Title:

Autonomous Cooperation – A Way to Cope with Critical Incidents in International Supply Networks (ISN)? An Analysis of Complex Adaptive Logistic Systems (CALS) and their Robustness

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Autonomous Cooperation – A Way to Cope with Critical Incidents in International Supply Networks (ISN)?

An Analysis of Complex Adaptive Logistic Systems (CALS) and their Robustness

Abstract

Mainly this paper focuses on the analysis of contributions and limitations of Autonomous Cooperation to ensure the robustness of International Supply Networks (ISN) in case of rising complexity and dynamics due to environmental impacts in order to prevent and cope with critical incidents. The contributions and limitations of Autonomous Cooperation regarding its abilities to increase the robustness of ISN and their performance in dealing with critical incidents are evaluated from the perspective of complexity theory and especially in context to complex adaptive systems (CAS). A discrete-event simulation is used to model and test the robustness of an ISN whilst rising complexity and dynamics.

Keywords

Autonomy, Autonomous Cooperation, Self-Organization, Supply Network Management, Complex Adaptive Logistic Systems, International Supply Networks, Logistics

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Prof. Dr. Michael Hülsmann is professor of strategic management and leads the research unit “Management of Sustainable System Development” (www.wiwi.uni-bremen.de/mh). He is also academic director of the SCOUT-Institute for Strategic Competence-Management. Both institutions are part of the faculty of business studies and economics at Bremen University, Germany. Hülsmann received his diploma degree in business from the University of Bayreuth and graduated summa cum laude with a PhD degree from the University of Bremen. He gained professional experience in various companies. Currently, Hülsmann is a board member of the collaborative research centre “Autonomous Cooperating Logistic Processes – A Paradigm Shift and its Limitations” (www.sfb637.uni-bremen.de) that is supported by the German Research Foundation as well as a member of the International Graduate School for Dynamics in Logistics. Additionally, he is an associate of the research clusters for mobile technologies (MRC) (www.mrc.bremen.de) and dynamics in logistics (LogDynamics) (www.logistics-gs.uni-bremen.de) at Bremen University. He is a member of several academic societies (e.g. EGOS, AOM, SMS). His research focus includes strategic management of organisational competences; coping with corporate crises & organisational change; designing the self-organization, co-ordination & co-operation in networks (especially in supply chains & international supply networks); strategic controlling of corporate performance, risk, and sustainability.

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1 Introduction

The perspective of research in the field of logistics management has changed from analysing single supply chains to analysing interwoven and cross-national supply networks (Surana et al. 2005; Mason 2007). This change of the research perspective is due to the observation, that organizational structures in logistics are currently characterized by a growing grade of interrelations between the actors in logistic processes and not by linear processes (Hülsmann et al. 2007). One phenomenon that might lead to growing interconnectedness is real-time economy that can be described by timely convergence of order, production and distribution of goods and services (Tapscott 1999; Siegele 2002). Real-time economy evolved from the necessity for organizations to meet consumers' demands like shorter delivery times or diversified preference structures in order to ensure the long-time survival (Tapscott 1999). If an organization wants to meet this demand, it has to adapt its processes and structures constantly to the real-time changing consumer's requirements (Hülsmann et al. 2006).

One possible solution to cope with characteristics of real-time economy might be to intensify business relationships with the aim to supply the organization with needed resources (Geoffrion and Powers 1995). Therefore, the phenomenon of real-time economy can explain growing grades of interrelations between economic actors and evolving network structures in logistics. Due to this development, logistic systems cannot be analysed as linear supply chains any more but they have to be analysed as supply networks in order to model their grade of inter-connectedness. Hülsmann and Grapp considered these interwoven supply systems to be International Supply Networks (ISN) (Hülsmann and Grapp 2005). Hence, ISN can be characterised by companies that are legally separated but economically to a certain extend dependent on each other. Therefore, a large number of interorganizational relationships exist between the entities of the system which might lead to increasing complexity and dynamics (Sydow 2002) due to increasing quantities of and often changing information. A system is complex due to high amounts of interrelations between the system's elements as well as between the system and its environment whereas dynamics describes the rate of modification of a system over a specific time (Probst and Gomez 1989). For ISN complexity results from the number of sub-systems (e.g. forwarders, consumers, or goods) and from the amount of interrelations between the system's elements (e.g. flows of information or material) and between the system and the environment (e.g. legal system). Dynamics derives from changes within the system and its structure (e.g. new contractors, new machinery) and from changes in the environment (e.g. new laws or environmental disasters). Beside other phenomena (hypercompetition (d'Aveni 1995) or hyper-turbulence (Monge 1995)) the increasing amount of information and the change rates within the information can be explained by the phenomenon of hyper-linking (Tapscott 1999). Hyper-linking describes the development that enterprises are not only linked to their direct business partners, but as well indirectly to other actors in the field of logistics (e.g. via fourth party logistics) (Tapscott 1999; Hülsmann et al. 2006). These indirect and diffuse links connote, that not only alterations which originate at direct business partners of an organization (e.g. changing organizational structure, information systems or business processes) influence environmental complexity and dynamics, but as well alterations caused by indirect business partners. Occurrences in the relevant environment whose impacts and rate of appearance can be amplified by the growing interconnectedness are so called critical incidents or extreme events (Wycisk et al. 2008). This leads to increasing amounts of information about external factors that have to be absorbed and processed by the organization in order to sustain the strategic fit between environment and organization and therefore, to ensure the survival on the long run (Hülsmann et al. 2007). Hence, the dependency of and the sensitivity to environmental complexity and dynamics increase in ISN. This leads to the necessity for the management of ISN to implement structures and processes that are able to ensure the robustness of the network despite complexity and dynamics in order to prevent the system from information overload that might occur when the system is not able to process all the information it absorbs and leads to a lock-in situation (Hülsmann et al. 2007). Lock-in describes a dysfunctional situation of an organization that is due to limited ability of rational decision-making that results from lack of information or lack of capacity to process information (Schreyögg et. al2003). Hence, robustness is needed to prevent the system from getting into a lock-in situation due to information overload caused by complexity and dynamics.

Robustness of a supply system can be defined as extent of its ability to carry out its functions despite some damage (e.g. changes in the environmental conditions, breakdowns, changes of system elements or relationships between elements or between the system and its environment) that is done to the network and its structures (Meepetchdee and Shah 2007). Therefore, the robustness of ISN should be at least maintained in order to cope with complexity and dynamics that result from hyper-linking and real-time economy.

One concept which has been discussed in the context of increasing the robustness of logistic systems is Autonomous Cooperation (AC) (Hülsmann et al. 2007; Windt and Hülsmann 2007). Autonomous cooperation reflects on ideas in the context of self-organization and is enabled by recent information and communication technologies (ICT) like RFID or sensor networks. It aims at providing a better accomplishment of logistic objectives (e.g. throughput time) than conventional management approaches in cases of increasing complexity and dynamics (Windt and Hülsmann 2007). Therefore, Autonomous Cooperation might be an approach for the management of ISN in order to increase the robustness of the network.

To introduce a framework of analysis for the behaviour of supply networks Wycisk at. el. (2008) adapt the concept of complex adaptive systems (CAS), which originates in complexity science, to logistic systems in order to analyse complex adaptive logistic systems (CALS). Due to the perspective of CALS that focuses on the complexity of logistic systems and because of its existing research concerning critical incidents in logistics this can be a fruitful approach to analyse ISN (Wycisk et al. 2008). Hence, the idea of complex adaptive logistic systems will be implied into this research in order to analyse whether Autonomous Cooperation is a suitable approach to deal with critical incidents in complex adaptive logistic systems like ISN.

Using the concept of CALS, the question the paper is going to answer is: Is the concept of Autonomous Cooperation a reasonable way to deal with critical incidents in complex adaptive logistic systems like ISN? Accordingly, the descriptive aim of the paper is to depict Autonomous Cooperation and the behaviour of complex adaptive logistics systems. The analytical goal is to display the correlation between robustness, the capability of adaptivity and Autonomous Cooperation. Pragmatically, the paper aims at making suggestions for the design of complex adaptive logistic systems in order to increase their robustness.

In order to examine whether Autonomous Cooperation could contribute to cope with complexity and dynamics, the paper proceeds as follows. Section one represents the tendency from linear supply chains to ISN. This will be used to reveal the increasing sensitivity of ISN due to external events. Section two introduces the concept of complex adaptive logistic systems, which is grounded on theories of complexity. Based on this, a model of CALS will be sketched and described in its constitutive attributes and possible effects. Therefore, the concept of Autonomous Cooperation will be introduced and its potential abilities to improve the robustness of a complex adaptive logistic system like ISN will be shown in chapter three. Explicitly the aspect of Autonomous Cooperation in complex adaptive systems will be examined, so that possible effects on the robustness of CALS can be deduced. Section four comprises the simulation in order to test empirically the hypotheses on the causal interrelation between Autonomous Cooperation and the robustness of CALS. The simulation model that will be used is a discrete event simulation in the field of production networks. Section five draws conclusions of our findings and gives an overview on future research requirements.

2 International Supply Networks (ISN) as Complex Adaptive Logistic Systems (CALS) – Establishing a Complexity-Theoretical View for the Analyses of Logistics Phenomena

2.1 Vision of Complex Adaptive Logistics Systems

In logistics research an ongoing paradigm shift can be observed, moving 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 CALS most recently (Choi et al. 2001; Surana et al. 2005; Pathak et al. 2007; Wycisk et al. 2008). CALS comprise various logistics 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). According to McKelvey et al. (2008) the key feature of CALS is that they are composed of smart parts. The term 'smart parts' describes logistics entities, which possess the feature of interaction and autonomous decision-making by usage of modern communication and information technologies, such as RFID, GPS, and sensor networks. Smart parts can be all kinds of logistic entities listed above. The 'smartness' lies in the ability of the parts to decide autonomously about their optimum behaviour regarding their given individual goals (of e.g. time, quality, costs) (McKelvey et al. 2008). The objective of developing CALS is the self-producing self-delivering product, which initiates its own production according to customers' requirements, autonomously plans and finds the most efficient way to the customer and flexibly react to changes or hurdles affecting its progress.

2.2 Definition of Complex Adaptive Logistics Systems

Since the basic idea of CALS derived from the concept of complex adaptive systems, these are introduced first in order to generate a common understanding of the character of CAS and then define CALS afterwards.

Defining CAS. The concept of CAS derives from biology – and pertains to living entities (Gell-Mann 2002). Holland (1995) describes CAS as systems that emerge over time into a coherent form, adapting without a central 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; Wycisk et al. 2008).

Defining CALS. The usage of new communication and information technologies as well as agent-based computational models aiming for more robustness, flexibility, autonomy, and emergence, forces a tendency to a more complexity-based perspective in logistics. Approaches that aim at establishing new logistics concepts are for example from bionic (Okino 1993), genetic (Ueda 1993), holonic (Winkler and Mey 1994), random or (Iwata and Onosato 1994), virtual manufacturing concept (Gunasekaran and Ngai 2004). In the context of production and logistics, one example is the concept of the fractal factory[1] (Warnecke 1993). 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).

According to McKelvey et al. (2008), a complex adaptive logistics system (CALS) describes a system consisting of connected, autonomously acting heterogeneous agents that all fulfil a logistic task, which emerges over time into a coherent form, adapting itself due to internal or external demands without any singular entity deliberately managing or controlling it. Due to these characteristics of CALS the framework given by this approach is a functional basis for analysing ISN because CALS focus on complexity and robustness in systems that have to adapt constantly to changing environmental conditions. Additionally CALS offer the opportunity to analyse the system on its different levels and therefore allows analysing an ISN not only on the level of the whole system but on the level of sub-systems and elements as well.

[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.

2.3 Properties of Complex Adaptive Logistics Systems

McKelvey et al. (2008) present several characteristics that reflect a more detailed description of CALS from an individual, intrasystemic, and intersystemic level perspective.

Individual Level. Natural CAS consist of a number of constituent entities that are called **agents**. Agents can 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 different action patterns. This both creates, and results from, their heterogeneity (Wycisk et al. 2008). According to Holland (2002) agents of 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 logistic goals (Hülsmann et al. 2006). Interaction takes place within the whole supply network in the form of flows of information, resources and/or finances (Göpfert 2005). Due to their **ability to learn**, agents are able to adapt to environmental changes by modifying their rules of action and improve their performance as experience accumulates (Holland 2002). Furthermore, where agents represent higher-level organisational entities within a supply chain, organizational learning may be present. In contrast, at lower levels, where agents represent physical entities, we can not ascertain a general ability of learning in existing logistics systems yet (Wycisk et al. 2008).

Intra-systemic Level. From a complexity theory 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). According to Mainzer (1994), **Self-organisation** results from the autonomous interaction of single agents within a CAS. It gives rise to bottom-up (new) order creation by a system itself. Within logistics systems, self-organizing processes result from the interaction of individual agents (e.g. employees, physical entities) from an intra-systemic perspective. What Kauffman (1993) calls the **‘melting’ zone** is a region between the ‘edge of order’ and the ‘edge of chaos’ where self-organization and emergent system behaviour arise (McKelvey 1999, 2007). 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 autonomous with only the most essential connections and interactions with other units remaining. Agents in a logistics system connect via interaction and interdependency.

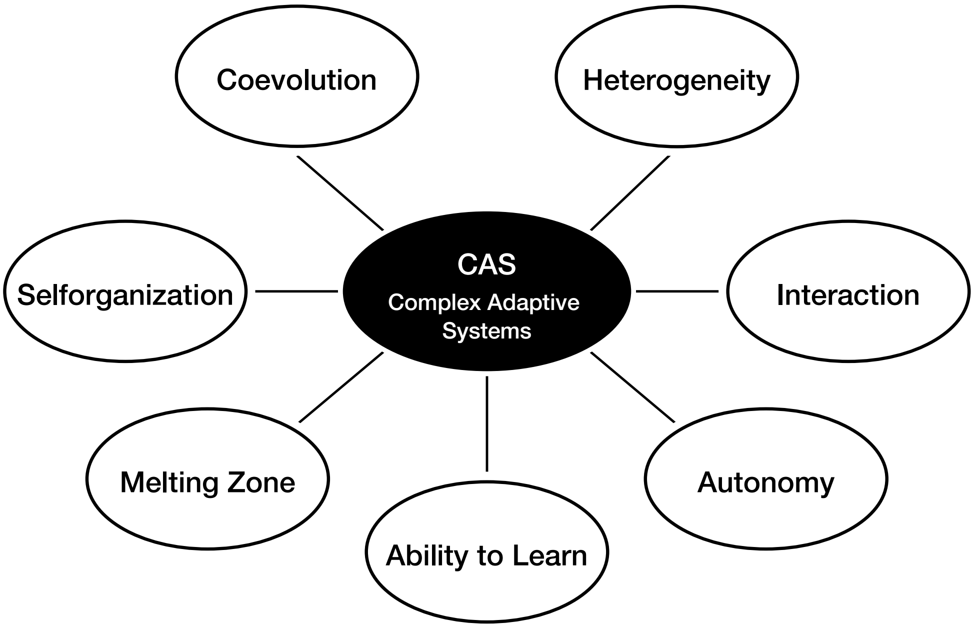

Fig. 1: Characteristics of Complex Adaptive Systems

Inter-systemic Level. Through autonomous decisions by any participating firm, an autonomously-created, spontaneously-ordered structure keeps evolving within the supply network (Choi et al. 2001; Surana et al. 2005). Kauffman (1993) emphasises **coevolution**, in which positive feedback loops may emerge as agents sequentially respond to each other's actions. According to Choi et al. (2001) coevolutionary processes within logistics systems are initiated and influenced by non-linear state changes, and path dependences in the development of supply networks. Holland (1988, 2002) states that CAS behaviour is **non-linear** because agents interact in non-additive ways. Choi et al. (2001) as well as Surana et al. (2005) point to non-linear interactions among autonomous agents comprised within 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 (Wycisk et al. 2008; McKelvey et al. 2008).

2.4 Outcomes of Complex Adaptive Logistics Systems

There are several identifiable outcomes of CALS like for example emergence, butterfly effects, robustness, scalability, and power laws (Wycisk et al. 2008; McKelvey et al. 2008). 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. Emergent phenomena have been experienced 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 organisation of the overall SN emerges through the natural process of order and spontaneity’ (2001). 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 non-linear though simple behavioural rules that operate based on local information’ (2005).

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 Industrial Dynamics (1961). 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 remarkably chaotic and critical incidents within the supply network. These are especially likely as systems become more complex and self-organizing, with resulting dynamical non-linear processes. Due to strong interdependencies among the actors of a supply chain trying to adapt to each others demands (e.g. regarding stocks), each decision and action by an individual agent will affect the others. Consequences of the bullwhip effect are for example overfilled warehouses alternating with periods of resource and product shortages (Lee et al. 1997).

Heylighen (2003) states that well-working CAS have a high degree of **robustness.** Robustness means that a system is relatively insensitive to perturbations or errors, and has a strong capacity to restore itself. Carlson and Doyle define robust systems as ‘…systems designed for high performance in an uncertain environment and operated at densities well above a standard critical point.’ (2000, p. 2529). McKelvey et al. (2008) emphasise the attribute of robustness within CALS due to its restoring abilities.

There is a growing view that CAS causal dynamics may often be self-similar and **scalable** (fractal) across multiple levels termed fractal geometry (Mandelbrot 1982). Fractal means that the same kind of dynamics works at multiple levels (Peitgen and Richter 1986; Kaye 1989;

Schroeder 1991; Andriani and McKelvey forthcoming). According to McKelvey et al. (2008) the presumption of supply networks as CALS implies that scale-free causes and consequent dynamics may occur at multiple levels of supply networks.

Pareto rank/frequency distributions are to be expected as a probable outcome of any effective self-organizing CAS (Bak 1996; Brock 2000; Gell-Mann 2002) most identified by **power law** distributions (Newman 2005; Andriani and McKelvey 2007). A 'power law' is a Pareto distribution graphed that appears as a negatively sloping straight line if using log scales for the X and Y axes. McKelvey et al. (2008) conclude that efficaciously adaptive CALS networks will also exhibit the power law signature.

2.5 Demands for the management of ISN by Complex Adaptive Logistic Systems

From literature in the field of CAS it is very clear that non-linear behaviour with the probability of butterfly events and spiralling into negative and positive extremes is a result of the main characteristics of CAS. Therefore, it can be assumed that CALS like ISN will show similar behaviour as well. Hence, the butterfly 'levers' by Holland (2002) can become a tool for managers in order to enhance positive extremes and avoid negative ones. Therefore, possible outcomes for ISN from CALS are on the one hand to enable the system to respond efficiently to tensions in the relevant environment of CALS. On the other hand extreme events might cause critical incidents for ISN which has been proofed by modelling over ten years ago (Scheinkmann and Woodford 1994). In current literature on logistics systems a movement towards CALS can be observed but without realizing potential downside extremes (Wycisk et al. 2008). If managers introduce supply chains comprised of both human and smart-part agents to become CALS, then, they have to have solutions for managing critical incidents or preventing them in the first place. Therefore, Wycisk et al. (2008) list several possible options to reduce the risks of critical incidents from a complexity theoretic perspective:

1. One solution is to stay with low cognition parts. They could keep checking in with a neural network program that would monitor all possible shipping options – trucks, trains, ships – and give up-to-date information about the fast/expensive or slow/cheap choices. In this case, the system would be still far away from true autonomous self-organizing agents and CALS, and thus the management of ISN could not take advantage of emergent system behaviour and fast reacting logistics processes.
2. Given really smart parts, one option is to treat Holland's tiny initiating events as 'butterfly levers' by which possible negative extremes can be detected. In all of the

analyses of disasters such as Challenger, Pioneer, 9/11, Enron, Airbus, or Parmalat, all sorts of small events were evident after the occurrence, but missed before.

a. One option is to use a monitoring system of the dynamics caused by smart parts in order to detect when the system is heading to an extreme and forestall the negative extremes before the tipping point is reached.

b. A second option is to use a neural net instead of human monitors. The neural net would monitor all decisions taken by the 'parts', analyse what system dynamics their collective decisions will possibly produce at any given time. Then the neural net would alert human operators, or even better, inform the parts to try other options in case of possible critical incidents.

c. A third option is to keep smart parts but also give them the option of checking with a neural net as a 'monitor' so the parts, themselves, can keep checking in order to avoid the tipping point.

d. One of the things we learn from LeBaron's model of the stock market (2001) is that crashes occur when agents lose their heterogeneity – they all end up with the same set of rules for decision-making. A fourth option, then, is to constantly monitor (via neural net or humans) the heterogeneity of smart parts choices. As they lose their heterogeneity in decision-making, at some point they become treated like 'dumb' parts and the system reverts to option one above.

e. A fifth option resulting as well from LeBaron's model is that smart parts could mix in routing options constantly produced by the neural net with options they learn about from other parts in order to ensure their heterogeneity.

Hence, for the management of ISN the concept of CALS implies that introducing characteristics of CALS into ISN could improve their robustness and therefore enhance their ability to cope with environmental and even internal complexity and dynamics. On the other hand this leads to non-linear behaviour and therefore to the possible occurrence of critical incidents. One approach that has been discussed in order to implement characteristics like non-determinism, interaction and emergence into a logistic system is Autonomous Cooperation. Therefore, Autonomous Cooperation will be introduced as a possible concept of control for enabling ISN to act as CALS and hence to increase their robustness.

3 Effects of Autonomous Cooperation on the Robustness of International Supply Networks

3.1 Origins of Autonomous Cooperation

The concept of Autonomous Cooperation and its basic ideas derive from the concepts of self-organization that tries to analyse the emergence of robust and ordered structures in complex systems (Paslack 1991; Hülsmann et al. 2007a). The academic roots of the research field of self-organization can be found in different academic disciplines like Biology, Chemistry or Physics. First attempts date back to 500BC when the pre-socratic Aristotle and Heraclites identified self-organized processes in natural phenomena (Paslack and Knost 1990; Paslack 1991). From the 1970's on an increasing number of publications that are directly dealing with self-organization can be found. Main concepts are Synergetics by Haken (1973), Disspative Structures (Prigogine 1969); Cybernetics (von Foerster 1979) Chaos Theory (e.g. Lorenz 1963; Mandelbrot 1977), Ecosystems (e.g. Bick 1973; Odum 1999) and Autopoiesis by Maturana and Varela (1973).

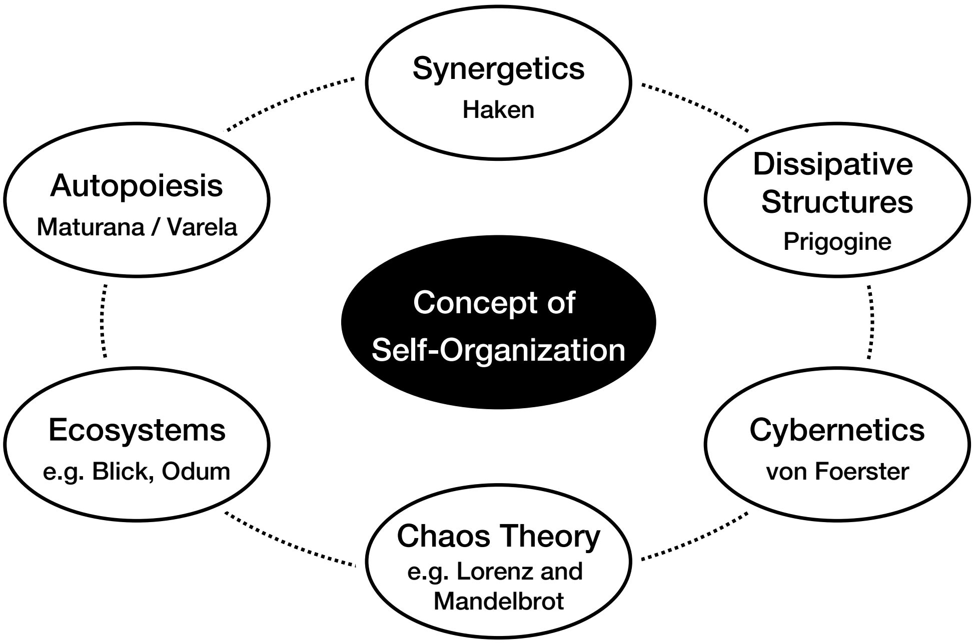

Fig. 2: Primal concepts of the idea of self-organization (Hülsmann et. al. 2007a)

One characteristic of self-organizing systems is the essentiality of the relationships between the systems elements in order to grow, develop and react so as to become alive (Mishra 1994; Hülsmann et. al. 2007a). Therefore, self-organizing systems focus on relationships between the systems elements and not on the elements themselves. Interaction between its components can be seen as essential for the development of the future conditions of the system (Hülsmann et. al 2007a). Additionally the structure of self-organizing systems is assumed to be open to absorb information and resources in order to adapt to significant changes in the environment. But the more information and resources are absorbed, the more changes of the system's status are needed and therefore more internal dynamics occur (Varela 1979; Malik 2000). Another mentioned characteristic is that through interaction of the single elements ordered structures evolve autonomously. This enables a self-organizing system to cope with complexity and dynamics. Hence, it is presupposed that self-organizing systems contain autonomous system elements (Hülsmann et. al. 2007a). Therewith, self-organizing systems are found to be non-linear and non-deterministic. A framework of general rules of decision-making might be defined and a desired system state as well but not the mode how to achieve this state. Complex systems are defined to be in a state far from equilibrium as well and therefore permanently open to absorb information and resources from their environment (Prigogine and Glansdorff 1971). The last characteristic is flexibility which provides the system with the ability to adaptiveness in order to ensure its survival in dynamic, complex, and competitive environments (Hülsmann and Wycisk 2005). Overall it can be said, that self-organization can enable a system to organize itself autonomously (Manz and Sims 1980; Hülsmann et. al. 2007a).

3.2 Basic idea of Autonomous Cooperation

In recent times a paradigm shift in logistics from a centralized control of "non-intelligent" parts in hierarchical structures to a decentralized control of intelligent parts in heterarchical structures can be observed. Main drivers for these developments are for example heterogeneous vendor markets, short product life cycles, traceability, new ICT-technologies like RFID or wireless computing and demands for high degrees of accuracy (Windt and Hülsmann 2007). In order to react to those drivers the concept of Autonomous Cooperation has been developed as a factor to guarantee changeability of logistic processes by enabling logistic objects to act autonomously. Hence, main enablers for Autonomous Cooperation are evaluation systems, self-identification and –detection, execution systems, the ability to identify alternatives, information processing, and the ability to communicate by ICT (Windt and Hülsmann 2007). Hence, the major aim of Autonomous Cooperation is to implement a flexible self-organizing system structure that enables the system to cope with complexity and dynamics (Hülsman et al. 2007a).

Therefore, Autonomous Cooperation can be defined as:

> "*Autonomous Control describes processes of decentralized decision-making in heterarchical structures. It presumes interacting elements in non-deterministic systems, which possess the capability and possibility to render decisions.*

> *The objective of Autonomous Control is the achievement of increased robustness and positive emergence of the total system due to distributed and flexible coping with dynamics and complexity."* (Windt and Hülsmann 2007, p. 9)

According to this definition, main characteristics of Autonomous Cooperation are decentralized decision-making, autonomy, interaction, heterarchy, and non-determinism. **Decentralized decision-making** specifies the delegation of decision power from a central entity of a system to the system's elements. The single elements are allowed to render their decisions independently and are capable of making decision by gaining access to relevant resources (e.g. necessary information) (Windt and Hülsmann 2007). **Autonomy** describes that elements of a larger system are responsible for their own system design, direction and development. The elements can make decisions independently from external entities (Probst 1987). Hence, autonomy is the result of processes of decentralisation and delegation (Kappler 1992). In the context of Autonomous Cooperation autonomy is understood as autonomous decision-making of elements within a system (Windt and Hülsmann 2007). **Interaction** describes successful contacts between system elements whereas successful means that communication takes place (Staehle 1999). Within Autonomous Cooperation interaction is crucial and is realized by communication between elements like vehicles, goods or warehouses. Due to advanced technologies like RFID elements can not only communicate within the own system but as well with the environment (Windt and Hülsmann 2007). **Heterarchy** describes the parataxis of elements within a system (Goldammer 2002). In heterachical systems there is no permanently dominant control entity. This results in fewer superordinate and subordinate relationships (Probst 1992). For logistics systems this implies a higher independence between logistic elements and a central logistic coordination entity (Windt and Hülsmann 2007). The last characteristic is **non-determinism** which means that the system's behaviour cannot be predicted over a relatively long period even if all system laws are known and precise measurement methods are used (Flämig 1998). By non-determinism Autonomous Cooperation strives for higher efficiency when dealing with complexity and uncertainty within processes (Windt and Hülsmann 2007).

3.3 Lessons Learned from the Idea of Autonomous Cooperation for the Management of the Robustness of International Supply Networks (ISN)

In order to evaluate the potential but as well the limits of Autonomous Cooperation to ensure the robustness of and to avoid critical incidents in ISN, the characteristics of Autonomous cooperation will be analysed separately. Therefore, a possible technical enabler will be introduced and possible impacts on the structure of ISN will be described. Afterwards positive and negative effects on the robustness will be analysed and factors that might avoid or foster the occurrence of critical incidents within ISN will be highlighted.

Decentralized decision-making can be enabled by smart parts that are provided with the power to render decisions independently. In order to ensure their ability to render decisions, smart parts have to be provided with processing capacity and a rule set of decision-making algorithms (Windt and Hülsmann 2007). For the structure of ISN this can lead to an increased capacity for information processing and decision-making of the whole system. Hence, the robustness of ISN might be increased by decentralized decision-making because the higher amount of information processing capabilities can avoid lock-in situations due to information overload. Negative for the robustness might be that local decision-makers might not be able to take into account the necessities of the global system as extensive as a central planning unit. To avoid critical incidents decentralized decision-making might enhance smart parts within the logistic system to detect butterfly levers and take these into account while rendering decisions, in order to avoid tiny initiating events. In the same time a global inconsistence (decisions that are not coordinated with other elements) might foster the occurrence of critical incidents. For example if all goods head for the same cheap shipping opportunity most of them will be left behind.

In order to enable **autonomy** within an ISN the logistic objects or smart parts can be provided with learning algorithms. Hence, they are able to develop their rule sets and capacities in order to enable the ISN to adapt its structures and processes to changes in the interlinked environment. Due to this ability, the robustness of the ISN can be ensured, even in cases of dynamics and complexity, in order to maintain the fit between the ISN and its environment. At the same time the adaption processes within the ISN cause dynamics because of changing relationships and the heterogeneity of the elements within the system can cause complexity whereas complexity and dynamics foster the demands of robustness in ISN. In order to avoid critical incidents the heterogeneity of the smart parts is an essential point because variations in the smart parts and therefore within their decision-taking can avoid the risks of critical incidents that are caused by all smart parts making the same decision (e.g. all heading for the same transportation unit). Therefore, the risk of critical incidents by global inconsistence of decisions (smart parts only seeking for their own optimum and not for the optimum of the system) might be decreased. Hence autonomy can reduce the fostering affects that can be caused by decentralized decision-making if learning features that ensure the heterogeneity of smart parts are implemented. Beside the positive effects autonomy might increase the danger of critical incidents because no central entity is able to monitor the whole network in order to detect butterfly levers and tiny initiating events.

Attributes of AC	Technical enabler	Structure of ISN	Robustness of ISN		Critical Incidents in ISN	
			Increasing Effects	Decreasing Effects	Avoiding Effects	Fostering Effects
Decentralized decision-making	Delegation of decisions to smart part (e.g. rule sets)	Increased capacity of decision making and information processing	Increased ability to handle information and to avoid lock-in	Local decisions might be suboptimal for global system	Smart Parts detect butterfly levers and render adequate decisions	Global inconsistence of decisions can cause critical incidents
Autonomy	Smart Parts responsible for own design (e.g. learning algorithms)	ISN enabled to develop itself (e.g. processes, structures)	Autonomous self design could adapt structures to ensure survival	Adaption can cause dynamics and heterogeneity complexity	Heterogeneity of Smart Parts prevents critical incidents	No monitoring system to detect butterfly levers
Interaction	Smart Parts communicate directly (e.g. RFID)	Altered, more target oriented information flows	Less capacities for processing information is needed	Complexity due to increasing amounts of relationships	Heterogeneity of Smart Parts due to different informational basis	Local communication avoid global decision-making
Heterarchy	Independence of Smart Parts from central entity (e.g. sensor networks)	Less influence on single elements, variable processes	Less permanent relationships therefore less complexity	Changing relationships hence increased dynamics	Alterations of decisions by heterachic Smart Parts	No central entity to monitor butterfly levers
Non-determinism	Smart Parts able to alter behaviour (e.g. variable control algorithms)	Emergence and non-predictable future system status	Ability to adapt flexibly to changes in the environment	Changing behaviour causes dynamics	Constant adaption enables heterogeneity	Dynamics may cause difficulties in detecting butterfly levers

Fig. 3: Abilities of Autonomous Cooperation for the management of International Supply Networks

Interaction between the elements of the system can be implemented by communication technologies like RFID or ad-hoc networks (Böse and Windt 2007). Interaction can provide the ISN with altered and more target oriented and therefore lower amounts of flows of communication. Hence, the robustness of ISN can be increased by interaction because a lock-in situation can be avoided if less information has to be processed and therefore the needed capacity for processing of information can be lower. Otherwise the complexity of the ISN can rise due to larger amounts of relationships between the elements within the ISN which are needed for successful interaction. This can decrease the robustness of ISN. Because the smart parts are equipped with different informational bases and due to their interaction between each other, their heterogeneity and the heterogeneity of their decision can be ensured. Therefore, critical incidents can be avoided. Otherwise local interaction can lead to an informational basis that does not comprehend data for the global optimum. Therefore, the danger of critical incidents can increase.

The fourth characteristic is **heterarchy** and can be realised by providing smart parts with independence from a central planning unit (Windt and Hülsmann 2007). Therefore, the decision power within the system is split between the single elements and processes of decision-making and communication are more variable because they do not have to stick to hierarchy. Hence, lower amounts of permanent relationships (from every single element through hierarchy to the central planning unit) can lower the complexity of the system and increase the robustness of the system. Meanwhile the changes within the relationships can increase dynamics and therefore decrease robustness. For preventing ISN from critical incidents heterarchy enforces the alteration of decisions due to the heterarchy of the smart parts because they are not affected by other decisions or rule sets of other elements. At the same time the absence of a central planning and monitoring unit cannot provide an overall monitoring unit in order to detect butterfly levers.

Non-determinism occurs due to emergent behaviour of the ISN which can be supported by smart parts that are able to alter their behaviour enabled for example by variable or learning control algorithms. Therefore, the future states of the system are not predictable (Windt and Hülsmann 2007). On the one hand non-determinism enables ISN to adapt flexibly to changes in the environment and therefore to increase the systems robustness. On the other hand this increases as well the system’s dynamics and hence the risk of a lock-in and decreasing robustness. For the prevention of critical incidents non-determinism ensures the heterogeneity of the smart parts due to the variation of algorithms and therefore the variance within the rendered decisions. An aspect that might foster critical incidents is that occurring dynamics can cause difficulties for a monitoring system to detect butterfly levers.

Overall it can be assumed that Autonomous Cooperation is able to enlarge the robustness in CALS like ISN. This is mainly due to an increased information processing and decision making capacity, as well as an increasing ability of the structures and processes to adapt flexibly to changes in the environment in order to cope with complexity and dynamics. At the same time Autonomous Cooperation can increase internal complexity and dynamics of ISN themselves thus the robustness can be decreased if the enlarged capacity to process information is not sufficient. Additionally Autonomous Cooperation can provide feasible ways to avoid critical incidents, on the hand by increased robustness and on the other hand by setting the basis for technologies that are able to detect butterfly levers. Critically it can be said, that the technologies as well as monitoring systems that are able to prevent critical incidents are not yet developed. Therefore, providing existing technologies with the ability to detect butterfly levers is one of the main research tasks in the future.

4 Empirical Test

4.1 Design of Empirical Test

In section four a simulation study will be presented to test empirically the hypotheses on the causal interrelation between Autonomous Cooperation and the robustness of CALS. The simulation model that will be used is a discrete event simulation in the field of production networks. Figure 4 shows the developed scenario which has been implemented as a discrete event simulation.

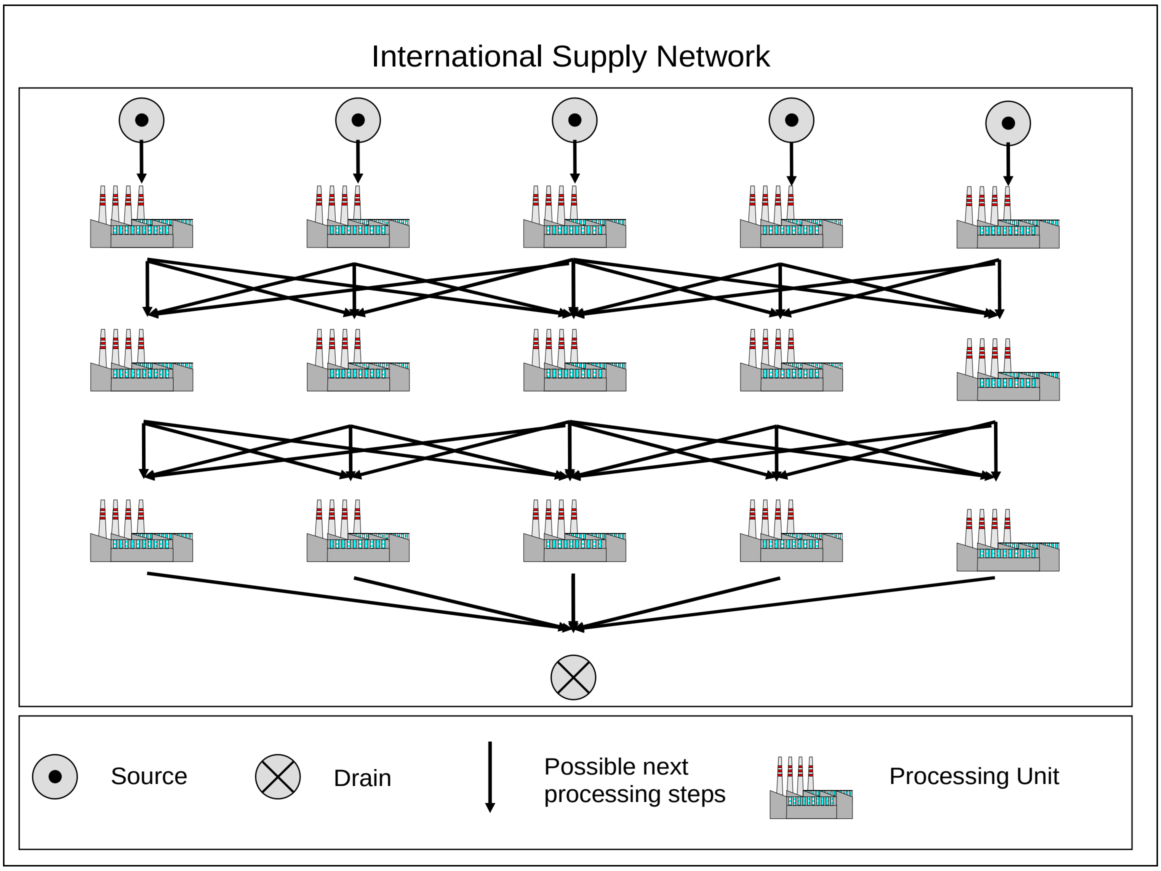

Fig. 4: Matrix-Model of an ISN as an example for CALS

For abstraction purposes the scenario has been defined as a matrix like network of different production stages that are interlinked and able to exchange information, resources and orders to perform a multi-stage production process. On one stage the parallel arranged facilities are able to perform resembling production steps whereas the lead times differ at the different production facilities. This model allows for analysing the effects of different Autonomous Cooperation methods on the robustness of production networks with different levels of complexity and different levels of external dynamics. The complexity can be varied by using different numbers of production facilities or different kinds of orders and products. The orders enter the system at the sources. Here the external dynamics can be varied by using different functions that define the arrival rate of different kinds of orders. In earlier work of the authors, this model has been used to analyse effects of Autonomous Cooperation on ISN (Hülsmann et al. 2007). A similar approach will be used here to analyse the effects of Autonomous Cooperation on the robustness of CALS. Autonomous Cooperation is integrated into the model by enabling each order to render decisions on their next processing step autonomously using different concepts of Autonomous Cooperation. Each order has a specific processing plan i.e. a list of processing steps that have to be undertaken to be produced. Following the different concepts of Autonomous Cooperation the orders decide about the next processing step without a central control entity. Depending on the different Autonomous Control methods, the overall system shows altered behaviour and dynamics which could be called emergent.

The effects of this emergent behaviour on the systems robustness, depending on different Autonomous Cooperation method,s can be analysed by measuring the systems performance with varying levels of complexity and external dynamics.

4.2 Control Methods of Autonomous Cooperation

The applied autonomous control methods will be described in the following. The first method is called **Queue Length Estimator** (QUE). The Queue Length Estimator compares current buffer levels at all parallel processing units that are able to perform the next production step. Instead of counting the buffer level in number of parts, the parts are rated in estimated processing time and the actual buffer levels are calculated as the sum of the estimated processing time on the respective machine. When a part has to render a decision about its next processing step it compares the current buffer level i.e. the estimated waiting time until processing and chooses the buffer with the shortest waiting time (Scholz-Reiter et al. 2005).

The second method is called **Pheromone Method** (PHE). Parts that use the Pheromone Method do not use information about estimated waiting time, i.e. information about future events but use data from past events. This method is a so called bio analogue method because it is inspired by the behaviour of foraging ants that leave a pheromone trail on their way to food. Following ants use the pheromone trail with the highest concentration of pheromone to find the shortest path to the food. In the simulation model this behaviour is imitated in a way that whenever a part leaves a processing unit, i.e. after a processing step is accomplished, the part leaves information about the duration of processing and waiting time at the respective processing unit. The following parts use the data stored at the unit to render the decision about the next production step. The parts compare the mean throughput times from parts of the same type and choose the machine with the lowest mean duration of waiting and processing. The amounts of data sets that are stored define the up-to-datedness of the information. This number of data sets can be used to tune the Pheromone Method. The replacement of older data sets resembles to the evaporation of the pheromone in reality (Scholz-Reiter et al. 2006).

The third method is the **Due Date Method** (DUE). The Due Date Method is a two-step algorithm. When a part leaves a processing unit it uses the Queue Length Estimator to choose the subsequent processing unit with the lowest buffer level. The second step is performed by the processing units. The Due Dates of the parts within the buffer are compared and the part with the most urgent due date is chosen to be the next product to be processed (Scholz-Reiter et al. 2007).

The following simulation analyses the overall systems ability to cope with rising structural complexity and rising external dynamics using different autonomous control methods. At each source the arrival rate is set as a periodically fluctuating function. The logistical goal achievement is measured using the key figure throughput time for different levels of complexity, different external dynamics and different autonomous control methods.

Therefore, the simulation model is able to represent the main characteristics of CALS and therefore able to render conclusions about the ability of Autonomous Cooperation to increase the robustness of ISN. The agents within the model can be assumed to be **heterogeneous** because of different characteristics they are provided with (e.g. different production steps, different due dates). **Interaction** is enabled by the ability of smart parts to communicate with each other. In this scenario communication is implemented between the orders and the processing facilities by using the stigmergy concept and leaving information in the environment for following smart parts. Due to their ability to render decision about their next processing themselves they can be called **autonomous**. A constrain about the modelling of autonomy in this scenario is the limited learning ability within the model. The ability to learn can not be found in the smart parts because they are modelled very simple and are not able to change their rule set but in the ability of the whole system to **learn** about changes in the system structure. For example, the system is able to learn about a breakdown of a processing unit and avoid this unit in the future. The **melting zone** within CALS is a part of the analytical aim of this empirical test. Different grades of Autonomous Cooperation (the extend of Autonomous Cooperation can be seen as a continuum on a scale between 100% decentralized decision-making and 100% centralized decision-making (Grapp and Hülsmann 2006)) are represented by the different control methods and therefore compared to each other concerning their ability to increase the robustness of ISN. Hence, the different methods of Autonomous Cooperation might be seen as different locations within the melting zone. Finally, by applying the ability to the smart parts to organize their processing autonomously **self-organization** is implemented.

4.3 Results of Empirical Test

Figure 5 shows the results, i.e. the mean throughput times for the three different autonomous control methods, in dependence to the systems complexity. To the right of the figure the systems complexity is increased by enlarging the amount of processing units horizontally, as well as vertically, and the number of sources. Furthermore, the minimal throughput time, which is rising with an increasing complexity level, is shown. The first result is that the curves for the Due Date Method and the Queue Length Estimator show almost the same results. They are almost parallel to the minimal throughput time and can be fitted by linear functions which are shown in the inset of figure 5. This means that a constant logistical goal achievement is accomplished during rising complexity. The Pheromone Method shows an inferior behaviour which is proved by the fact that the curve can be fitted by a 2[nd] degree polynomial.

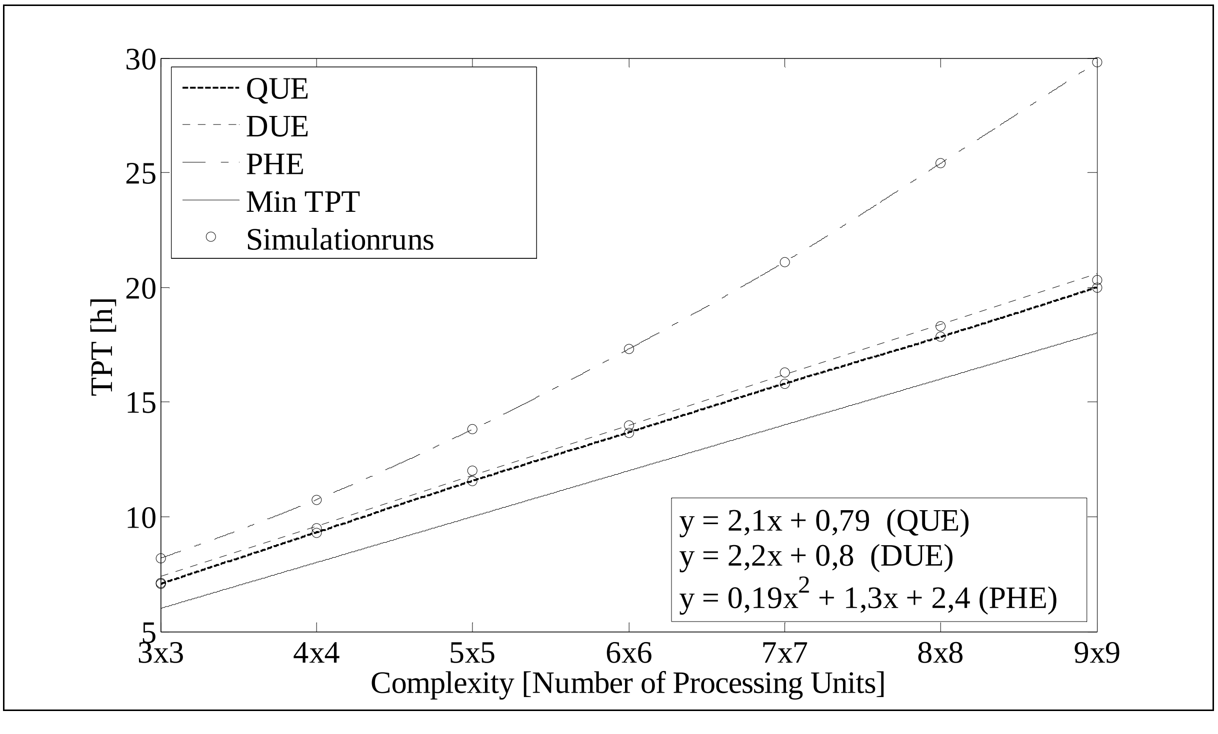

Fig. 5: Logistical goal achievement for different organisational level of complexity and multiple autonomous control methods

The pheromone method is not able to adapt to changing conditions because dynamics are too high and the boundary conditions change faster than the pheromones are updated. This effect seems to cause more problems the more complex the scenario gets. With rising complexity of the model the Pheromone Method shows declining performance which is caused by the fact that the pheromone method is not able to use the higher amount of degrees of freedom during frequently changing boundary conditions and is not able to maintain the robustness of the ISN. The Due Date Method as well as the Queue Length Estimator are able to maintain the robustness of the network even in the case of rising complexity.

In a second simulation, external dynamics are varied to determine the system's robustness, i.e. the system's ability to cope with external dynamics without getting unstable. In this simulation the system is called unstable if one of the system's parameters increases without restraint, for example if the work in process (WIP) or the throughput time rises infinitely. To determine this boundary of stability, the mean arrival rate at all sources has been increased and the highest possible arrival rate before the system starts to be unstable has been measured. Figure 6 shows the results. The Queue Length Estimator shows the highest level of robustness. The model shows stable behaviour until a mean arrival rate of 0.43 parts per hour is reached. The other two methods show unstable behaviour at lower work load. They begin to destabilise at 0.35 respectively 0.36 parts per hour. This is caused by reordering in case of the Due Date Method and the above mentioned inertia of the Pheromone Method respectively.

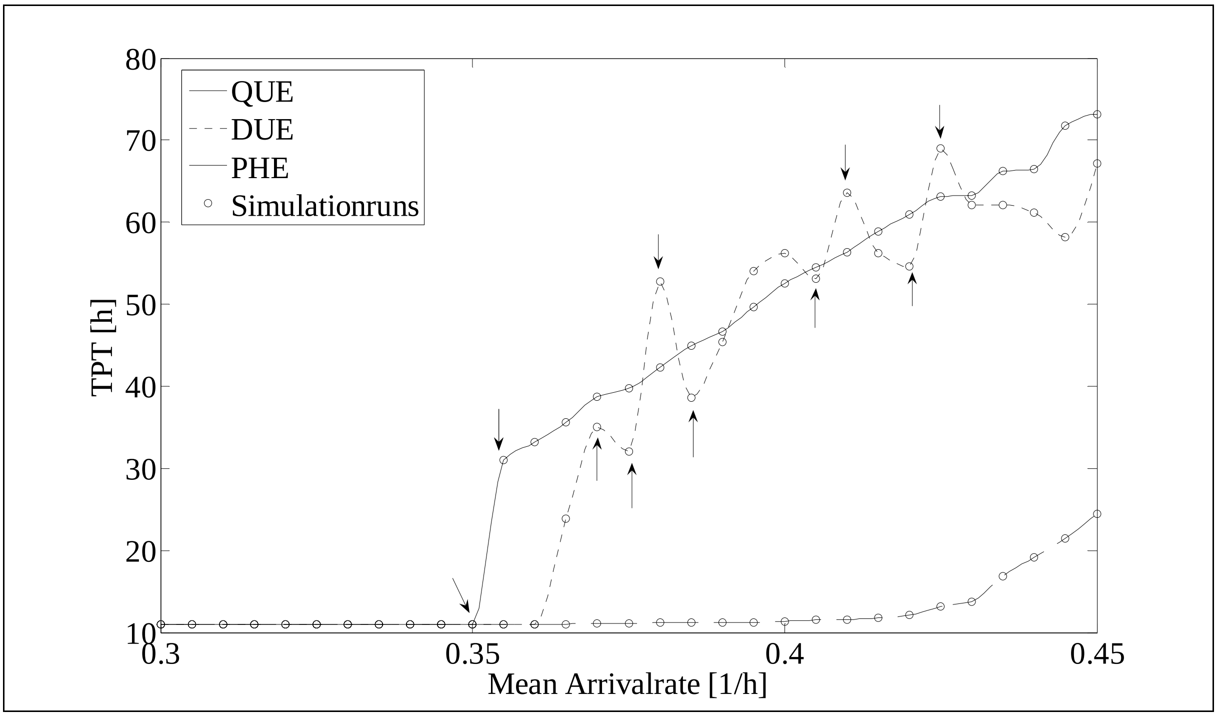

Fig. 6: Logistical goal achievement for different mean arrival rates and multiple autonomous control methods

The system shows altering phases of worse and improved behaviour although the external dynamics is continuously enlarged. This is caused by the fact that the system shows different characteristics of internal dynamics at the different parameter constellations which cause different performance rates. The arrows in figure 3 highlight the measurement points where the overall dynamics of the system changes. Scholz-Reiter et al. (2007) have shown that at these points a decrease in performance and the appearance of periodical fluctuations are correlated. This strong correlation between certain parameter constellations, dynamics and performance is typical for complex systems and especially those with elements of Autonomous Cooperation. Those systems tend to show chaotic-like dynamics including critical incidents and their behaviour strongly depends on initial conditions. Hence, in this scenario the Queue Length Estimator would be the most appropriate method of autonomous control to ensure robustness of the ISN under dynamic circumstances.

Summarising, it has been shown that Autonomous Cooperation could be a possibility to enlarge the robustness of CALS in circumstances of complexity and dynamics. However, in order to determine the adequate degree and concept of Autonomous Cooperation the effects on the systems' dynamics have to be taken into account.

5 Conclusions and Outlook

Main aim of this research was to examine the ability of Autonomous Cooperation to maintain and strengthen the robustness of ISN even in case of diverse as well as changing environmental conditions. Therefore, this paper intended to analyse the effects of Autonomous Cooperation on the capabilities of complex adaptive systems to deal with increasing complexity and dynamics in order to prevent and cope with critical incidents. From a theoretical perspective, it has been found that ISN can be seen as CALS and therefore be analysed on the background of complexity theory and non-linear systems.

Using this complexity-theoretical framework it has been found that Autonomous Cooperation can be a suitable approach to expand the robustness and cope with or prevent critical incidents in ISN because:

- It enlaregs the robustness of ISN by increasing the capacity to process information and to render decisions. Therefore, the situation of a lock-in can be avoided even in cases of rising complexity and dynamics.
- The ability of Autonomous Cooperation to maintain robustness is limited by the fact that autonomous processes might cause complexity and dynamics themselves, due to

increasing amounts of relationships and changes of relationships between the elements within an ISN.

- It could be shown, that different methods of Autonomous Cooperation can be more or less effective to ensure the robustness. Therefore it can be assumed that for implementing Autonomous Cooperation into practice extensive research has to be done in order to identify a suitable degree and to identify a suitable method of Autonomous Cooperation. This is necessary to implement a system that is adapted to the special context and therefore robust.
- Additionally, Autonomous Cooperation may be able to prevent critical incidents due to heterogeneity and learning abilities of smart parts. Heterogeneity of agents can avoid the bullwhip effect because variations between the decisions of smart parts can be ensured and therefore spiralling-up of processes should not occur.
- Another possible option to prevent critical incidents in ISN could be to implement monitoring features within smart parts enabling these to detect butterfly levers and therefore to prevent tiny initiating events.
- At the same time it could be shown that suboptimal implemented autonomous processes (e.g. without a monitoring system) can foster the occurrence of critical incidents. If the smart parts loose track of the optimum of the whole system, bullwhip effects might occur. Because no technologies or algorithms that are able to detect butterfly levers and therefore prevent critical incidents have been implemented yet this can be identified as an essential precondition for putting Autonomous Cooperation in to practice successfully

Even if some first findings could be developed within this research, there are limitations and future research requirements, which can be identified:

- By implementing complexity theory and the concept of CALS as theoretical foundations the expressiveness of the research is limited to this perspective. In order to enlarge the existing research base concerning issues of robustness and critical incidents in ISN other theoretical approaches like transaction-costs or learning approaches should ne applied.
- The findings in this research are mainly qualitative. Therefore, the need for quantitative research in this field can be identified. Starting points could be for example to measure the degree of Autonomous Cooperation implied in different methods or in existing ISN.
- A demand for the monitoring of butterfly levers and tiny initiating events has been developed theoretically in order to build up non-linear systems like CALS or ISN that are safe of critical incidents or at least able to cope with these. But the technologies to monitor

butterfly levers within ISN have not been developed yet (e.g. monitoring by neural nets or learning smart parts with ensured heterogeneity).

- In order to model the behaviour of ISN a discrete-event simulation has been implemented which is limited in its abilities to model non-linear behaviour and therefore limited in its abilities to model critical events. Hence, in addition other modelling approaches e.g. continuous or hybrid-modelling have to be accomplished in order to model non-linear behaviour caused by learning smart parts that might cause critical incidents.

For the practice of managing ISN the results imply that Autonomous Cooperation might be a suitable concept for ensuring the long-term survival in cases of complexity and dynamics because adaptivity and flexibility of the ISN can be extended. But before putting Autonomous Cooperation into practice successfully, some theoretical premises have to be fulfilled. This is in order to ensure the fit between the existing organizations (e.g. structures, processes, resources, management) its context and the implemented technologies and methods of Autonomous Cooperation.

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