REQUIREMENTS AND APPROACHES FOR A COMPLEXITY SCIENCE-BASED MODELLING OF INTERNATIONAL SUPPLY NETWORKS - LESSONS LEARNED FROM FINANCIAL MARKET MULTI-AGENT MODELS FOR THE SIMULATION OF COMPLEX ADAPTIVE LOGISTICS SYSTEMS

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ABSTRACT
International Supply Networks have to cope with changing customer demands, innovative technologies, and increasingly ecological awareness in a complex context, whereas the challenges' consequences are hardly predictable. Hence, a modelling concept might be useful to analyse and develop system designs and deduce design options, which can applied to the real world in order to enable the system to react to these challenges by adapting its behaviour. In order to identify a catalogue of requirements for the modelling of logistics systems, the paper intends to analyse the application of LeBaron's stock market model to logistics systems from a complexity theoretical perspective. Therefore, the feasibility and possible contributions of applying the introduced financial stock market model to logistics systems in order to learn from an existing modelling approach will be examined.

INTRODUCTION
Globalization combined with accelerating production times, new communication technologies and increasing ecological awareness forces companies to establish global alliances in order to develop and maintain sustainable competitiveness (Klaus & Kille 2006). These Global networks, having interconnections among their actors, work together to reach their goals and are therefore one approach to face these challenges (Hülsmann & Windt 2007). Therewith, the understanding of logistics systems has changed from linear structures to complex systems (Bowersox et al. 2002; Hülsmann & Grapp 2005). Hülsmann and Grapp (2005) describe the resulting logistics structures as International Supply Networks (ISN). ISN consist of heterogeneous agents (e.g. suppliers and manufacturers on macro-level and containers and cars on micro-level), which are to a certain extent autonomous, interactive and able to learn. In addition, the system as a whole co-evolves with other systems and its environment over time (Wycisk, McKelvey & Hülsmann 2008). These are the constitutive characteristics of the concept of Complex Adaptive Systems, which originates in complexity-science (Holland 2002). Hence, ISN can be described as Complex Adaptive Logistics Systems (CALS) (Wycisk, McKelvey & Hülsmann 2008). CALS are emerging (e.g. new kinds of orders evolve), evolving (e.g. the behaviour of the whole system adapts to environmental changes), self-organising (e.g. self-initiated changes of the system's structure and behaviour), dynamic (e.g. the system and its inter-relations change over time) and behave like living systems to a certain degree (e.g. CALS interact and act together to reach their goals) (McKelvey, Wycisk & Hülsmann 2009). Since complexity theory-based modelling considers these characteristics, it can be used for the designing of CALS (Choi et al. 2001). Financial markets feature parallel characteristics with CALS (McKelvey, Wycisk & Hülsmann 2009). These markets also consist of heterogeneous agents (e.g. traders having different information), which are to a certain extent autonomous, able to learn, and interacting. These markets as well co-evolve as a whole with their environments over time (LeBaron 2001a).

Considering the parallels in the characteristics of ISN and financial markets, a model approach for modelling financial markets could be applied to the modelling of ISN. As LeBaron's model has already shown its capabilities in representing and predicting complex market structures and dynamic market behaviour, it shall be used as a starting

point for developing an approach for modelling ISN (LeBaron 2003). The overarching objective of this paper is to analyse the feasibility and possible contributions of applying LeBaron's model to logistics systems in order to identify and describe a catalogue of requirements for a modelling and simulation of ISN.
Therefore, the paper proceeds as follows:
Firstly, the paper illustrates the motivation and requirements for modelling ISN to reason its demands and constraints. **Secondly**, possibilities and limitations for a multi-agent-based simulation based on an analogy between the characteristics and the behaviour of stock markets on the one hand and logistics systems on the other hand shall be identified. This section also introduces and describes Le Baron's stock market model as a feasible and well-performing investment-theoretical approach of modelling complex adaptive systems (CAS), like ISN are. Furthermore, an approach for the modelling of ISN based on LeBaron's model is presented in order to show, how the elements of LeBaron's model can be transferred to logistics systems. **Thirdly**, some contributions and deficits of the introduced approach are outlined regarding its fit to the goals and requirements of modelling ISN in order to identify potential benefits and limitations of the approach. **Finally**, the paper provides implications for future research on complexity science-based simulations of logistics structures and processes.

MOTIVATION OF MODELLING ISN

To develop an efficient functioning of ISN, timely responses to environmental changes are required to achieve the system's goals (Hicks & Gullet 1975), as these changes influence the input-output relations and therewith the efficiency of ISN. In consequence, frictions at the interfaces within ISN, which might occur due to different agents with different goals, have to be reduced (Hülsmann & Grapp 2007). There are e.g. suppliers, who want to increase their sales for maximizing revenues. On the other side, there are wholesalers aspiring for a minimal purchasing amount in order to reduce stocks. These conflicting goals might reduce the overall logistics system efficiency and compromise its goals (Tohamy 2005). Thus, and because a real world application and testing of ISN regarding critical elements for reducing frictions are very expensive and complex tasks, a model for simulating the behaviour and the dynamics of ISN is desirable (Macal & North 2005). In addition, problems like frictions or extreme events like butterfly effects (describing the system's sensitivity to initial changes) can be potentially minimized, if they become visible. In conclusion, weaknesses and the risk of critical incidents can be identified and potentially reduced while costs caused by new technologies can be estimated through designing ISN (Wycisk, McKelvey & Hülsmann 2008).

ISN could be modelled as networks of auctions, in which every single agent bids for resources (e.g. space on transports) (Moyaux 2007). Learning features and a set of rules shall directly be implemented within the agents' functionality (Bonabeau 2002). Due to the complexity of ISN, a model design requires as many details about the real world as possible in order to create a representation which is as realistic as possible (Pedahzur & Pedahzur Schmelkin 1991). As common modelling approaches do not cover the requirements appropriately in order to match the characteristics of ISN (e.g. emergent phenomena), agent-based modelling techniques can be applied to achieve the most sophisticated results (Bonabeau 2002). And the learning capabilities of ISN have to be considered in the designing process in order to realize the ability to react on changes in the environment (McKelvey, Wycisk & Hülsmann 2009). Due to the application of new information and communication technologies in ISN, the immanent complexity of ISN, and the usage of agent-based computational models, a complexity-based perspective considering the relevant characteristics for modelling ISN is useful (Choi et al. 2001).

Two modelling approaches in complexity-science, the fractal factory in production logistics (Warnecke 1993) and the approach from Scholz-Reiter et al. (2004) in transport logistics, shall give a briefly overview about the characteristics of existing approaches. They have four central elements in common: They are based on adaptive processes (1^{st}), embedded in a topology of interconnectivity among the respective supply chain

(2[nd]), running autonomously without external interventions (3[rd]), and initiated by changing environmental constraints (4[th]) (McKelvey, Wycisk & Hülsmann 2009).

Current modelling approaches' software components and the decision support systems in particular are lagging behind their technical components. Thus, true market behaviour cannot be illustrated by these approaches (Crainic & Gendreau 2004). However, to avoid frictions etc. the planning and designing of ISN call for a market-based model including its behaviour comprised of agents, which have varying amounts of smartness.
The modelling of ISN aims for an illustration of true market behaviour to improve the understanding of real markets. The required smartness to achieve behaviour of the model as close to reality as possible shall be distributed among the agents of the supply chain (Roy 1998). Decentralized agent-based self-organization and the implementation of learning features in the functionality of the agents shall allow the system to adjust its behaviour in real-time, enabling it to react to changing circumstances (Srbljinovic & Skunca 2003). Thus, changes from macro-level affecting the micro-level (e.g. a new seaport is constructed offering new transport mode) and vice versa become visible to agents (McKelvey, Wycisk & Hülsmann 2009).

Some desired results can already be achieved by the mentioned examples. A better understanding of a system's behaviour is currently possible through them. This is how critical elements and interfaces can be identified and handled to a certain extent by implementing features into the agent's functionality that represent the capabilities resulting from new information and communication technologies in the real world. That might lead to a higher system flexibility and robustness (Hülsmann & Windt 2007). Finally, monitoring of processes and therewith tracking of agents offers further benefits (e.g. detecting of critical processes and package tracking). The reason is that potential problems caused by critical processes can be identified and handled at an early stage and package tracking offers additional quality and service to the customers.

However, by looking at the two examples there are some deficits remaining and the listed contributions need to be improved. For example, due to ISN complexity and dynamics, the learning features and self-organization to allow a high level of autonomy and interaction among the agents, are currently not realized at an adequate level (Macal & North 2005). Thus, the system remains vulnerable against unexpected changes and extreme events (McKelvey, Wycisk & Hülsmann 2009). At present, the illustration of the true system behaviour is not adequate due to missing software components for agent features. And finally, current software and hardware are lagging behind the theoretical research situation of complex systems (Crainic & Gendreau 2004). In consequence, current theoretical research approaches from complexity-science in the context of logistics systems cannot be appropriately transferred into and tested in the modelling world. Hence, an approach based on LeBaron's model is introduced in the next section.

A COMPLEXITY-SCIENCE BASED APPROACH FOR MODELLING ISN AS CALS

LeBaron's model (LeBaron 2001a, b, 2003) consists of three central elements: an **electronic market** (EM), a **neural network** (NN), and **learning traders**.

Firstly, an operating EM is created consisting of agents and their interrelations. This EM is well validated against dynamics and behaviour of stock-markets (LeBaron 2003). Thus, it is used as starting point for developing a modelling approach for ISN, which also have to cope with dynamics. Agents in LeBaron's model compete with each other in their trading activities, whereas the fittest agent regarding the fulfilment of his specific objectives survives and simultaneously the used strategy. This strategy is either represented by and internal rules or set of rules (LeBaron 2001b). Following this strategy, some agents are replaced by others in every cycle based on either a strategy or randomly. Thus, a more realistic representation of the market can be achieved. To further enhance this, different agents use different past information in deciding on their optimal trading strategies. Thus, encouraging the agents to interact heterogeneity of the agents is achieved (Wycisk, McKelvey & Hülsmann 2008). By following this approach (agents are replaced and use different past information), different strategies (e.g. more or less risky) leading to different results become available in the model. The second element of LeBaron's model is the NN, as basically described by Holland (1975). The NN observes market changes and keeps updating six investment strategies based on pre-defined criteria (current or past returns, price-dividend ratios, and technical trading rules). Thereby, the NN acts separated from the agents (traders) and can be regarded as a kind of "investment advisor", giving hints how to behave via updating the investment strategies, which serve as rules for the behaviour. Agents can choose from the strategies as if they would consult a real advisor. The third element of the model is intelligent traders with learning capabilities, which are implemented by a genetic algorithm (Mehrotra et al. 1997). These learning capabilities are based on 250 investment rules, which are, in combination with three different strategies, the basis for the genetic algorithm. This algorithm aims at adapting and changing learning capabilities. Initiated by changing conditions, the genetic algorithm evolves the investment rules in relation to the three different strategies. Following the idea of a genetic algorithm, rules are modified (mutation) or combined with parts of other rules (crossover) (Fogel 1995).

To pick up again the description of the parallels in the characteristics of ISN and financial markets and to continue it in more detail, the parallels shall be divided into three levels: the **individual level**, the **intra-systematic level** and the **inter-systematic level**.

On the individual level there are agents, which are present in both ISN and financial markets and distinguished by different features like rules, patterns of actions etc. Heterogeneity can also be found in both systems (ISN and financial markets) and results from different goals of the agents as well as from different features (Holland 1988). In ISN agents might strive for the fastest and most expensive transport versus the slowest but cheapest transport whereas agents in financial markets may differ in their attitude towards risk (low risk and low profit versus high risk and potentially higher profit). Interaction among agents is also given in ISN and financial markets. They exchange for example routing information depending on traffic or stock-information regarding price, respectively. One motivation is e.g. to work together in order to match logistics goals they could not fulfil as single agents (Hülsmann et al. 2006). In ISN, the agent's ability to learn is represented by their experiences (e.g. regarding traffic), which is considered via regularly updated decision rules. Thus, the performance of the system might be enhanced as experience is accumulated (Holland 2002). The same kinds of rules are used in financial markets to realize the agent's ability to learn based on past order experiences (e.g. experiences with placed orders).

On the intra-systematic level the system's organization is regarded. The characteristic autonomy is realized, described as self-initiated actions without being controlled by another entity (Holland 2002). As in ISN for example agents allocate required space for goods autonomously the same characteristic is present in financial markets, where agents place orders for stocks by themselves. Self-organization is another characteristic on this level, which occurs in both systems. It results from the autonomous interaction of the agents enabling a system to adapt self-initiated to changing constraints.

The inter-systematic level contains the characteristics non-linear behaviour and co-evolution. Since agents act autonomously and respond to each other's actions, the system's structure co-evolves with other systems and the environment over time (Kaufmann 1993). Due to co-evolutionary processes within the system and the non-predictability of the systems' behaviour (caused by their autonomy and interaction), the behaviour of the whole system is non-linear. Thus, extreme events may occur compromising the system's goals (Surana et al. 2005).

Following McKelvey, Wycisk and Hülsmann (2009) the three main elements of LeBaron's model (electronic market (EM), Neural Network (NN), and learning traders) are assigned to categories one to three, whereas each category consists of two or more designing alternatives. In each category, all designing alternatives have at least the functionality of its predecessor(s) and those, which are explained additionally.

Category one (EM) starts with the designing alternative *'Baseline Model'*. This model comes from a graph-theoretic perspective and consists of a set of nodes and links. Agents (goods, components etc.) are represented by nodes and the links connecting the nodes can be streams of goods, financial etc. There is neither communication between non-human parts nor any kind of artificial intelligence. In consequence, the parts are totally dumb and the only data companies exchange within the supply chains is about orders. In conclusion, this reflects the traditional concept of supply chain management. The second designing alternative is *'Baseline Model with Speculative Reserve Space'*. This alternative enhances the Baseline Model by adding a human space-cost speculation. Humans for example try to get cheaper space on transports through very early or late bidding, respectively. In addition, they try to reserve big amounts of space in order to receive sales discounts. This strategy causes a higher risk as reserving the required space immediately, because early bidding might be more expensive than late bidding whereas late bidding includes the risk, that available space might be insufficient.
In category two (NN), *'NN'* in its basic form as the first designing alternative watches the market on a timely basis. It offers much shorter update periods than LeBaron's model (minutes or less versus weekly updates). Parts are still dumb, but they are constantly connected to the NN and the NN always tells the parts which alternatives to take (e.g. which transport vehicle or route). The parts have no choice, their progress is tracked and they are routed by the NN. The second designing alternative in category two is *'NN Auction-based'*. An own auction house is set up as a central kind of a buyers/sellers portal. Sellers make their resources available on the auction and buyers can buy desired resources. The prices are varying in dependence of the characteristics of resources (e.g. a faster ship is more expensive than a slower one). However, the parts still remain dumb. The third designing alternative is *'NN with Less Dump Parts'*. Parts check in to the NN to get the best strategies. They can also keep checking in and update their strategy, if a better one becomes available over time. However, the total number of options depends on the information given by the NN. Additionally, parts are not able to share information with other parts and the use of resources is limited by the options offered by the NN, which itself only can offer resources preliminarily obtained by a human.

The first designing alternative of the third category (learning traders) is '*Smart Parts learning from the NN'*. The NN makes options available to the parts and it constantly watches the market. Parts can now choose which option to take as the NN offers various transportation strategies. The next designing alternative is '*Smart Parts learning from the NN and from Each Other'*. Parts are able to learn from the NN and from other parts. In the designing alternative '*Smart Parts with Grouping Capability'* Parts can decide either to reserve required space or to bundle similar requirements to one bigger reservation to get better conditions. The fourth designing alternative *'Smart Parts having Full Choice'* is currently the vision of a fully-designed smart part model. Parts can learn from the NN, from each other and from the environment. In addition, all available options are accessible for each part and each of the parts can decide which one to take. In certain situations (e.g. extreme events), both, the NN and the smart parts, may benefit from human guidance. The last designing option of category three '*Speculating'* adds the idea of speculation to the model. As described above this causes a higher risk. Since the last designing alternative has the most sophisticated features regarding smartness of the agents, its contributions and deficits are evaluated in the next section.

CONTRIBUTIONS AND DEFICITS OF THE INTRODUCED MODELLING APPROACH:
The following table gives a briefly overview about some selected contributions and deficits of the designing alternative '*Speculating*':

Selected Contributions	Selected Deficits
- true market behaviour illustratable - better understanding of markets - monitoring and tracking of agents - smart agents are autonomous, interactive and able to make decisions - system can adapt to changes	- market behaviour in the model inappropriate - approach abstracts from the real world - learning abilities in the model not adequate - software lagging behind theoretical and technical development

Table 1: Contributions and deficits regarding the introduced modelling approach

Several contributions and desired goals - as described in section two - are already attained through the designing alternative '*Speculating*'. An illustration of true market behaviour is theoretically possible, since interrelations and the behaviour of the agents are displayed. That leads to a better understanding of markets, as different scenarios can be applied and tested by the model. Monitoring of processes and tracking of agents is also currently possible. Hence, critical elements and interfaces in the system can be identified leading to potential higher system robustness. Agents would be completely integrated smart parts, acting autonomously and having full choice over the actions they take and the interactions between them. Thus, smartness can be distributed among the agents as desired in order to attain decentralized decision making. Thereby, self-adjusting of the system's behaviour through an agent-based self-organization would also be possible, since the agents are able to exchange information and interact without the need of a control instance. The implementation of learning features in connection with the other features (autonomy, interaction etc.) could enable the system to react to changing circumstances.

Currently, possible contributions of the designing alternative '*Speculating*' are limited by the missing of adequate software technologies, which are necessary to implement the required artificial intelligence in order to achieve an appropriate level of smartness within the agents. The deficits of modelling ISN remain due to the systems complexity and dynamics. Thus, the illustration of true market behaviour is theoretically possible indeed, but practically it is not appropriate since there are too many entities and interrelations between them. In consequence, a modelling has to abstract from the real world in order to create computable models. The learning abilities are not yet available at a desired level leading to a further gap between modelling and the real world regarding true market behaviour. Thus, the self-organization of the agents for self-adjusting the system's behaviour in real-time is insufficient and the vulnerability against unexpected changes persists.

Beside the basic contributions and deficits, there are some pre-conditions which need to be taken into account when applying the introduced model. First, in financial markets only information and immaterial goods are exchanged whereas in ISN the goods have both immaterial and physical character. Thus, physical limitations (limited transport space etc.) and transportation times have to be considered when adapting LeBaron`s model to logistics systems. That affects mainly the investment strategies in the NN. Second, different environmental constraints have to be regarded. Financial constraints (laws, prohibitions etc.) are different from trading constraints (e.g. dependencies on embargoes). And third, the agents in ISN themselves are both physical and non-physical (e.g. cars and the NN). Hence, the smartness realized within the agents also has to consider both non-physical and physical constraints.

CONCLUSIONS

This paper intended to analyse the feasibility and the contributions of applying LeBaron`s model to logistics systems in order to identify and describe a catalogue of requirements for the modelling and simulation of ISN.

The main contributions towards the described modelling approaches (Warnecke 1993; Scholz-Reiter et al. 2004) is the improvement in illustrating the market behaviour and therewith to realize a faster reaction to changes, since the approach explicitly focuses on the characteristics of ISN in order to realize a behaviour as close to reality as possible. In addition, some required pre-conditions are outlined in the previous section.

There are various parallels in the characteristics of financial markets and ISN. Significant similarities between both systems are existent. However, some adaptations have to be made, especially concerning different environmental constraints and physical properties of agents. If these aspects are considered, it is feasible to use the introduced approach for designing ISN. Therewith, some desired goals and contributions of simulating can be achieved (e.g. self-adjusting of a system to a certain degree) whereas some other still remain (e.g. vulnerability against extreme events). The achieved contributions are partially not in an appropriate quality (e.g. illustration of true market behaviour). Following the ten designing alternatives in the three categories, they are getting better regarding the realization of the characteristics of ISN from one to the next alternative in the order they are listed. The reason is, that the implementation of the characteristics of ISN is improved from alternative to alternative originated by enhanced features (e.g. smart parts getting smarter each step, new characteristics like interaction are realized from one step to another).

Further research should focus on the remaining deficits (e.g. true market behaviour not illustratable at adequate quality) to improve the model regarding the desired goals. The next step could be to develop and compute a real simulation model. Therefore, on the one hand the software technologies to further improve mentioned features like learning capabilities etc. have to be advanced in order to enable agents to interact and act autonomously. On the other hand, due to the complexity and dynamics, essential problems like vulnerability against changes and non-predictability of the system behaviour persist and have to be investigated.

At last, there are practical implications as well. Learning features in an ISN can lead to a higher system flexibility and adaptability and therewith to higher system robustness (Hülsmann & Windt 2007). Since there are lots of agents, relations, and resulting interactions within a model, the application of new information and communication technologies in order to enable agents to act autonomously is one possibility to implement the characteristics of ISN (Wycisk, McKelvey & Hülsmann 2008).

However, since the main contributions beside financial aspects of ISN are currently unknown (strategic benefits e.g. in form of system flexibility and adaptivity), they cannot be considered in the decision making process whether to implement new technologies or not. In addition, there are financial barriers for the implementation of the required technologies, as managers have to face that their decisions are always made in the context of profitability and strategic considerations (Bowersox et al. 2000; Bowersox et al. 2002) and the costs of the required technologies cannot be estimated easily.

ACKNOWLEDGEMENT

This research was supported by the German Research Foundation (DFG) as part of the Collaborative Research Centre 637 "Autonomous Cooperating Logistic Processes - A Paradigm Shift and its Limitations.

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