SELF-ORGANIZING SUPPLY NETWORKS
Autonomous Agent Coordination based on Expectations

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Abstract: Supply networks are faced with the contradictory requirements of achieving high operational efficiency while retaining the ability to adapt to a changing environment. Decentralized approaches representing logistics entities by autonomous artificial agents must therefore be enabled to structure and operate supply networks efficiently according to the domain's inherent dynamics caused, for instance, by changing customer demands and network participants entering or leaving the system. In this paper, a novel approach to self-organization for multiagent systems is presented, avoiding a priori assumptions of agent characteristics by generating expectations from observable behavior.

1 INTRODUCTION

Logistics plays a major role in globalized economy. Industrial production and trade require efficient and reliable supply networks. Growing interrelations between these networks and the inherent dynamics of the logistics domain result in a high complexity of global supply processes (Hülsmann et al., 2008). Application of conventional centralized planning and control to these processes suffers from that complexity. Therefore, a need arises for decentralized methods employing autonomous actors representing logistics entities and objects (Hülsmann et al., 2006).

From the artificial intelligence point of view, these autonomous entities can be represented by intelligent software agents to model logistics networks as multiagent systems (MAS). These systems may be used to simulate, evaluate, and actually implement new approaches in autonomous logistics (Schuldt, 2010).

Coordination and cooperation of autonomous entities is the challenging task that has to be addressed in order to develop such approaches. In the logistics domain, coordination is faced with the contradictory requirements of achieving high operational efficiency while retaining the system's ability to adapt to a changing environment. Supply networks, therefore, need to achieve high performance rates concerning asset utilization, cost reduction, and customer satisfaction on the one hand. On the other hand, they are required to employ flexible and robust structures in order to react to unforeseen changes caused by the domain's inherent dynamics.

In this paper, a novel approach for self-structuring multiagent systems is presented. Considering particular challenges in logistics network configuration and operation, as elaborated in the next section, agent coordination mechanisms are investigated as a means for organizing decentralized behavior in logistics networks. These considerations form the basis for the development and application of *expectation-based self-organization* as an adaptive structuring paradigm for multiagent systems based on social systems theory. That approach is evaluated in a simulated supply network scenario according to coordination effort and logistics performance. Finally, the achievements of this paper are recapitulated in a concluding summary.

2 SELF-ORGANIZING SUPPLY NETWORKS

In order to solve repeatedly occurring coordination problems in decentralized systems efficiently, organizational structures have to be established (Horling et al., 2004). Yet, it is unclear which kind of structure is applied best, given a particular coordination problem. Consider, for instance, a supply network as partly shown in Figure 1: In this network, the participants must choose which subset of the depicted possible relationships between each two tiers (pictured as arrows in the direction of material flows) actually to establish. This decision has to take into account cost considerations as well as the responsiveness and reli-

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ability of possible business partners in order to enable efficient operations within the network.

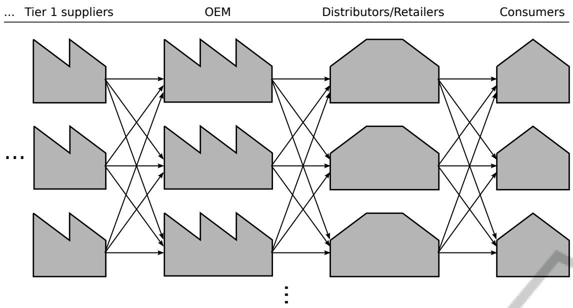

Figure 1: Schematic diagram of a supply network showing all possible relationships between the participants.

Thus, a supply network can be represented as a graph consisting of logistics entities as its nodes and their possible business relationships as edges. Establishing an organizational structure refers to the choice of a subgraph restricting the set of edges to a subset of all possible ones. An efficient organizational structure then minimizes the actually instantiated relationships while maximizing the achieved operations outcome according to logistics performance measures.

However, due to the dynamics of logistics processes, conventional design time evaluation and optimization of these organizational structures is not sufficient in terms of flexibility and robustness. Increasing demands of the final consumers, for example, require structural modifications in the distribution part of the supply network in order to fulfill those demands: Additional storage capacity has to be allocated and even completely new channels of product distribution must be established. Thus, the structures in that part the supply network need to be refined, i.e., further or other options of business relationships must be instantiated.

This is but an example for the dynamics in logistics that is further aggravated by the *openness* of those systems (Brauer et al., 2002): Not only consumer demand changes as well as unforeseen failures of scheduled operations may happen (leading to the need of dynamic replanning and reallocation of resources), but the logistics market itself may alter. New competitors as well as new customers may enter, causing further changes in demand, prices, and requirements of products and services. These developments evoke the need for each participant to constantly adapt his relationships to customers and suppliers in order to secure market shares and to fulfill the customers' needs. Such an adaption, furthermore, affects other business relationships within the network, requiring an extended refinement of supply partnerships therein.

Thus, modeling and operating supply networks with multiagent systems requires the agents' ability to establish organizational configurations that allow for efficient operation, while being flexible enough (i.e., alterable) to cope with the dynamics of logistics processes. Hence, the need arises for self-organizing MAS that autonomously arrange their structure in accordance with dynamically changing conditions. In this context, self-organization is therefore considered as the emergent evolvement and modification of organizational structures defining business relationships between supply network partners.

3 AGENT COORDINATION

In order to be able to autonomously coordinate their activities (e.g., to establish and operate logistics networks), artificial agents need to interact with each other. For this purpose, agent communication languages that are based on speech acts between agents are commonly used (Finin et al., 1994; Foundation for Intelligent Physical Agents [FIPA], 2002a). On the basis of these speech acts, a range of interaction and negotiation protocols haven been developed that may be used to coordinate agent behavior. Patterns of interaction then reflect relationships between the participants and, thus, express the structure of the multiagent system. In the opposite sense, structuring a supply network modeled as a MAS means to define channels and modes of agent communication.

Consequently, a wide variety of different structuring paradigms for MAS has been proposed (cf. Horling and Lesser (2005) for a comprehensive overview). These structures range from strict hierarchies to market-based methods. While the former use centralized decision-making at the top and distributed processing of concrete tasks at the bottom, the latter are completely decentralized and rely on negotiations for each single task rather than on any middle or long termed relationships. In order to make use of such predefined mechanisms, the expected dynamics of the application domain must be estimated, as they differ in their ability to handle changing conditions as well as in their required effort for coordinating the actions of a network's members (Schillo and Spresny, 2005).

However, choosing a prototypical organizational approach for a whole network may not be sufficient. In fact, heterogenous relationships may be required between agents in different parts of the supply network. Moreover, predetermining agent interaction patterns will neccessarily lead to a compromise between efficient operation and adaptive behavior: While, for example, negotiation based interaction paradigms are highly adaptive when it comes to changing behavior of participating agents (as they allow for determining the best result given any conditions), they lead to a large overhead of communication and computation effort as every interaction task involves all possible participants among the agents.

In order to overcome that problem, methods have been proposed for subdividing MAS into teams of agents with similar properties and objectives. The model for cooperation (Wooldridge and Jennings, 1999) provides a formal description of such team building among any number of autonomous agents for distributed problem solving. It includes determination of potentials for cooperative acts, formation of teams, distributed planning, and the actual processing of plans. In the logistics domain, team formation methods have shown benefits in terms of increased resource utilization efficiency while reducing the communication effort of agents performing similar tasks (Schuldt, 2010).

Yet, clustering agents in teams usually focuses on short termed behavior and tasks, rather than on middle and long term structures in agent interaction. Furthermore, team formation processes rely on the exchange of information about agent properties and goals. Hence, they assume any participating agents to behave benevolently, i.e., to be trustworthy. In an open system, however, agents may be confronted with deceitful behaving participants (Nickles et al., 2005) or others simply not willing to share such information.

Thus, potential interaction partners in open MAS cannot be assumed a priori to exhibit particular behavioral characteristics. In fact, they appear as *black boxes* and, therefore, must be observed by the other agents or the system designer in order to determine their characteristics during runtime of the system. Based on such observations, a structuring approach for MAS has been proposed, using explicit modeling of *expectations* concerning communication flows (Brauer et al., 2002; Nickles and Weiß, 2005). This approach which is inspired by the sociological theory of communication systems (Luhmann, 1995) establishes a notion of communicative agent behavior that is reflected by the modeled expectations.

Feeding those expectations back into the decision-making process of interacting agents offers a promising foundation for self-structuring MAS, as they reflect other agents' characteristics inferred from their observable behavior. Customer demands, for instance, can be observed from the incoming orders on the supplier's side. The supplier can establish expectations regarding the customers' behavior and then adapt his own behavior based on these expectations. Hence, the system as a whole is enabled to adapt to implicit characteristics and external impacts by the agents refining their communication patterns in terms of business relationships accordingly, i.e., the system organizes itself.

To summarize, agent coordination refers to communication processes between these agents. Prototypical coordination mechanisms lead to a compromise between operational efficiency and flexibility with regard to dynamic environments while dynamic team formation requires additional behavioral assumptions to overcome these problems. The systems-theoretical perspective of expectations structuring agent interaction (rather than assumptions and commitments), however, provides a promising foundation for self-organization as a paradigm for multiagent coordination.

Nevertheless, in the approach by Brauer et al. (2002), expectations reflecting and guiding agent behavior are modeled by the system designer as an external observer. Yet, self-organization requires organizational structures to emerge from the system's operations without external intervention; i.e., the mentioned feedback loop has to be closed within the multiagent system. Thus, in the next section, the notion of *double contingency* is introduced, describing the emergence of mutual expectations structuring communication systems between agents appearing as black boxes. In the following, this concept is operationalized in order to demonstrate its ability to enable autonomous coordination of agent communication systems.

4 EXPECTATION-BASED SELF-ORGANIZATION

According to the sociologist Niklas Luhmann, *double contingency* denotes both the fundamental problem of social systems constitution as well as its own solution leading to the emergence of such systems (Luhmann, 1995, pp. 103–136). Referring to Parsons and Shils (1951), he points out that, given two black boxes *alter* and *ego*, "if alter makes his action dependent on how ego acts, and ego wants to connect his action to alter's" (Luhmann, 1995, p. 103), they reciprocally block their ability to act at all.

The solution to that problem, however, lies in the interdependency of actions, as well. As soon as alter or ego behave in whatever way, action becomes not only possible, but social structures emerge from the self-referential circle of mutually dependent actions. In fact, those structures consist of expectations evolving from, e.g., ego's observation of his own as well as alter's actions that, in turn, guide the selection of ego's subsequent actions. Hence, a feedback loop of observation, expectation, selection, and operation (action) emerges.

In the context of multiagent systems, double contingency may be viewed analogically as the problem of determining interaction opportunities. It also denotes its own solution through the emergence of expectations guiding agent communication as the fundamental operation in MAS. As a starting point, the simulation model by Dittrich et al. (2003) can be used: They simulate and analyze Luhmann's concept of double contingency in a scenario of two agents interacting with each other by exchanging messages with varying content. The agents memorize a certain number of these messages and select their response according to expectations calculated from the entries in their memories. The approach by Dittrich et al. shows the evolvement of stable interaction patterns from the agents' behavior under a wide range of parameter conditions (Dittrich et al., 2003, sec. 3 and 5).

In an extension of their own model, Dittrich et al. furthermore examine the emergence of social order among an arbitrary number of agents (Dittrich et al., 2003, sec. 6). To this end, they introduce a random choice of two agents in each simulation step, letting them interact in the same way as in the basic dyadic setting. Their results show that, for growing numbers of agents, stable interaction patterns only evolve if alter's behavior reflects the average agent behavior within the system and if the agents are able to observe more pairwise encounters than they are involved in themselves Dittrich et al. (2003).

Those requirements as well as their abstract model of message contents, however, prevent an application of that approach for self-organization in MAS following particular puposes. Choosing agent pairs for interaction at random contradicts the objective of emerging agent relationships. In fact, self-organization as defined above refers to the choice of interaction partners among the set of all agents in a MAS in its very core. Thus, that selection must be based on expectations regarding interaction outcomes, as well. Moreover, in applied self-organizing MAS (e.g., for modeling supply networks), the semantics of message contents depending on the respective application domain is a crucial factor for the determination of such outcomes. Hence, it has to be considered when generating agent expectations.

Therefore, in the following, a model of double contingency is developed, based on the basic approach by Dittrich et al. (2003), allowing for the application of self-organizing coordination of an arbitrary number of agents. Moreover, the original model using meaningless messages is enriched with semantics derived from the logistics domain, being compatible with a standard interaction protocol.

4.1 Modeling Double Contingency

In this model, agent operations consist of sending FIPA-ACL compliant messages (Foundation for Intelligent Physical Agents [FIPA], 2002a). Observing them refers to their storage in an agent's memory, which is used to calculate selection values for all possible replies. The next message to be sent by the observing agent is then selected according to these values. Thus, an agent's communicative behavior exclusively depends on its memorized observations of other agents' behavior, avoiding any further assumptions of their internal properties and characteristics. The basic steps enabling the agents to self-organize hence are:

1. The *observation* of incoming messages sent by other agents
2. The *selection* of messages to be sent to other agents

The memory of an agent is modeled as a vector $MEM = (mem_1, \ldots, mem_n)$ with a fixed length n, where each entry mem_i denotes a tuple of messages $m \in M$ (M being the set of all possible messages), the second one being the response to the first one: $mem_i = \langle m_{received,i}, m_{sent,i} \rangle$. An agent possesses two of those memories, MEM_{ego} and MEM_{alter}, storing its own reactions to perceived messages and observed others' reactions to its own messages, respectively. Thus, observation takes place when sending a message m_{sent} by adding it to MEM_{ego} together with the last received message $m_{received}$ as well as when receiving a message $m_{received}$ by adding it to MEM_{alter} together with the last message m_{sent} the agent sent itself. Each time, a tuple of messages is memorized, if this would lead to a memory size $> n$ the oldest entry is removed from the memory.

This way to model an agent's memory is an important modification of that by Dittrich et al. (2003), differing in alter not only being considered one single agent, but the whole community of agents other than ego. This reflects Luhmann's understanding of double contingency as a phenomenon not restricted to an encounter of two individuals, but occurring between systems in a generalized manner (Luhmann, 1995, pp. 105–106). Thus, expectations may well be established regarding the behavior of the whole MAS, considering it as a social system. The entries in its memory therefore reflect an agent's observations of its interaction with all of its fellow agents.

Moreover, this interpretation of double contingency between an agent and the whole agent community allows not only for the content of a message to be selected according to memorized experience from former agent interactions, but also for using the selection mechanism to determine its receivers (i.e., the interaction partners). Hence, the advantages of the dyadic model by Dittrich et al. (2003) regarding structural emergence can be retained while avoiding the drawbacks of its extension for an arbitrary number of agents.

In order to calculate expectations from the agents' memories, a function *lookup* : $MEM \times M \times M \longrightarrow [0,1]$ is defined, that estimates the probability of one message being observed as the response to another:

$$lookup(MEM, m_{received}, m_{sent}) = \frac{l_{m_{received}, m_{sent}}}{\sum\limits_{m_j \in M} l_{m_{received}, m_j}} \quad (1)$$

where

$$l_{m_{received}, m_{sent}} = \frac{c_M}{|M|} + \sum_{i=1}^{n} \frac{n+1-i}{n} \cdot \begin{cases} 1 & \text{if } mem_i \hat{=} \langle m_{received}, m_{sent} \rangle \\ 0 & \text{else} \end{cases} \quad (2)$$

Here, $mem_i \hat{=} \langle m_{received}, m_{sent} \rangle$ denotes the pairwise equality of the received and sent messages compared to those in memory entry mem_i according to their performatives, sets of receivers and contents. This is the second major modification of the original model, allowing for considering advanced message semantics (in contrast to the very abstract message representation by Dittrich et al. (2003)). Especially the content of messages depends on the application domain, enabling the usage of domain dependent equality measures (e.g., the distinction of orders for different product types). The constant c_M is used to avoid message combinations to be regarded completely impossible in case of missing observations (cf. Dittrich et al. (2003, sec. 9.4)). With mem_1 being the most recent observation, this function uses a linear discount model to reflect the agent gradually forgetting past observations.

Two kinds of expectations are then calculated for selecting an agent's next message: An *expectation certainty* (EC) that denotes an agent's certainty about which reaction to expect from the MAS following its own message and an *anticipated expectation* (AE)[1] that reflects an agent's anticipation of other agents' expectations towards its own behavior.

[1]Dittrich et al. (2003) call this *expectation-expectation* (EE), literally translating Luhmann's original German term. Luhmann, however, uses *anticipated expectation* in the English edition of his main work (Luhmann, 1995).

The EC is calculated using a function *certainty* : $MEM \times M \longrightarrow [0,1]$ that is based on a modified version of the standard deviation in order to estimate an agent's assuredness over the possible reactions on its next message m_{sent} (Dittrich et al., 2003, sec. 2.1 and 9.5):

$$\mathrm{EC}_{m_{sent}} = certainty(MEM_{alter}, m_{sent}) \quad (3)$$

with

$$certainty(MEM, m_{sent}) = \sqrt{\frac{|M|}{|M|-1} \sum_{m_j \in M} \left(\frac{1}{|M|} - lookup(MEM, m_{sent}, m_j) \right)^2} \quad (4)$$

This linear function returns a value of 0 for uniformly distributed probability estimations over the others' possible reactions to an agent's message and a value of 1 for the most inhomogenous distribution of those estimated probabilities. Thus, it reflects the certainty of the agent expecting a particular response to its message. Note, however, that the *lookup* of each value for the possible reactions of the MAS is used with the sent message as its first argument. This is because MEM_{alter} contains ego's observations of himself from alter's perspective. Thus, as ego's m_{sent} is what alter receives from him, it is treated as the received message in MEM_{alter}.

On the other hand, the AE is calculated directly through the *lookup*-function as the estimated probability of the agent's next message m_{sent} in response to the last received message $m_{received}$ (Dittrich et al., 2003, sec. 2.1):

$$\mathrm{AE}_{m_{sent}} = lookup(MEM_{ego}, m_{received}, m_{sent}) \quad (5)$$

As MEM_{ego} stores all observations of ego's responses to received messages, Equation 5 reflects ego's anticipation of alter's perception of his behavior. Hence, the AE denotes an agent's estimation of what is expected from itself by the community of its fellow agents.

Both types of expectations are finally combined in a weighted sum to a selection value V for each option for a next message $m_{sent} \in M$. This value represents the potential of a given message to stabilize the system, as high selection values reproduce themselves when a corresponding message is chosen and thus fed back into the control loop. Differing from Luhmann's theory and the model by Dittrich et al., at this stage, an explicitly represented utility function $utility : M \longrightarrow \mathbb{R}_+$ is further introduced. This function enables V not only to reflect the system's stability, but also directs the agent's behavior towards domain dependent performance criteria. Thus, $V_{m_{sent}}$ is given by the following equation:

$$V_{m_{sent}} = (\alpha \mathrm{EC}_{m_{sent}} + (1-\alpha)\mathrm{AE}_{m_{sent}}) \cdot utility(m_{sent}) + \frac{c_f}{|M|} \quad (6)$$

Here, the parameter $\alpha \in [0,1]$ weights the balance between EC and AE, while c_f is another constant to avoid marginal differences in the weighted sum to cause overly high effects on the selection of messages and to retain an agent's ability to try out alternative messages, i.e., to occasionally explore the possibility space (cf. Dittrich et al. (2003, sec. 9.1)).

Calculating $V_{m_{sent}}$ for all possible message options $m_{sent} \in M$ enables an agent to select its operations (i.e., the messages to be sent) according to the expectations calculated from observations of its interaction with other agents within a MAS. As the selection of an operation leads to further observations, the aforementioned feedback loop is closed. Yet, the method of actually choosing an operation in accordance with the calculated selection values remains to be determined. That method depends on an agent's role in the MAS and is introduced in the next subsection.

4.2 Representing the Logistics Domain

When modeling supply network participants as autonomous agents, these agents may have different capabilities. As shown in Figure 2, they can be classified in *primary producers* that produce raw materials without consuming anything, *final consumers* that only consume products, and *manufacturers* that consume materials and semi-finished parts in order to transform them into new parts and products. Concerning the business relationships between the entities, it is sufficient to distinguish the agents by their roles as producers and/or consumers of certain goods (manufacturers acting both as producers and consumers). Their respective possible relationships as *suppliers* and *customers* are depicted by the edges between the entities in Figure 2 (with the left hand side of an edge being attached to a supplier and its right hand side being connected to the respective customer).

These relationships denote possible occurrences of order/delivery processes, that form the fundamental operations of a logistics system. They are modeled using the FIPA-REQUEST interaction protocol (Foundation for Intelligent Physical Agents [FIPA], 2002b): An order is placed by sending a REQUEST message containing a product type and the requested amount of that good to any subset of the possible suppliers for this product. An answer with the REFUSE or FAILURE performative is considered a failure to deliver while an INFORM leads to the supplier agent removing the specified amount of products from its inventory and the customer adding it to its own one.

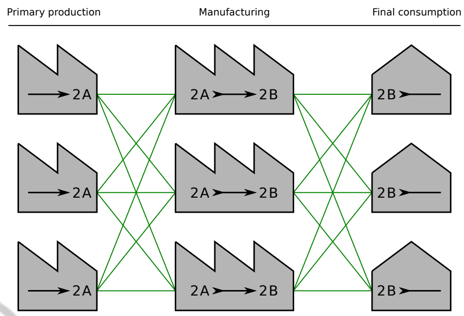

Figure 2: A simple supply network depicting agent roles and relationships in the logistics domain.

For selecting their messages based on their expectations, the agents have different objectives, according to their respective roles. These are represented in:

1. An agent's utility function;
2. The selection method used by an agent.

From a customer's point of view, there are two objectives: On the one hand, a customer strives to maximize the number of fulfilled orders to enable continuous product consumption. On the other hand, this role is also responsible for the amount of messages to be handled in the MAS depending on the number of receivers per message. In order to ensure a low communication effort, the second objective is to minimize the number of order receivers. Thus, when calculating the selection values for each message, the following utility function is employed:

$$utility(m_{sent}) = \frac{1}{|rec(m_{sent})|} \cdot eor(m_{sent}) \quad (7)$$

Here, $rec(m_{sent})$ denotes the set of receivers of message m_{sent} and $eor(m_{sent})$ is the estimated order fulfillment rate, calculated by:

$$eor(m_{sent}) = \sum_{m_j \in M} lookup(MEM_{alter}, m_{sent}, m_j) \cdot \begin{cases} 1 & \text{if } perf(m_j) = \text{INFORM} \\ 0 & \text{else} \end{cases} \quad (8)$$

As $perf(m_j)$ indicates the performative of message m_j, the *eor* represents the estimated probability of a positive answer to the given order. Hence, this utility function favors those orders that have a small number of receivers while having a high estimated probability to be fulfilled.

A message m_{sent} finally is randomly chosen out of the set of all possible messages with a probability based on its selection value. In order to be able to adjust the level of randomness in this selection, the selection value is further modified by an exponent γ, allowing for choosing from a range between completely random selection ($\gamma = 0$) and deterministically selecting the maximum value ($\gamma = \infty$). Therefore, following Dittrich et al. (2003, sec. 2.1) again, selection is done using a probability distribution over all possible messages m_{sent}, calculated as follows:

$$p(m_{sent}) = \frac{V_{m_{sent}}^{\gamma}}{\sum\limits_{m_j \in M} V_{m_j}^{\gamma}} \tag{9}$$

From a supplier's point of view, on the other hand, the objectives are easier to represent. A supplier is assumed to be generally interested in fulfilling an order if possible. If it is not possible to fulfill all orders, a supplier prefers to maximize the system's stability in terms of predictability of further incoming orders and anticipated expectations of the customers. In other words, a supplier favors orders by his regular customers as he can expect them to place further orders in the future and he can anticipate the expectation of their orders being fulfilled. This setting is directly represented in the weighted sum of EC and AE. Thus, the supplier's utility function remains unused ($utility(m_{sent}) = 1$).

For the choice of a message, the selection value $V_{m_{sent}}$ is calculated for each answer $m_{sent} \in M$ with $perf(m_{sent})$ = INFORM. The answers are then sorted by their respective selection values. Beginning with the highest value, the messages are processed in descending order. As long as the supplier's inventory stock level allows for fulfilling the processed order, an INFORM message is sent. If that is no longer possible, all subsequent orders are refused.

5 EMPIRICAL EVALUATION

In order to validate the ability of expectation-based self-organization to efficiently structure and operate multiagent systems modeling supply networks, that approach will be compared to the performance of a system with a previously defined communication structure. For this purpose, the approach is implemented and applied to an example scenario using the multiagent-based simulation system PlaSMA (Schuldt et al., 2008).

5.1 Experimental Setup

In this evaluation, a network with three tiers and three parallel operating entities is modeled as depicted in Figure 2. In this sample scenario, each agent produces and/or consumes an amount of two units of the product types A and/or B (two A being transformed into two B by the agents at the manufacturing tier). Furthermore, every agent has an outbound inventory capacity of four units per product type, restricting the amount of goods that can be produced and stored by a single logistics entity. The agents acting as customers pursue a policy of ordering an amount of four units if the respective inventory stock level reaches six or less.

In the simulation, a message sent by an agent can be received and processed in the next time slice at the earliest. Therefore, sending an order and receiving the response takes two simulation cycles. In that time, four units of the required type of products can be consumed. Thus, the amount of goods ordered enables maximal utilization of production and consumption processes while requiring minimal outbound storage capacity on the suppliers' side. However, the threshold of six units for placing an order enables the agents at the manufacturing tier to build up safety stocks, allowing for continued production in case of supply shortfalls and thus compensating disturbances at the early network tiers.

Prestructuring this network can easily be done by choosing an arbitrary bijection out of the possible relationships between each two tiers. For each order following the mentioned policy, this ensures the number of receivers being one (the possible minimum) and the supplier to be able to fulfill that order as soon as enough raw material has been produced in an initialization phase (as the amount of consumed goods equals that of produced ones). Thus, such an arrangement of relationships necessarily leads to a maximized operation efficiency of the modeled supply network using a minimal number of sent messages. Regarding these objectives, it therefore guarantees optimal results making it especially suitable as a reference for the self-organizing approach.

Yet, without prior knowledge of other agents' capabilities and relationships, the choice of interaction partners leading to an efficient and reliable network structure is not an obvious one. As the possible configurations of message receivers for each order correspond to the power set of the set of available suppliers (without the empty set), in a network with n tiers and m parallel actors at each tier, the total number of potential relationships is $(m \cdot (2^m - 1))^{n-1}$ (the possible communication paths through the network).[2] Thus, in the chosen scenario the self-

[2] There are m agents at a tier with $2^m - 1$ possible interaction partners, each. The potential paths throw the network are given by the combination of those options over all $n - 1$

organizing agents can choose between 441 possible interaction patterns leading to different performance rates. Therefore, in this simple scenario, agent coordination is already complex enough to make it suitable for evaluating the efficiency of emerging communication structures.

For this purpose, the expectation-based agents are configured as follows: The set of possible orders to be sent by a customer is given by the possible combinations of their receivers, their performatives, and their content. As there is only one type and a fixed amount of units to order per customer, there is only one possible content. The same holds for the performative, as an order is always a REQUEST message. Thus, the set of possible orders is determined by the possible combinations of a message's receivers (the power set of the set of receivers). For the replies, on the other hand, the receiver as well as their contents are preassigned by the incoming orders. Hence, a supplier's only choice is between the message performatives according to the FIPA-REQUEST interaction protocol.

For generating the results presented in the following subsection, the constant values are based on those used by Dittrich et al. (2003): $c_M = 2$ and $c_f = 0.02$. The agent memory size is set to $n = 25$ for both MEM_{ego} and MEM_{alter}, the balance between EC and AE to $\alpha = 0.5$, and the customers' selection value gain to $\gamma = 3$. All agent memories are initially populated with randomly chosen messages.

In order to validate the approach to expectation-based self-organization, it is compared to an optimal configuration as outlined above. The performance is measured with regard to the final consumers customer satisfaction rate (i.e., the number of fulfilled orders), the number of receivers per order, and the utilization of the final consumers' product consumption. The first two criteria directly reflect the customers' utility function and give information about the reliability of emerging relationships between agents (customer satisfaction) as well as about the communication effort needed to operate the network (message receivers). Thus, these measures reflect the extend of stability of the emerging network structures. The consumers' utilization, on the other hand, is an additional logistics performance measure that allows to validate the supply network's overall operating efficiency in terms of product throughput rates.

5.2 Results and Discussion

The results depicted in Figures 3–5 show the customer satisfaction, number of receivers, and consumer utilization as average values over 200 simulation runs. Each run consists of 1000 production and/or consumption operations. For the calculation of the order fulfillment rate, the last ten messages received are considered for each time slice while the utilization is measured over the last ten attempts to consume the respective amount of products.

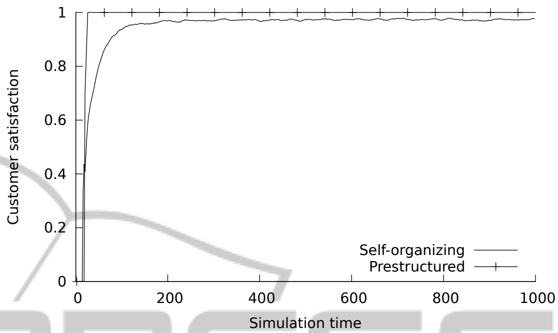

Figure 3: Customer satisfaction among the final consumers.

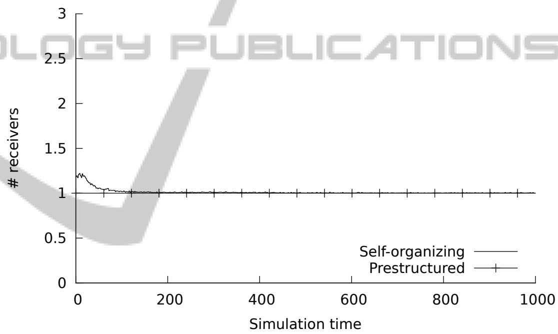

Figure 4: Number of message receivers (orders of final consumers).

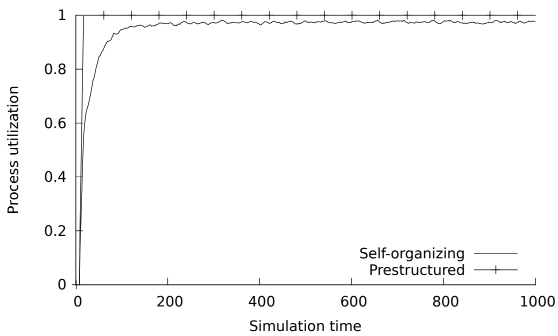

Figure 5: Consumption rate (utilization) among the final consumers.

For the prestructured reference configuration, the figures show that there is a short initialization phase until the inventories of the suppliers are filled high enough to be able to fulfill the customers' orders. After that phase, the optimal values are reached for the order fulfillment rate and the customers' utilization

links between two tiers.

while the number of receivers per order is always one by definition.

In the self-organizing network, these levels are not reached completely. However, the values converge near the optimum, showing that the agents autonomously establish one to one interaction relationships (Figure 4) that still lead to a near optimal order fulfillment rate of more than 97% (Figure 3). The process utilization (Figure 5) as a logistics performance indicator corresponds to these values, as the agents always order the minimal amount of products which directly leads to supply shortfalls in case of refused orders.

These results reflect the capability of generating social order as it is observed by Dittrich et al. (2003) in their original model. Thus, changing their interpretation of a dyadic encounter between individuals to a more general understanding of double contingency regarding alter a whole community of entities allows for transferring the properties of their basic approach to a multiagent scenario. Therefore, an application of expectation-based self-organization in MAS based on Luhmann's notion of double contingency is possible without the requirement for a reduction of interaction to pairwise communication processes or the need for extended agent observation activities.

Concerning the logistics application, the results demonstrate that the expectation-based approach to self-organizing agent interaction is not only capable of efficiently structuring and operating the modeled supply network. In fact, it is even able to establish an optimal configuration of agent communication channels (one to one relationships) leading to similar performance rates compared to the benchmark arrangement in the course of the simulation. As the agents occasionally explore alternative interaction options, delivery failures occur from time to time leading to slightly less than optimal customer satisfaction and utilization rates due to the minimal order size and inventory capacities. Regarding these measures, safety stocks and increased order sizes may compensate that disturbances to further improve the logistics performance.

To summarize, the feedback loop of agent observation and expectation-based selection of operations shows the ability to reach near optimal results without the requirement for a priori assumptions about agent characteristics (as, e.g., determining the benchmark configuration requires knowledge of the agents' production and consumption rates) or repetitive negotiations between several agents. As it is not generally possible to optimally prestructure a logistics network due to the dynamics of the logistics domain and the black box nature of agents in open MAS, expectation-based self-organization provides a promising coordination method for supply systems being adaptive as well as operating efficiently.

6 CONCLUSIONS

In this paper, the requirement for adaptive yet efficient supply networks has been identified. As multiagent systems provide a means for decentralized modeling of logistics networks, possible coordination techniques have been investigated in terms of their applicability to address the identified challenges in supply network organization. In this context, expectations regarding observable behavior have been presented as a means for dynamically structuring agent relationships, avoiding the need for a priori assumptions regarding agent properties and behavior.

Based on theoretical foundations from sociology (Luhmann, 1995), a simulation approach to emerging interaction patterns using expectations has been adapted and generalized to be applicable in multiagent systems. That method has been evaluated in a simulated supply network scenario according to coordination efficiency and reliability as well as logistics performance.

The simulation results illustrate that self-organized agent coordination based on mutual expectations is able to establish organizational structures approximating optimal performance values regarding the evaluation criteria. Hence, the approach has been shown to enable efficient interaction of autonomous entities to emerge solely based on locally observable agent behavior.

However, there are still questions open for future examination. While the presented approach performs very well in a stable agent community with repeating interaction contents (i.e., a static supply network setup), it remains to be analyzed in a setting with dynamically changing agent memberships and activities. In such a scenario, a self-organizing network can be assumed to actually outperform a predefined structure as the latter is not able to adapt to changing conditions. Furthermore, in that context, an examination of the different parameters' impact on the predictability and speed of convergence (learning rate) and the limits of overall performance of the emerging system structure will give further insights into the capabilities of expectation-based self-organization and may motivate further refinements of that approach to agent coordination.

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