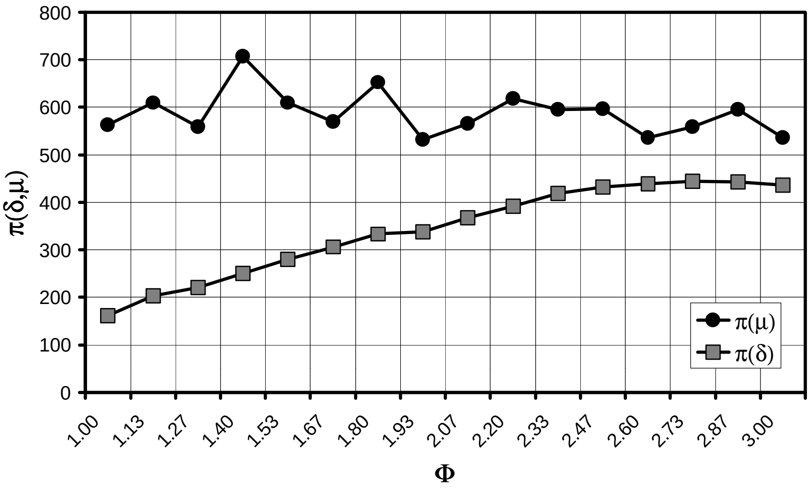

Figure 2: Values for total credits π over speed factor Φ is 1.00 to 3.00 for δ-agents and μ-agents at turbulence factor T is 1.

6.3 Increasing turbulence

In this simulation, we have run the model with turbulence factor T ranging from 1 to 5. In each run the speed factor Φ ranges from 1.00 to 3.00, where the speed of the μ-agents was kept constant. Our initial expectation here was that the centralised supply chain concept Δ would begin to 'lose' over the decentralised supply chain concept M as the turbulence factor T increases due to the apparent insensitivity of the former to the environment. For this simulation, the highest obtained value for the performance factor Π is 1.93 at speed factor Φ is 2.47 for a turbulence factor T is 5. Figure 3 shows turbulence factor T versus performance factor Π for speed factor Φ is 1.00, 2.00 and 3.00. It shows that the decentralised supply chain concept M begins to 'lose' out on the centralised supply chain concept Δ as the speed factor Φ increases – and – as the turbulence factor T increases. It is interesting to note that as turbulence factor T increases, the centralised supply chain concept Δ achieves increased better performance and 'beats' the decentralised supply chain concept M at increasingly lower values for speed factor Φ.

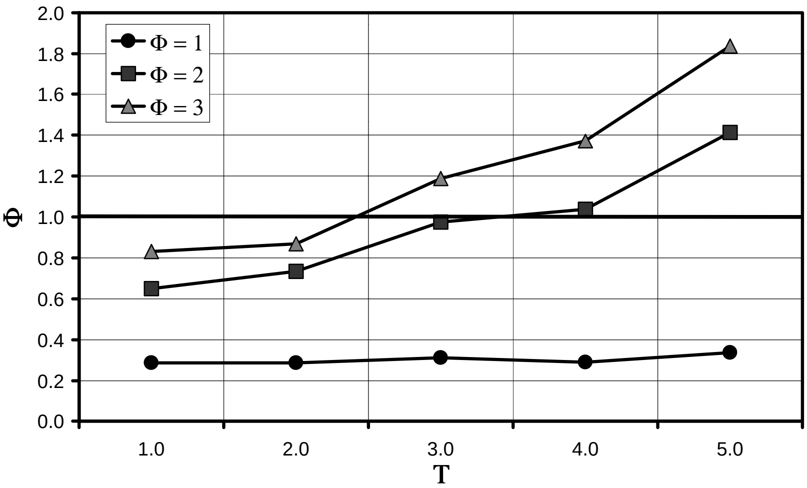

Figure 3: Performance factor Π over turbulence factor T is 1 to 5 for speed factor Φ is 1.00, 2.00 and 3.00.

When looking at these simulation in turn, there is a noteworthy change in the behaviour of the agents of the two supply chain concepts –vis-à-vis- their environment. Again, δ-agents will continue to move for their assigned σ-agent and ρ-agent indifferent to the environment, whereas μ-agents move to whatever σ-agent and ρ-agent that is closest in response to the environment. However, as the speed τ of the σ-agents and ρ-agents increases, the μ-agents appear to get 'confused' by the abundance of choice of passing σ-agents and ρ-agents and hence have increased difficulty to actually 'reach' those agents. One can observe hardly any cluster forming by μ-agents as the σ-agents and ρ-agents move too fast to enable the μ-agents to exploit such situations. The δ-agents on the contrary are not hindered by such distractions and continue to fulfil their missions, only having slightly more difficulty in reaching their assigned σ-agents and ρ-agents due to their increased speed τ.

Figure 4 shows the total values for credits π for both δ-agents and μ-agents at speed factor Φ is 1.00 for turbulence factor T is 1 to 5. From this figure it is apparent that the performance of the δ-agents is more stable that the performance of the μ-agents as the turbulence factor T increases. This is in line with the notion that μ-agents are more sensitive to the environment and thus that their performance is more volatile than that of δ-agents. Noteworthy here is also that the overall performance of – both – supply chain concepts drops as the turbulence factor T increases, but as said at different rates.

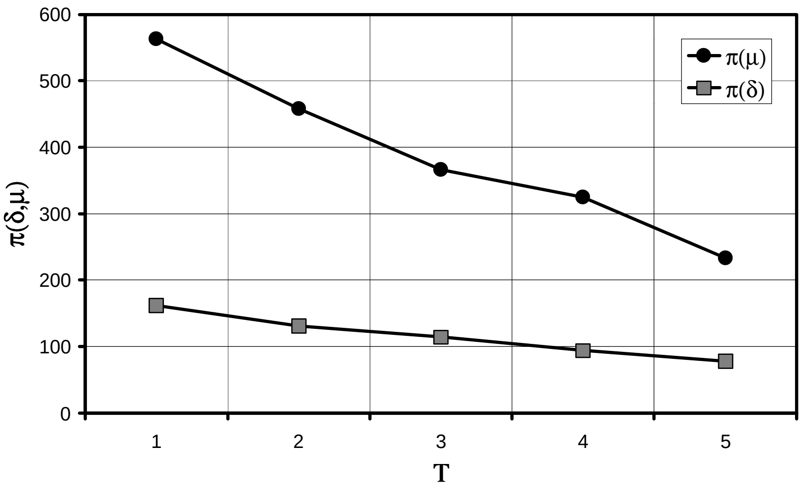

Figure 4: Values for total credits π over turbulence factor T is 1 to 5 for δ-agents and μ-agents at speed factor Φ is 1.00.

7 Discussion

In this section we reflect on three selected aspects of the exploratory research described, namely (1) on the relation between turbulence and the performance of complex adaptive systems, (2) on the counter-intuitive results of all our three simulation experiments and (3) on limitations inherent to our model and the agent-based modelling environment it was developed in.

7.1 Turbulence and complex adaptive systems

Our third experiment showed that, with increasing environmental turbulence, the centralised supply chain concept Δ deteriorated relatively less than the decentralised supply chain concept M. Within the context of our simulation experiment, this seems perfectly explainable. But can we also understand this in a broader context? Many people will, when given a choice, associate centralised control with relative stability and decentralised control with relative turbulence. As turbulence increases so does the complexity of making decisions at the central level, one would be inclined to say. And yet, upon further thought this is not so obvious. Let us consider two examples to explain this, one from supply chain management and the other from biology.

When an army is based in a fixed camp, quite often local caterers and suppliers can start tending to its logistical needs, much like a city usually has a two-week food supply without any form of central co-ordination [53]. But when, during wartime, this army is on the march from one place to another, its location and needs change so quickly that one will rarely see local caterers supply the soldiers' needs. In such a situation of extreme turbulence, only centralised control survives, as the Desert War has once again illustrated in the past decade.

In ecology, rain forests are counted among the most complex ecosystems. Hundreds of thousands of species interact with each other in an infinite variety of eat-or-be-eaten, symbiosis and co-evolution. This must be, because actually the underlying soil is extremely poor in nourishment, and so just about every useful element in it is recycled endlessly above-ground. Yet in all its apparent dynamism, this ecosystem is extremely stable. When destroyed by a fire or deforestation it can easily take hundreds if not thousands of years before it returns in a resemblance of its original state [18]. So in this case, complexity and decentralised co-ordination thrive with stability, not with turbulence.

7.2 Counter-intuitive findings

Not just in the third, but in all three experiments described in Section 6, we found the simulation results different from what we had expected beforehand; they ran counter to our initial intuition, however limited or flawed that by definition must have been. We believe this underscores the potential value of this type of simulation-based exploratory research as well as the applicability of an experiential learning approach. Rather than trying out conceptual theories on real firms in the real world, it would surely be beneficial if newly emerging ideas on how to make decentralised co-ordination work were first explored thoroughly in appropriate modelling environments. In this way, theory and simulation will continue to go hand in hand, the one highlighting flaws in the other and, at the same time, reinforcing each other's strengths.

7.3 Limitations in model and modelling environment

A tautological criticism of our simulation results would be to say that they are strongly determined by the formulation of the model and by the characteristics of its simulation environment, the agent-based modelling environment STARLOGO. Tautological, because by definition, "each simulation language has an implicit view of the world that must be invoked when we use it" [58, p.108]. One may draw this broader by comparing the agent-based modelling 'world view' with *paradigms* in the philosophy of science [31]. According to Kuhn: "Led by a new paradigm, scientists adopt new instruments and look in new places (...) [They] see new and different things when looking with familiar instruments in places they have looked before."

In the context of research in operations management, Amundson [76] draws the analogy between theories – or, in our case, modelling environments – and 'lenses' that frame our awareness and cognitive processing towards specific phenomena and aspects and away from others. Therefore, rather than a weakness of our approach, we would like to position its independent agent bias as a strength: an agent-based modelling environment may help us see different things in familiar settings and new things in new settings thanks to its distributed world view. System dynamics simulation may be said to have made the production and operations management field much more sensitive to time delays, bull-whip effects and business cycles [36]. Discrete-event simulation in production and operations management has highlighted (amongst others) the complexities of goods flowing through networks of queues and has been helpful in the development of adequate job shop control concepts [77]. Time will tell what part of future production and operations management theory agent-based modelling environments will turn out to have been instrumental in developing. To us, decentralised co-ordination in supply chain networks seems a strong candidate.

8 Conclusion

Our main objective in this article has been to introduce to the field of supply chain management research a new formal modelling method, agent-based modelling, that may be helpful in developing theories on how to co-ordinate activities in decentralised supply chain networks. Increasingly, the relevant level of analysis in supply chain management is that of the network of independent supply chain partners. Conceptual research on this area is beginning to take off but formal modelling is still lagging behind. One important reason for this may be that adequate representation of such decentralised networks is cumbersome in existing modelling environments. These invariably arrive at the conclusion that centralised control would be optimal and preferable whereas this runs counter to what one sees happening in the business world today.

In this article we describe three simulation experiments of a simple supply chain. The model used to run these experiments was built using an agent-based simulation environment. Each experiment proved to produce counter-intuitive findings vis-à-vis our initial assumptions as to the expected behaviour and shows the validity of such exploratory research and experiential learning. Firstly, we found that in such a decentralised modelling environment a 'swarm' of independent agents outperformed a similar number of agents under centralised control. Secondly, we found that economies of scale would have to be very considerable indeed for the centralised supply chain concept in order to yield performance results superior to the decentralised supply chain concept. And thirdly, we found that increasing levels of turbulence led to a rapid deterioration of the performance of the decentralised supply chain concept and a far less severe set-back for the centralised supply chain concept. Obviously, these results can at least partly be ascribed to the simplistic nature of our model and the biases inherent to the implicit world view of a decentralised modelling environment. This however is precisely our point for this article: we suggest that a modelling approach which has decentralised operations at its core might yield useful and interesting insights to the domain of supply chain management – precisely because of its biases.

We propose further research into this area using theorems and tooling that enable us to capture an inherently decentralised world view. We propose exploration along three lines of thought. On the supply chain management side, a next step to extend the model used in this article would be to introduce multiple tiers, multiple supply chains, pluriform suppliers and receivers and grid-agent interaction. In addition, other concepts besides market turbulence, such as compression of the supply chain, integration and possible optimisation schemes could be introduced. On the agent-based modelling side, a powerful validation experiment would be to repeat the research done in this article by using a different agent-based modelling environment to see to what extend the results found here can be repeated [c.f. 66, e.g. 44]. Finally, from the complex adaptive system side, there is also ample room for improvement of the model. The performance system could be extended so that agents share information. Next, credit assignment could be extended to grant 'life' to agents so that under-performance causes an agent's death and over-performance the spawning of a new agent. Another extension might be to introduce multiple supply chain concepts per agent type to enable them to choose the optimal behaviour for a given environmental situation. The final stage here would be the ability of agents to derive at the optimal supply chain concept themselves through the ability to discover rules of behaviour that increase their performance. When such is achieved, it is quite conceivable that one would see supply chains behaving as true 'swarms'…

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