Role-Based Knowledge Structures in Complex Adaptive Logistics Systems

A Methodology for Building an Autonomous Cooperation-based Simulation Model

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Abstract—**The goal of this paper is to provide a fundamental methodical approach for identifying actors in Complex Adaptive Logistics Systems to deduce knowledge that can be implemented into the decision structures of intelligent logistics objects. This serves as a basis for further simulation-based studies regarding the efficiency of the usage of autonomous cooperation-based technologies in logistics services. For this purpose, role theory is applied and connected to knowledge engineering, and the resulting methodology is critically discussed regarding its contributions and limitations.**

Keywords- role theory; complex adaptive logistics systems; knowledge engineering; multi agent-based models

I. INTRODUCTION

Today's logistics networks can be, from a complexity science-based perspective (e.g. [1-4]), regarded as Complex Adaptive Logistics Systems (CALS) [5-10]. These large logistics networks evolve from the co-operation of a number of different agents on a macro-level (as manufacturers, logistics service providers, etc.) as well as on a micro-level (e.g. containers, trucks, etc.) which interact on their particular level [7, 8, 11]. Interaction on a micro-level between so-called 'smart parts' (intelligent logistics objects) [6] becomes possible through developments in information and communication technologies as RFID [12]. The smart parts can have certain characteristics as learning capability [5, 6], ability to decentralized decision-making [12, 13], heterogeneity [6, 7], and autonomy [8]. One option to realize a CALS is to increase the degree of autonomous co-operation (AC) in a logistics network. AC is understood as processes of decentralized decision-making of autonomous logistics objects in non-deterministic system structures [12].

However, does it economically make sense to increase the degree of AC in a logistics system? How would a company perform in terms of efficiency compared to a company with less smart parts? These questions can be answered by programming CALS as multi-agent-based models and conducting a simulation [5, 9]. Thus, a model of a CALS on both macro- and micro-level is needed.

To begin with the micro-level, the smart parts' decision behavior needs to be modeled to analyze the behavior's effects on the company's performance. The decision behavior depends – amongst others – on the parts' goals and on their knowledge about decision alternatives [14]. The parts' goals (being part of the company as a system) orientate on the company's goals (being the overall goals) which leads to the model's macro-level.

Pfeffer and Salancik (1978) call a company efficient if it fulfills its stakeholders' expectations. Stakeholders [15] are understood as other actors (e.g. companies, customers) which provide essential resources if the considered company fulfills their expectations [16]. Thus, for modeling a company's functions and expectations (its role) must be known. As each company has to know its most important stakeholders' expectations and how to fulfill them, also its knowledge should be displayed in the model.

The knowledge distribution between the parts is important to consider as it affects the company's ability to fulfill its stakeholders' expectations. As the company's knowledge about the expectations is the basis for its goals and thus for the parts' decision structure, there is need to develop a role- and knowledge-based model on the macro-level. This requires a methodical approach which considers the expectations within the network through roles and the necessary knowledge for each role.

Thus, the paper proceeds as it follows: In section II, CALS will be described from a complexity-science based perspective with special focus on knowledge as a key performance driver. In section III, knowledge engineering and role theory assumptions will be depicted to be able to identify roles, expectations and necessary knowledge of actors in CALS. A methodical approach will be designed to be able to develop a role- and knowledge-based model as a basis for further multi-agent-based research. The paper will conclude in section IV with a short summary of the main results and a discussion of the contributions and limitations of the presented approach.

II. LOGISTICS NETWORKS AS COMPLEX ADAPTIVE LOGISTICS SYSTEMS

A. Complex Adaptive Logistics Systems

The vision of Complex Adaptive Logistics Systems (CALS) [5-10] is based on the concept of Complex Adaptive Systems [1, 2, 4]. CALS consist of a high number of agents

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that interact with each other on both a macro-level (e.g. suppliers, logistics service providers) as well as on a micro-level (intelligent logistics objects – so called 'smart parts' – e.g. products, containers) [7, 8, 11]. These agents are capable to control themselves to certain degrees leading to adaptivity based on decentralized generation and usage of knowledge; in other words, the agents have certain learning capabilities [5, 6], which allow for a decentralization of decision-making [12, 13]. Furthermore, these agents are heterogeneous [6, 7] as well as autonomous [8, 12]. The overlying levels are self-organizing and they are neither pre-configured, nor are they totally chaotic [5, 6, 12]. Instead, they consist within a so-called melting zone (see on this [1]). Finally, co-evolution takes place within these systems (agents co-evolve with each other) as well as between different systems and other systems in their environment [5, 6].

CALS being realized becomes possible through developments in information and communication technologies (e.g. GPS, RFID etc.) which enable autonomous co-operation (AC) of the smart parts. AC "*…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*" [12, p.8].

How would a company in a logistics system perform in terms of efficiency if it increases its degree of AC? Would it be more efficient than a company with less smart parts?

B. Knowledge as a key driver for CALS performance

In order to analyze the raised questions, several authors suggest programming CALS as multi-agent-based models (ABM) [5, 9]. Based on the simulation's results, the effects of increasing the degree of AC on a company's efficiency can be evaluated.

To be able to simulate an ABM, a model needs to be built [17, 18]. It has to display the companies on the macro-level as well as their smart parts on the micro-level as the parts are finally simulated within the context of their company. To display the CALS's behavior depending on the degree of AC, the parts' decisions need to be displayed in the model. Thus, the decision structures lying behind the parts' decisions (e.g. goals, alternatives etc.) are included in order to reflect the parts' decisions in the model. As a decision is understood as the goal-oriented selection between action alternatives [14], the decision structure depends – amongst others – on the one hand on the company's goals which determine the parts' goals (e.g. low CO_2 emissions) and on the other hand on the parts' knowledge regarding the alternatives (e.g. possible routes).

As the company's goals determine the parts' decision structures, they need first to be determined. Following Pfeffer and Salancik's efficiency approach (1978), the companies acting within the CALS on a macro-level need to ensure that they fulfill their stakeholders' expectations in order to obtain essential resources from them [16]. For example, a logistics service provider has to transport goods reliably as expected by its customers in order to receive further orders leading to financial resources to ensure the company's continuity. Thus, the service provider has to consider the customer's expectations when defining his goals for organizing transportation (e.g. high punctuality) to remain efficient.

Thus, in order to be able to analyze a company's efficiency depending on the degree of AC, the model's macro-level needs to be developed which displays the company in relation to its stakeholders and the stakeholders' expectations. Therefore, a role model could be suitable for the macro-level as roles are described as expectations towards the holder of a certain position [19].

Additionally, the company's knowledge as a basis for the decision structure needs to be displayed. This refers on the one hand to the company's knowledge about the stakeholders' expectations, which have to be fulfilled (e.g. expectations of environmentally friendly transportation) in order to obtain essential resources (e.g. receive orders). On the other hand, it refers to the company's knowledge how to fulfill the expectations (e.g. how to reduce CO_2 emissions). If this knowledge is displayed in the macro-level model, the parts' decision structure – goals and knowledge about action alternatives – can be deduced (e.g. a kind of guideline for the company's parts to consider CO_2 emissions and knowledge about transport modes and routes).

However, a certain amount of knowledge is an important precondition for decision-making. It is also a basis for interaction, as knowledge is exchanged when communication takes place between the elements [12] and interaction is stimulated by an asymmetric knowledge allocation [6]. Furthermore, knowledge availability is essential for the elements' learning capabilities.

As it is strategically reasonable (e.g. secrecy reasons, competitive advantage) to restrict knowledge distribution between companies [20], it is also reasonable not to distribute all available knowledge within the company. For example, gathering knowledge in preparation of a decision leads to costs (e.g. for labor and time) which need to be opposed to the value of the knowledge [14]. Procuring knowledge can also lead to information overload [20]. Thus, it is reasonable to provide only necessary knowledge to the parts (e.g. a container loaded with goods from Spain to Germany does not need to know about transport options in China). This leads to an asymmetric knowledge allocation within the company and between companies. However, for two companies cooperating, it might be reasonable to allow the companies' parts to exchange information (e.g. about congestion, advantageous transport routes, certain orders to improve coordination). This needs to be considered when designing the model for simulation.

Thus, a role- and knowledge-based model (on the macro-level) needs to be developed. To be able to develop such a model, a methodical approach is necessary which considers on the one hand the described knowledge and on the other hand role theoretical assumptions to display the stakeholders' expectations as roles.

III. Developing A Methodical Approach Based On Knowledge Engineering And Role Theory

A. Knowledge Engineering

Referring back to Huber (1991) [21] and Nonaka (1994) [22], Alavi and Leidner (2001) define knowledge to be "*...a justified belief that increases an entity's capacity for effective action*" [23]. Following Nonaka and Takeuchi (1995), knowledge in organizations can be described by two dimensions: explicit and tacit [24]. Explicit knowledge can be "*…articulated, codified, and communicated in symbolic form and/or natural language*" [23] (e.g. transport prices). The tacit dimension of knowledge was first mentioned by Polanyi (1966) [25] and describes knowledge which is gained through experience and difficult to communicate [24]. Thus, as the tacit dimension is important for problem-solving capabilities [26], it is necessary to consider both dimensions for the smart parts' decision structure, i.e. to implement also certain learning capabilities enabling the parts to acquire tacit knowledge (e.g. a container avoiding a certain route having learned that it is prone to congestion).

Knowledge engineering is the process of integrating problem-solving capabilities – which are based on knowledge – e.g. into an ABM in order to enable the model to solve complex problems [26, 27]. Knowledge acquisition – which is an important sub process of knowledge engineering [28] – externalizes tacit knowledge [29] to make it explicit in order to be able to collect and use both dimensions [30]. Following Birk (1999), a knowledge acquisition method consists of pre study, knowledge elicitation strategy development, knowledge elicitation, and knowledge modeling [30]. Authors like Cooke (1994) or Buchanan (1983) propose different forms of sources to elicit knowledge: observations, interviews, publications, data bases, task analyses, verbal and non-verbal reports, protocol analyses, decision analyses, concept elicitation methods, data collection methods, structural analyses, and automation of conceptual techniques [29, 31].

Having accomplished the elicitation of knowledge, this knowledge needs to be represented in a knowledge base [28] which can be assessed by technical systems – as the smart parts – or human beings [32]. One possible knowledge base concept – amongst others – for representing knowledge are ontologies which consist of classes, relations, and axioms, and which provide "*...the basic structure or armature around which a knowledge base can be built*" [33] and have useful characteristics as e.g. different forms of representation, possibilities for knowledge sharing, or reasoning [34].

Thus, knowledge engineering methods could – in principle – be used to display relevant knowledge in a role- and knowledge-based model of CALS. In the following, also role theoretical assumptions will be depicted as a basis for the methodical approach to develop the described model.

B. Role Theory

Role theory is a subfield of sociology and social psychology. It is considered to deal with the link between the individual and the society [35, 36]. There are various ambiguous definitions of a role. Biddle (1979) e.g. defines a role as "*...those behaviors characteristic of one or more persons in a context*" [37]. Another definition which has been used in an organizational context is the one by Katz and Kahn (1966) who define a role as "*...activities which in combination produce the organizational output*" [38]. The organizational output in the present case is the total value added by the considered network, and the activities can be applied to all value adding operations.

Following the symbolic interactionist approach [39], roles evolve through interaction [40]. Building on this notion of interaction as an important point when making a role, Katz and Kahn (1966) develop a role episode [38]. This process is based on four elements:

- role expectations
- role sending
- role perception
- role behavior.

In a logistics network e.g., a manufacturer would expect his logistics service provider to transport a certain good from A to B (role expectation). He would authorize the service provider to execute this order (role sending). The service provider would receive the order and interpret the instructions (role perception). Then, the service provider would transport the mentioned good from A to B (role behavior).

Hence, in order to analyze the roles in logistics networks, the elements' roles need to be observed and analyzed. Biddle (1979) mentions three options for empirical studies of roles: first, to observe a person's behavior under real-world conditions; second, to observe under laboratory conditions; and third, to conduct interviews [37].

In the following, the presented concepts of knowledge engineering and role theory will be connected in order to develop a methodical approach to develop a role- and knowledge-based model as a basis for further multi agent-based research on the efficiency of CALS.

C. Methodical Approach

Considering Biddle's (1979) suggestions for the empirical study of roles, observations of logistics networks could be generally made to determine roles and the required knowledge [37]. However, as tacit knowledge is difficult to communicate, it is hardly observable. Thus, considering that both dimensions of knowledge are important for problem-solving capabilities [26] it would be feasible to conduct interviews with logistics actors. Another option could be to conduct a secondary research. Possible sources could be interviews, databases [31] or case studies etc. The necessary knowledge can be acquired by using knowledge elicitation methods [29].

Developing the role- and knowledge-based model, the role episode by Katz and Kahn (1966), containing expectations, sending, perception, and behavior [38], could serve for guidance as it considers the interplay of two actors when making a role. Before adopting the role episode, the companies and their stakeholders must be identified, because a role episode is based on two companies in each case. Having identified essential resources the company needs to fulfill its goals and where to obtain them, the stakeholders can be identified by considering all actors the regarded company interacts with and eliminating all it does not need any essential resources from. Then, the following four steps need to be conducted for each pair of companies in both directions.

The first step “role expectations“ is to identify the following kinds of expectations. The questions to be answered are: Which expectations does company A have of company B (as stakeholder of A) regarding the resources A needs to obtain from B? What does A (as stakeholder of B) expect of B to fulfill in order to provide resources for B? What does company A need to know in order to fulfill B’s expectations?

The second step *"*role sending” is to identify which parts of the expectations are communicated from A to B. Thus, as the expectations are both explicit and tacit knowledge of company A, the explicit dimension is communicable [23] while the tacit dimension can only be communicated if it is externalized [24]. Thus, there can be a difference between role expectations and role sending.

The third step “role perception” is to identify which expectations B receives and how B interprets the expectations sent by A. Thus, B combines A’s expectations with its own knowledge and expectations which again could lead to a different understanding.

The fourth step “role behavior” is to identify how company B reacts to the expectations sent by A and how B fulfills his own role. Thus, the questions to be answered are: Which resources does B provide? What function does B fulfill? Company B’s role develops also from all its stakeholders’ expectations and B’s perception of these expectations. B’s reaction to its stakeholders’ expectations determines later on the micro-level the parts’ decision structures and the parts decisions determine B’s behavior. In order to be able to fulfill its own role, B needs to know its own expectations and needed resources. Thus, following the role episode, the previously presented four elements need to be studied for all actors involved in the logistics network to identify roles and required knowledge.

The resulting findings can be represented as an ontology. The companies of the logistics network could be represented as classes while relations and axioms could represent the expectations and knowledge identified during the research. This could serve as knowledge base which the smart parts could refer to in a simulation.

However, can the proposed approach to develop a role- and knowledge-based model be used to analyze and display a CALS for research on a company’s efficiency depending on its degree of AC? This will be discussed in the following section as well as the limitations of this approach considering the characteristics of CALS.

IV. Contributions And Limitations

The aim of this paper was to find a methodical approach to be able to develop an ABM for a CALS on the macro-level which can be used to identify possible decision structures of a company’s smart parts in order to analyze the effects of increasing the degree of AC on a company’s efficiency.

By using the role episode as guidance, the actors in a logistics network, their functions, expectations and knowledge can be to certain degrees identified and displayed as all actors and their role-building communication (role sending and perception) are considered. The resulting roles will fulfill the CALS characteristic to be heterogeneous as they have to be different, because otherwise they wouldn’t need another actor‘s resources as they would have these resources themselves. If an actor can receive other actors’ expectations and interpret them, he has to have certain learning capabilities. If the actor receives the necessary knowledge by fulfilling his stakeholders’ expectations, this would enable him to decide decentralized and autonomously. Thus, the roles in the resulting model fulfill the characteristics of a CALS, leading to a self-organizing system with emergent structures.

The proposed approach can contribute to the overall aim to analyze the effects of increasing the degree of AC in a logistics company on the company’s efficiency. By using the approach, a role- and knowledge-based model can be developed as a basis for further multi-agent-based research. The model will be able to reflect companies in logistics networks, their expectations, functions and necessary knowledge. Based on the model, the decision structures and knowledge distribution for the companies’ parts can be deduced. For example, if a company knows that its stakeholder expects a low carbon footprint, the parts need to know about that goal and they need knowledge e.g. about low emissions transport modes. That is important to analyze the effects of increasing the degree of AC in a company in a CALS on the company’s efficiency in comparison to other companies with a lower degree of AC. The methodical approach is based on a role-building process (the role episode) which reflects interaction as an important part when finding a role.

There are some limitations of the proposed approach. The approach does not define any system borders, thus, it is possible that the model becomes infinite. Further research should analyze where to define borders. Furthermore, it could be difficult to retrieve all data as e.g. in an interview, the interviewer could possibly not decide between role expectations and role sending. Conducting a secondary research, it would also be challenging to retrieve the data as these sources possibly do not consider all elements of a role episode. Further research should also consider how the parts decision structure can be deduced from the company’s goals.

However, this methodical approach can serve as a basis for further research on the effects of increasing the degree of AC of a company in a logistics system on the company’s efficiency.

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