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A Framework for Distributed Knowledge Management in Autonomous Logistic Processes

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Abstract

The trends and recent changes in logistics lead to complex and partially conflicting requirements on logistic planning and control systems. Due to the lack of efficiency of currently available strategies and methodologies, a new paradigm for logistics planning and control is required. An emerging approach is the analysis and design of autonomous logistic processes. Agents represent a modern approach for implementing autonomous systems. The challenge for the design of agent systems is to integrate the complex and dynamic knowledge required for reliable decision-making in logistics. To address this problem, we introduce a framework for distributed knowledge management in competitive environments. Our approach combines a general role model enabling distributed, flexible agent-based knowledge management services and a set of general decision parameters for rational agents.

1 Introduction

Continued and strong demand for increased customization of products and their delivery has brought about a sea change in the economical landscape: from markets that were predominantly controlled by sellers to markets that are now driven by buyers and their demands. To meet the resulting requirements in the *logistics domain*, participating enterprises investigate ways to restructure their business processes to allow for more autonomy in order to provide flexibility and rapid response when reacting to customer requests. Such restructuring away from the traditional centralized way of doing business is made possible by an emergence of hardware technologies including GPS-based telematics for trucks, more reliable and longer ranging wireless communication and identification facilities as well as low-power sensor devices.

In addition, innovative software is being developed to support autonomous decision-making and to provide the right information to the right processes when it is needed. Software systems implementing autonomous logistic processes (e.g., agents) need to share information on a continuous basis, for example, product specifications, manufacturing capabilities, delivery schedules, etc., and are required to make decisions which are consistent with the policies and overall economical situation of the enterprise they represent.

The goal of knowledge management (KM) is to support the agent in improving its decisions in the presence of incomplete, imprecise, or debatable information as well as the inherent uncertainty that results from the dynamic of the domain. Thus, context-based, situation-aware, and local decision-making, which in turn supports autonomous, self-managing behavior of agents, calls for the integration of knowledge management functions with the agent's planning and situation assessment sub-systems, e.g., for risk management [16]. Knowledge is and evolves locally in different agents and organizations whereas knowledge processing capabilities may differ from agent to agent. Thus, we need a distributed, dynamic, and trans-organizational knowledge management infrastructure.

We describe a new approach to enable robust decision-making in a highly distributed, multiagent environment where agents need to act in an autonomous fashion. Our application is the logistics domain where autonomous agents are seen as a promising and effective approach to represent the different planning, scheduling, and controlling processes in an enterprise. For example, we can envision a scenario in which agents are used to represent real-world entities such as truck and container, abstract objects such as weather or traffic service, or even human decision makers, such as the ramp agent at a loading dock. We believe this kind of autonomous, decentralized decision-making can help make the operational processes more efficient, cost-effective, and allow the participating enterprise to stay competitive. It is also a major improvement over traditional centralized approaches in which individual agents are ill-equipped to deal quickly with sudden events since control usually resides with the entities that are removed from the scene of the event and thus have only delayed access to the relevant information.

In addition, agents must be able to negotiate, form coalitions, and thrive in the presence of competition, for example, for customers (orders) or resources, and are also subject to unpredictable changes in their environment.

Furthermore, the dynamics of logistic processes require the ability to plan and re-plan even in light of uncertain, incomplete, or false knowledge. Standard scenarios of logistic processes typically have been modeled on the basis of static graph-theoretic representations. The well-known *traveling salesman problem* (TSP), the *vehicle routing problem* (VRP), or the *pickup & delivery problem* (PDP) reduce the complex task of transportation to a route optimization problem. They neglect both the important role of knowledge and communication in real-world logistic processes (c.f. [13]) and the fact that relevant parameters, e.g., traffic flow, incoming orders, etc. change over time. Thus, in order to migrate from a centralized decision-making to one that is carried out by multiple, distributed processes acting autonomously, the traditional communication and data management infrastructures must be augmented with a sophisticated yet flexible knowledge management system to support the requirements described above.

The goal of our project, which is part of the Collaborative Research Center (CRC) *Autonomous Cooperating Logistic Processes – A Paradigm Shift and its Limitations*,[1] is threefold: (1) To investigate the effects of different degrees of autonomy on the flexibility and robustness of logistic processes. We are specifically focusing on the role of knowledge and the flow of information in such processes. (2) To develop an agent-based distributed knowledge management system for the logistics domain. (3) To conduct and analyze experiments from large-scale simulations in order to assess how the accuracy, precision, and promptness of knowledge influences the quality of decision-making in complex and dynamic environments.

In this paper, we survey the requirements of autonomous processes in logistics with an emphasis on intelligent agents and knowledge (Sec. 2). In Section 3 a role-based framework for distributed knowledge management is proposed. We illustrate the application of this framework and the challenges in autonomous logistic processes with a real-world scenario from the logistics domain (Sec. 4). Section 5 describes our efforts to implement and deploy the presented approach. The paper concludes with related work (Sec. 6) and a summary (Sec. 7).

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2 Autonomous Logistic Processes

The trends and recent changes in logistics introduced above, lead to complex and partially conflicting requirements on logistic planning and control systems. A strong notion of autonomy in logistic objects, such as cargo, transit equipment, and transportation systems, can be enabled by novel communication technologies like radio frequency identification (RFID) and wireless communication networks. These and others permit and require new control strategies and autonomous decentralized control systems for logistics processes. In this setting, aspects like heterogeneity, flexibility, adaptivity, reactivity to dynamically changing external influences while maintaining the global goals are of central interest. The underlying logistic models may include transportation as well as manufacturing logistics.

In a standard approach to logistics, local entities make decisions on the basis of a predefined set of rules, short-term objectives of the enterprise, and current information about their environment. Strategic goals of an enterprise are not considered within this kind of local decision-making. The innovative approach of *autonomous logistic processes* involves even the transfer of limited aspects of strategic goals in dynamic decision-making on an operational level.

Engineering autonomous processes in logistics includes three perspectives: material, information, and management. The challenge for the implementation of autonomous decision behavior is to enable distributed systems, where the different levels gain the ability to interact autonomously and flexibly. For the design and implementation of agents as autonomous decision-makers this challenge includes high-level decision-behavior which may not be realized by simple reactive agent architectures. Therefore, we assume, that intelligent agents with deliberative decision behavior and explicit knowledge representation and reasoning capabilities are required to meet these requirements. In conventional research on multiagent systems, it is claimed, that the local interaction of autonomous systems (microscopic behavior) should lead to a optimized behavior on the global level (macroscopic behavior).

The challenge in logistics however arises from the different interests within the system. On the interaction level, agents should maximize their utility. Each agent is a representative of an enterprise and, therefore, its local decision behavior should improve the performance of the corresponding enterprise. However, on a global level, we hope to achieve a better performance of the overall logistics resp. the optimization of the global system. For practical applications, it still has to be proven, that optimization is realized at least on the enterprise level, as the enterprises have to invest into this innovative technology and transfer competence on the agents' level. Thus, the conclusion of straightforward emergence of macroscopic optimality from microscopic autonomy has to be questioned especially in this domain.

Summarizing the various requirements in the logistics domain introduced within this section, it is obvious that knowledge is core element of an approach to autonomous logistics, as it is constitutive for sophisticated decision-making within the agents. In conventional approaches, the implementation of a knowledge management system within a company could help to improve the situation for local decision-making. However, we assume that it is impossible to establish a single knowledge management system within an open network of autonomous decision makers of various enterprises. Therefore, we are in need of an innovative approach to knowledge management.

The infrastructure for knowledge management has to integrate aspects of cooperation and competition with regard to the relationships of the corresponding enterprises. As knowledge is one of the key factors for establishing efficient logistics, knowledge is considered as a resource. This includes the ability to use knowledge as a tradable good, such that even competing enterprises may share knowledge in a concrete situation. Following this assumption, knowledge may also be used for establishing trust networks or new cooperation relations between enterprises dynamically and autonomously. Obviously, agents resp. autonomous decision makers in the logistics domain can use knowledge in different ways, e.g., using knowledge from another agent, providing knowledge to another agent, etc. Furthermore, intelligent agents have the ability to reason on knowledge and infer new knowledge from current situations. This ability can also be used for trading new knowledge within the systems.

Taking this background into account, we propose the following requirements for knowledge management in autonomous logistics:

- Autonomous decision makers meet each other on a process level, e.g., the package, which is unloaded at the port, the truck arriving at a transshipping facility. Thus, knowledge management should be able to emerge in ad-hoc networks.
- Autonomous agents should be able to identify knowledge needs and requests knowledge from other agents.
- Knowledge needs may not be fulfilled by a single agent, thus, there is a strong need of a service, which gathers knowledge from various agents and knowledge sources and integrates this knowledge consistently.
- Agents should be able to provide perceived, received, or inferred knowledge to other agents.
- Due to the inherent heterogeneity of the logistics domain, translation of knowledge between different representations or semantical contexts should be possible.
- Embedded systems with limited resources are applied in autonomous logistics. Thus, the agents need the capability to remove knowledge which is no longer useful.

In the following we introduce an innovative distributed framework for knowledge management in autonomous logistics, which meets these requirements. On this basis, a prototypical implementation as well as case studies are provided.

3 Framework

Our framework consists of three main components: *agents*, *knowledge*, and *roles*. Agents represent process-owners (e.g., decision makers) or real-world entities in the logistics domain (e.g., cargo transport centers, vehicles, transport containers, or even single packages). In addition, an agent has specific *properties* (e.g., speed, weight, enterprise affiliation), *capabilities* (e.g., transportation or storage capabilities, or sensors for measuring humidity), *desires* (e.g., minimizing delay of a shipment or maximizing utilization ratio), and *intentions* (i.e., tactical plans). The set of beliefs forms an agent's knowledge base and is associated with specific inferential capabilities. We envision that these agents, which must act in a rational and autonomous fashion, can be implemented as goal-oriented agents following the *BDI (belief, desire, intention)* approach as introduced in [21]. The BDI approach is well suited for this purpose since it provides the appropriate concepts and structures for representing our agents. For example, the strategic layer of agents may be modeled within the desires, operational aspects within beliefs, and tactical features within intentions or plans. Furthermore, the BDI approach attempts to closely mimic human decision-making [5] and represents the dominant approach for modeling intelligent behavior within the agent research community [9].

The second component of our framework provides knowledge management functionalities including knowledge representation, storage, and manipulation. In our framework, the terminological domain knowledge is organized in associated ontologies for transportation and production logistics which include, e.g.,

- a representation of the transportation network as an annotated graph, together with a two-dimensional map-like representation (similar to geographic information systems) enabling spatial reasoning (e.g., inferring properties of proper subregions using a part-of relation),
- the basic types of agent and their properties (e.g., for a vehicle, its average and maximum speed, the types of routes in the network it can use, its load capacity, and its corporate affiliation), and
- the properties of 'inactive' objects, such as highways, traffic hubs, depots, etc.

The visibility of the ontology is determined by an agent's predefined tasks and capabilities. For example, in contrast to a shipment agent, an agent representing a navigation system has to have complete access to all relevant details of the transportation network part of an ontology.

Knowledge management enables agents to request new or missing knowledge, or update existing knowledge. Intuitively, our approach to knowledge management is similar to peer-to-peer knowledge management. Agents have the abilities to communicate with available data networks or form ad-hoc networks with other agents in their neighborhood. In these networks agents can interact on an operational level to coordinate activities with respect to their primary (logistic) task. Challenges include the handling of physical mobility of actors, building partially redundant systems (logistic and knowledge management), and providing adequate levels of interaction (collaboration, cooperation, competition, etc.).

The third component of our framework integrates the multiagent approach with knowledge management functionalities using *roles*. Examples of these roles are knowledge acquisition, brokerage, and processing. They are described in more detail in section 3.1. Depending on their capabilities and tasks in the logistics domain, agents may assume any one of these roles, which may change over time. For example, an agent representing a ship may assume the role of a knowledge provider reporting weather information to other ships. At a different point in time, the same agent may also assume the role of a knowledge consumer requesting information about its cargo and destination from a dock agent after loading is complete.

In contrast to conventional knowledge management approaches, our framework does not depend on centralized knowledge repositories. Communication among the roles is carried out over the already existing agent communication infrastructure. As an outstanding characteristic, our approach focuses on knowledge management performed *by* agents and *for* agents as decision makers in logistic processes. Nevertheless, humans remain an important factor because they need the possibility to monitor the logistic processes and the agents therein.

As a prerequisite to apply our framework we are tacitly assuming the existence of standard information technologies to provide the proper support such as networking, document storage, retrieval, metadata annotation, etc. Despite potentially existing connections by corporate affiliation, we do not presuppose initial structures in the knowledge management network. In contrary, as argued above, we emphasize the necessity of dynamic situation- and location-dependent interactions. In a sense, the structure of the knowledge management system *emerges* from the interaction of agents by virtue of implementing specific roles autonomously and in dynamic change.

Knowledge management as it is proposed in this framework is one key enabling factor to the envisioned autonomy of logistic processes. Autonomous entities need to make decisions based on a technically implemented decision-theoretic process. In order to achieve this they not only need knowledge about their environment, but also have to assess possible future states of this environment and judge alternative options. In [16] we propose a mechanism for assessing the risk associated with an option based on knowledge the agent has about its current environment. This risk management is very closely related to knowledge management. On the one hand it can trigger the acquisition of additional knowledge. On the other hand it may be necessary to evaluate the risk linked with a KM decision, e.g., giving away a certain information or asking an expensive but reliable source in spite of a free but inaccurate one.

It is important to note that knowledge management is restricted by various sociological and technological boundaries. For example, on a sociological level, agents may represent competing enterprises, which may lead to inconsistent or even incompatible desires. In addition, there is the important issue of trust. Low trust levels could prevent agents to assume certain roles (e.g., that of a knowledge broker or provider). High trust levels strengthen the connections between certain agents, causing an increase in traffic over time. As far as technological boundaries are concerned, the presence of embedded computational entities, which are partially moving in the physical world leads to hard restrictions on network availability and computational ability.

3.1 Agent Roles

The agent-oriented approach, which advocates decomposing problems in terms of autonomous agents that can engage in flexible, high-level interactions [14], employs a multitude of agents to solve the knowledge management problem. In our approach to distributed knowledge management the agents have a special primary task, e.g., self-organization of a logistic entity. Managing and sharing knowledge becomes an optional secondary capability orthogonal to their primary logistic task. Thus, in contrast to previous approaches to agent-based knowledge management [30], there is no one-to-one correspondence between agents and knowledge management functions, such as *providing* knowledge or *brokering* knowledge.

In order to cope with this system characteristic we map knowledge management functions onto agent roles. In [11] Herrmann et al. report on a number of case studies which show that in sociologically inspired systems (in that case a collaborative learning environment) users "attempted to take different roles and tried to change their roles dynamically in being able to structure their communication." They give an overview on application of sociological role concepts in computer-supported collaboration and state a need for role development in computer-supported knowledge management. In a sociologically inspired computer system, that a MAS is, it therefore seems straightforward to apply the role metaphor from computer-supported KM for humans to KM for agents. This is especially true as human agents are explicitly included in the overall concept. Within our framework a knowledge management role includes certain reasoning capabilities, a visibility function on an agent's beliefs, a deliberation pattern (i.e., a plan how to accomplish the KM task), and a communication behavior with interacting roles. The aim of KM roles is to provide a formal description of knowledge management tasks that eases the development of agents and reduces computational complexity by means of a minimum set of processed knowledge and applied reasoning capabilities.

One agent can assume different roles and may change them over time. The minimum role model includes the roles of a *provider* offering information and a *consumer* being in need of information. The next extension would be a *broker* mediating between the two [31]. Taking the agent-based approach, our claim to fully automate knowledge management raises new reasoning demands especially on the brokering and maintenance of knowledge, which have not been addressed so far. For example, in classical KM approaches, knowledge brokering and maintenance are performed by human actors (cf. [18]). We propose an

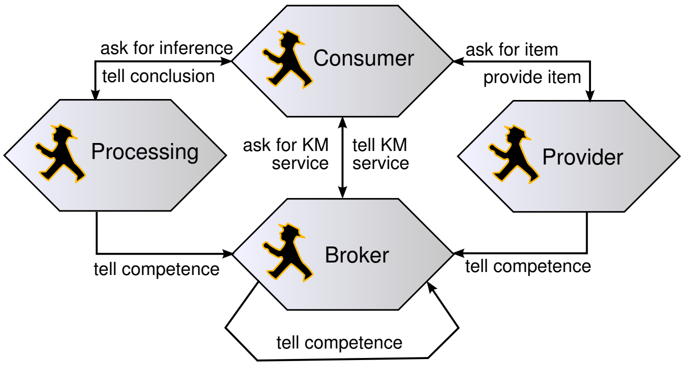

Figure 1: Inter-agent role-oriented communication acts.

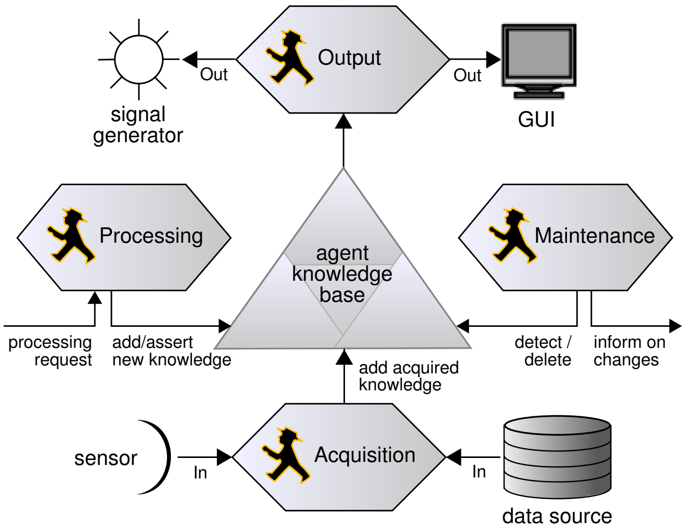

Figure 2: Internal roles' operations w.r.t. the agent's knowledge base.

extended role model that incorporates all knowledge management functions we identified as needed for autonomous logistic processes.

We distinguish *internal* and *external* roles. The latter are interactive and presuppose at least two involved agents, the former do not require inter-agent communication, but refer to intra-agent processes. Both types of role are independent from the primary logistic task of an agent and define a complex behavior which results in a modification of the agent's knowledge base.

Figure 1 depicts a conceptual overview of the most important external roles in our framework together with the corresponding communication acts. Figure 2 shows the internal roles' operations w.r.t. the agent's knowledge base. We briefly describe the resulting role set and their respective tasks in our proposed framework:

knowledge consumer: an agent acts as a knowledge consumer the moment it discovers a lack in its own local knowledge repository. Which knowledge it considers most important is situation-dependent and will be explained in more detail in section 3.2. In order to determine the most appropriate knowledge source the agent uses its meta-knowledge on its inferential abilities, own sensors, available data sources, and provider agents. If the agent decides to ask another agent and its meta-knowledge on adequate services is considered insufficient the agent may consult a broker as for who would be able to provide the needed service. Successful transfers with providers will strengthen the relationship to them and decrease the necessity to use brokers.

knowledge provider: provides parts from its internal knowledge repository either on demand or as part of pro-active behavior. To be able to provide knowledge pro-actively this role has to implement a publisher/subscriber mechanism. An agent that aims at providing knowledge will tell other agents, particularly esteemed brokers, about the kind of knowledge it is willing to offer. When asked for knowledge the provider weighs up whether or not to consent to the transfer depending on the importance and potential confidentiality of the requested knowledge and the social (e.g., organizational) relationship to the asking knowledge consumer.

knowledge broker: the knowledge broker acts as a yellow pages service within the system. It collects meta-knowledge on KM services (e.g., providers, other brokers, and processing services) and points a knowledge-seeking consumer to the right service. The broker also maintains a reputation list. Therefore it can rule out answers from unreliable partners upon request (Quality of Service enforcement). A broker may also act as a coordinator for adequate knowledge distribution within a legal organization or any other group of cooperating agents.

knowledge processing: this role provides services that generate or reveal new knowledge based on knowledge already available. This comprises semantic mediation and integration, learning, and inference which may be regarded as sub-roles, respectively. Inference is the KM function that reveals knowledge as a conclusion by logical deduction. Learning analyzes the knowledge base for generalization rules that may, e.g., allow deletion of inferable knowledge or prediction of recurring situations. The mediation function translates and possibly integrates knowledge of different sources and ontologies.
In general, this service will be used within an agent by request of the consumer role or other sub-systems. In some cases it may also be offered as a service to other agents. *Knowledge processing* is the most complex role and demands for sophisticated reasoning and learning capabilities. Thus, only some agents will implement this role entirely.

knowledge acquisition: this internal role is intended to provide an interface to external data sources including sensors. Therefore it needs the capability to query a specific source and build up an internal representation of it. Changes in the source might trigger the generation of new knowledge items.

knowledge maintenance: this internal role incorporates tasks needed to keep the knowledge base manageable and to monitor changes. If required the role informs the agent's sub-systems of relevant changes which may trigger an update of situation assessment and planning.

knowledge output: an internal role providing an interface to the external environment through signal generators and user interfaces. The communication for this role is unidirectional toward the external interface. Possible responses from the environment are handled by knowledge acquisition which can of course be implemented within one agent.

It is important to reiterate that one instantiated agent can incorporate more than one role (e.g., an agent representing a truck can first act as a knowledge provider and later as a knowledge consumer). Hence, the incorporation of roles is a decomposition of the KM problem, which is in essence orthogonal to the mapping of organizational entities to agents. Furthermore, since different roles of agents need different reasoning capabilities, encapsulation of roles reduces the complexity of tasks which have to be performed by an agent at any given time. This encapsulation is realized in our framework by a *visibility* function as introduced in [34].

3.2 Decision Parameters

A minimal role interaction model requires one agent $\mathcal{A}$ in the *knowledge consumer role* and another agent $\mathcal{B}$ in the *knowledge provider role*. In this section, we will discuss in a more detailed fashion under which circumstances an agent assumes the role of a knowledge consumer and provider, respectively. We will describe how different parameter settings determine the decisions and actions associated with these roles.

The parameters are involved in the knowledge transfer process between consumer and provider. The agent interactions in this process may be modeled as an (iterated) contract net protocol with the consumer as initiator and at least one participating provider.

3.2.1 Consumer Parameters

In general, the role of a knowledge consumer presupposes a situation which meets the conditions listed below:

1. The agent $\mathcal{A}$ intends to obtain a knowledge item k specified by a *knowledge item description* d. A knowledge item can be thought of as the truth value of a statement or the value of a variable. Its description d can, in principle, be provided by a query, possibly in combination with additional constraints, e.g., the definition of a minimum precision for the intended response and the deadline for response. These additional constraints make a knowledge item description different from a query or a sentence form which subsumes the intended knowledge item.

2. The knowledge item described by d is not already part of $\mathcal{A}$'s knowledge base.

3. The knowledge item described by d cannot be inferred from $\mathcal{A}$'s knowledge base, given $\mathcal{A}$'s currently available inferential capabilities.

4. $\mathcal{A}$ believes that the knowledge item described by d is, in principle, available now or later.

These prerequisites closely resemble the Gricean maxims on rational cooperative discourse ([10]) in many respects. They have to be combined with additional criteria, e.g., the (estimated) cost of obtaining k, in order to cover situations where knowledge is a tradable good and the knowledge consumer has a limited budget for acquiring knowledge from other agents. In its interaction with other agents an agent in the knowledge consumer role has to make many decisions, including the following:

- It has to assign a rank or weight to k in comparison to other knowledge items. This weight depends on how important k is for achieving its current goals, and if there are alternative knowledge items which might serve the same or very similar purposes, etc.

- The knowledge consumer has to choose among different knowledge sources, e.g., its own sensors and knowledge provided by other agents. This decision can make use of the agent's own experiences from earlier knowledge transfers, or it can be made solely on the basis of a general trust/reputation mechanism.

- The agent has to decide upon the maximum acceptable price being paid for k and the required response time.

- After each finished knowledge transfer, $\mathcal{A}$ has to assess its quality, e.g., if the actually delivered knowledge item deviated significantly from what the agent expected in advance.

- Finally, the agent has to decide upon the next steps, e.g., if k implies that other knowledge transfers are necessary.

These decisions of an agent assuming the knowledge consumer role are governed by the parameters *importance*, *confidence*, *cost*, *availability*, *similarity*, and *value* which are now discussed in more detail.

The *importance* parameter gives the (subjective) importance of a knowledge item k. The range of this parameter is between 0 (i.e., completely irrelevant) and 1 (maximum importance). As most other parameters, too, *importance* depends on the agent in question and time. Hence, we write $\mathrm{Imp}(\mathcal{A}, k, t)$ for the *importance* an agent $\mathcal{A}$ assigns to a knowledge item k at time t. The *importance* parameter thus reflects an agent's point of view at a particular time which may differ significantly from the 'true' importance. The process of determining the *importance* of a knowledge item can be based on the agent's planning or risk management component (cf. [16] for details).

By *confidence* we mean an agent's degree of certainty about the truth and precision of an knowledge item. This parameter relates to both agents involved in the knowledge transfer and to the actually obtained knowledge item k' which may be different from k. *Confidence* may change in time, and its range is between -1 (meaning that the knowledge item is certainly wrong) and 1 (certainly true). A *confidence* of 0 means that the agent is maximally uncertain about the truth of the knowledge item k'; strictly speaking, a knowledge item with a *confidence* value of 0 does not contain any subjective information, at all. Notice, that the *confidence* parameter only reflects the knowledge consumer's point of view, which may be different from a degree of certainty the knowledge provider agent would assign to the same knowledge item.

The *cost* parameter determines the maximum cost an agent is able and willing to accept for obtaining a knowledge item. Since *cost*, again, depends on agent and time, we write $\mathrm{Cost}(\mathcal{A}, k, t)$. This parameter includes costs arising in the communication process and possible costs to obtain k as payment to the knowledge provider or knowledge brokers. The maximum accepted costs are closely related to k's *importance* and the agent's budget. In general, the accepted cost do not correspond to the price actually communicated to the provider.

A successful knowledge transfer presupposes that the knowledge item intended by the knowledge consumer agent is, in principle, available. Hence, it is required that an agent assumes that there is a non-zero probability to obtain the intended item. This probability is given by the *availability* parameter. A zero availability, $\mathrm{Avail}(\mathcal{A}, k, t) = 0$, means that the agent does not believe there to be any chance to obtain k at time t and, hence, will not make any further attempt into that direction. Availability of knowledge is based on prior experiences and background knowledge. It is used, for example, in deciding which knowledge items should be acquired (in case there are choices).

$\mathrm{Sim}(k, k')$ denotes the *similarity* of two items of knowledge k and k' to compare the intended answer with the one actually obtained. The value ranges from 0 (no similarity) to 1 (exact match). The obtained item k' may differ in terms of integrity and accuracy. Integrity concerns missing knowledge, whereas accuracy concerns deviations, e.g., spatial, temporal, or precision of measurement. The consumer needs to evaluate kind and scale of a potential deviation in order to plan and execute appropriate actions (intentions) to finally get the knowledge needed. Similarity should be calculated based on information provided by the ontology, e.g., information on deviations and partonomies of spatial concepts.

After a completed knowledge transfer, an agent determines how successful the transfer has been, i.e., its (net) *value*. This parameter depends on the initial *importance* of k (the higher the initial importance, the higher is its *value*), the similarity of intended and actually obtained knowledge (divergence decreases the *value*), and *cost* (the higher the *cost*, the lower is the *value*). The *value* of a knowledge transfer will affect the future behavior of an agent. Successful knowledge transactions with a particular provider agent, for example, will strengthen the connection between the involved agents and increase the likelihood of future transactions between them.

3.2.2 Provider Parameters

Similar to the knowledge consumer role, the role of a knowledge provider incorporates multiple decisions during the transfer process which are characterized by a set of decision parameters to achieve rational behavior. These parameters may be engaged in decisions that determine whether the provider is willing to transfer knowledge, at all, or which transfer conditions the provider will propose and accept.

The proposed distributed knowledge management framework does also consider agents being in competition or just belonging to different organizations. Thus, a provider agent needs to deliberate whether a requested information may be propagated to some other agent or not. This *confidentiality* parameter is either defined by an explicit, predefined classification of the requested type or item of knowledge or may be determined by an intelligent estimation of the possible impact this knowledge may have on the providing agent and its organization if once revealed. *Confidentiality* is always specified w.r.t. an (agent) group of interest.

If the requested knowledge item is classified the provider agent will refuse to perform the answer action, except the asking agent has a sufficient security clearance which is organization-dependent. If the requested knowledge is considered basically confidential to some minor extent the provider's willingness to answer a given query strongly depends on the asking agent. This decision is influenced by the *trust* parameter. This parameter ranges from -1 to 1 and describes whether the consumer agent is supposed to comply with a non-disclosure agreement for the requested knowledge item. A trust value of 0 is neutral, i.e., the provider does not know anything about the consumer's trustworthiness.

Irrespective of confidentiality, trust, and transfer cost, an agent may have the disposition to agree to a knowledge transfer due to a social relation to the consumer agent. In this case, a transfer is motivated by a common organizational background, a current or past cooperation, or the aim to initiate new (long-term) cooperations and to increase mutual trust (cf. [1]). The *affinity* parameter describes this disposition w.r.t. a specific agent and time. The parameter ranges from 0 (minimum affinity) to 1 (maximum). A high *affinity* decreases the minimum accepted price. If *affinity* is 1 the price is 0, i.e., the knowledge is provided as a gift.

Because the consumer agent may demand for a minimum confidence of the provided answer the provider agent has to evaluate its own *confidence* or certainty for that answer (cf. consumer's *confidence* parameter). Thus, this value must not fall below the personal confidence assured in the provider's transfer proposal. If the consumer's requested minimum *confidence* is higher than the one affirmed by the provider the latter will refuse to agree to the transfer.

Whether the provider agrees to a knowledge transfer and under which conditions (minimum accepted price, response time) also depends on the expected expenses arising due to the transfer. This is represented by the provider's *cost* parameter. It may include a temporal and financial dimension consisting of, e.g., communication costs and reasoning costs.

If the provider is in general willing to answer an agent's query it determines the minimum accepted *price* for this service. The price is determined by the common value (if any), the provider's private value, the expected transfer *cost*, and the *affinity* to the consumer agent. The minimum accepted price, of course, may and in general will differ from the *communicated* price.

In section 4 we will give examples for the complex interaction of the decision parameters in a logistic scenario.

4 Case Study

Consider a scenario in which a shipping company manages the shipping, intermediate storage, and distribution of paper rolls. The paper is produced by paper mills in North America, Sweden, or Russia and sold to newspapers, publishers, and manufacturers of paper products in Europe. In order to help inventory management as well as to reduce the price of paper (e.g., through high volume discounts), the shipping company combines and brokers orders from the consumers to the manufacturers.

4.1 Characteristics

Each order typically includes the number of desired rolls, the delivery date (including possible late penalties) and for each roll, the required dimensions and quality (weight and purity) of the paper. To fulfill an order, the shipper locates the appropriate paper rolls in his distribution centers, preferably the one(s) closest to the buyer. Alternatively, the shipper brokers it to one or more of the paper mills if not enough rolls are available from the distribution centers. In either case, the rolls are shipped to the buyer via ship, rail, or truck or a combination thereof.

What makes this scenario interesting from a logistics point of view is the fact that despite their weight (a roll typically weighs between 400 and 1400 kg), paper rolls are very sensitive to shock, temperature changes, and moisture, and thus require special handling and care during loading and transport. For example, an accidental scrape by one of the forks from a fork lift during unloading at the dock can easily tear several inches of paper on a roll. In the best case, the damage can be controlled by unrolling and discarding the torn layers. In the worst case, the contact has caused the paper to misalign on the core of the roll. This renders the roll unusable for a high-speed printing press which unrolls paper at speeds in excess of 200 km/h during the printing process. Other problems include water damage caused by rain (e.g., during loading/unloading) or excessive moisture in the storage rooms (e.g., as a result of a sudden temperature change).

Considering that the cost of a roll ranges from € 1300 to € 2000, that delivery schedules are specified down to the desired hour of the day, and that paper rolls have to be handled several times on their way from the mill to the consumer, our scenario represents a very challenging transportation problem that requires careful planning and on-the-fly re-planning. For example, in case of a damaged paper roll, the shipper needs to decide whether to sell the roll at a reduced price to the intended recipient or to a new recipient (who has to be identified first) who uses less sophisticated printing presses.

If these processes are planned and executed autonomously by multiple intelligent agents they obviously need a lot of up-to-date knowledge on general properties and status of, e.g., paper rolls, schedules, used loading equipments, customers and their printing machines, the local weather situation just to name a few. In addition, many decisions are made based on incomplete knowledge, for example, whether or not a roll sustained damage during transport even though no visible marks exist[2]. Furthermore, many decisions require

[2]There are plans to outfit rolls with sensors that can detect certain damage during transport and store the information for later usage.

communication and possibly negotiations among customer, buyer and possibly the manufacturer, for example, to establish a new price a damaged roll or a new delivery time for a shipment that cannot be unloaded due to bad weather.

4.2 Applying the Framework

Let us clarify the role concept and its relevance to knowledge management using a simple example involving two roles, a *knowledge consumer role* and a *knowledge provider role*. Let us further assume that items of knowledge (k, k', etc.) are represented as definite clauses, ignoring the fact that a multi-modal logic might be more appropriate to formalize the roles. Moreover, $B(\mathcal{A}, t)$ and $I(\mathcal{A}, t)$, representing *beliefs* and *intentions* respectively, are finite sets of clauses associated with an agent $\mathcal{A}$ at time t. In the context of our scenario $\mathcal{A}$ could represent the loading/unloading foreman on the dock whose set of beliefs B during unloading of paper rolls from a ship on the 12^{th} of Dec. could include items k such as "the humidity is low and current temperature is 2°C" and one of his intentions i may be to "unload all paper rolls before 5pm." Another intention could be to "identify all rolls that do not meet the stringent quality requirements of the recipient before the rolls leave the dock." For the sake of simplicity we assume a discrete time line and ignore spatial and other parameters of the agent's environment.

As mentioned above, the knowledge consumer role presupposes that $\mathcal{A}$ intends to add k to the set of its beliefs, where k is a fully instantiated clause subsumed by another clause q, the *query*. In a knowledge transfer, k' is part of an informative communicative act directed to $\mathcal{A}$ by some other agent $\mathcal{B}$, which in this situation executes the role of a *knowledge provider*.

Continuing the example, the dock agent $\mathcal{A}$ is the knowledge consumer who would like to add accurate knowledge about the status of each paper roll that is being unloaded to its set of beliefs (presumably to improve its decision-making when identifying damaged rolls). In our example, this knowledge could be provided by sensors which are attached to each paper roll and monitor parameters such as temperature, humidity but also the occurrence of shocks or any kind of jarring that occurs during transport[3]. Each sensor agent $\mathcal{B}$ attached to a paper roll assumes the role of a knowledge provider which can be queried during unloading by the dock agent. Note that sensors measuring the condition of a paper roll are important knowledge providers since even small tears or scrapes that leave no visible marks can render a roll useless to some printing companies. Thus, the dock agent will favor the sensor data coming from the roll sensor (referred to as k' above) over its own beliefs formed as a result of a visual inspection (assuming the sensors have been properly calibrated).

In the simplest case, k is identical to k', i.e., the sensor data from agent $\mathcal{B}$ provides accurate readings about the status of a paper roll. However, since k and k' can differ (e.g., k' is empty or contains inaccurate data), we need the similarity measure $\mathrm{Sim}(k, k')$ in order to be able to estimate $\mathrm{Imp}(k')$ on the basis of the initial $\mathrm{Imp}(k)$.

In the case of the sensor agent attached to a paper roll, mechanical failure or calibration problems are the most likely reasons for inaccurate or inconsistent knowledge k'. Regular calibration would therefore allow for higher confidence values. On the other hand, if one considers a scenario in which a truck is providing traffic updates to another truck competing for the same business, confidence of k' might be low.

Now let us additionally assume, that the agent has an intention which tells it to maintain the intactness of paper rolls during unloading. It furthermore knows that water will damage the rolls and it beliefs k_4 = "Heavy rain during the unloading process". Following our risk management approach presented in [16] it can calculate from the evidences in

[3]We know of at least one company who is experimenting with RFID and sensor technologies to monitor the condition of paper rolls during transport.

its knowledge base, that k_4 has an ignorance factor of 0.75 which is too high given the importance of the intention in question. The agent therefore derives a need for an accurate short-term weather forecast.

Obtaining the needed weather information again is the task of knowledge management. It involves the ramp agent $\mathcal{A}$ in the role of a *knowledge consumer* and a weather service agent, $\mathcal{A}_w\mathcal{A}_{w2}$, in the role of the *knowledge provider*

5 Implementing Distributed Knowledge Management

Our proposed framework for distributed knowledge management allows for multiple implementation strategies in multiagent systems. It is an explicit goal of our project to evaluate different strategies in autonomous logistic processes including knowledge management. Nevertheless, the analytic approach presented here implies some implementation characteristics we consider as necessary or at least as important quality criteria in our domain.

In order to provide a platform and evaluation testbed for implementation we developed a distributed multiagent system for simulation of logistic scenarios. This simulation system is based on the FIPA agent platform JADE [2]. For system configuration there is a domain description formulated in the W3C Web Ontology Language (OWL) whereupon the logistic scenario is defined. The scenario primarily consists of the multi-modal transportation network of typed vertices and edges, sources and sinks for goods, trans-shipment centers, the involved means of transport (trucks, ships, trains) and transportation containers. An additional XML configuration maps instances of the scenario ontology onto software agents. For example, agents could model packages to be shipped as well as trucks, that want to maximize their utilization. The platform also provides a programming interface to share knowledge among agents based on the domain ontology. Queries are posed in the W3C query language SPARQL.

In the current implementation strategy a role is realized as an agent behavior based on the mechanism provided by JADE. The behavior implements the parameter-based decision process presented in section 3.2. An agent assumes a specific role, i.e., executes the corresponding behavior, either if it has an activating internal state (e.g., need for additional knowledge for decision support) or if it is involved in a KM-related communication started by another agent. Each interacting external role pair is specified as a FIPA interaction protocol. Internal roles, i.e., those roles that are designed for sub-system interaction or knowledge base manipulation within the agent (e.g., *knowledge acquisition* and *maintenance*), provide local Java interfaces to avoid unnecessary FIPA message handling.

6 Related Research

According to Dieng-Kuntz and Matta [8] "Knowledge Management (KM) [...] aims at capturing explicit and tacit knowledge [...] in order to facilitate its access, sharing out and reuse." This rather organization-centered view can be applied to information technology (IT) as supplementary technology (cf. e.g. [18]) as well as to KM within pure IT driven systems like the autonomous logistic scenario we propose in this paper.

Agent-based or agent-mediated knowledge management (AMKM, cf. [30]) is a relatively young but currently very active field of research. Van Elst et al. [31] give a comprehensive overview of approaches, that use agent concepts for knowledge management. They hereby distinguish three areas: single agent systems, homogeneous MAS, and heterogeneous or society-oriented MAS. Single agent approaches to KM usually are personal assistants like the well-known seminal works by Maes [17] and Lieberman [15], the anticipatory knowledge mediator "Watson" [6], and others. Nabeth et al. [19] explore how cognitive agents can be used to design systems that implement their vision of knowledge management and that in particular support the knowledge management processes in social, organizational and individual dimensions.

Applying the peer-to-peer (P2P) paradigm to personal information assistants (cf. [28]) gradually leads over to multiagent approaches, where Edutella [20], DIAMS [7], and relatives are mainly collaborative and not necessarily designed as agent platforms. The multiagent platform FRODO aims at building a formal, logic-based organizational memory framework, implemented by an Intranet-enabled agent platform [29; 30]. The SWF project [25] uses an ontology reasoning capable multiagent framework for semantic web retrieval and traversal.

Reasoning with multiple ontologies connected by semantic mappings is a problem present in many distributed KM approaches. Serafini and Tamilin [23] use a P2P architecture to define a sound and complete algorithm for global subsumptions based on local knowledge. Borgida and Serafini [3] investigate the issue of integration of information from multiple sources in a co-operative information system. They propose a distributed description logic to solve a problem also seen in our presented work.

In the logistics domain several MAS approaches have been described in the literature (e.g., [27]). Hofmann et al. [12] aim at replacing conventional tracking and tracing in the logistics domain based on sending (i.e., pushing) EDIFACT messages by an agent-based pull mechanism. Smirnov et al. [24] present a prototype of a multi-agent community implementation and a constraint-based protocol designed for the agents' negotiation in a collaborative environment.

Previous research on MAS in the logistics domain has put a strong emphasis on price negotiations and auctions. In these approaches the inter-agent communication often reduces to bidding (cf., e.g., [35]), or the internal structure is defined by a set of equations (e.g., [4]). Scholz et al. [22] apply MAS to shop floor logistics in a dynamic production scenario. It aims at flexible and optimal scheduling of production plans in a heterogeneous shop floor environment.

Our proposed approach employs deliberative agents for which Timm [26] introduces a formal model based on $\mathcal{LORA}$ [32] and $\mathcal{VSK}$ [33]. One unique characteristic of our approach to agents in knowledge management is the focus on knowledge management done *by* agents and done *for* agents at the same time. Thus, making knowledge management a secondary but just as well a constitutive function of an intelligent agent.

7 Conclusions

We envision an open system of autonomous decision makers of various kinds and origins. In our application domain autonomy means the decentralized control of autonomous logistic objects in a heterarchical structure. Following the thread of conventional approaches to knowledge management within organizations we have assumed an improvement to the situation for local decision-making by implementation of KM. Due to the open networked character of our application domain we take it for impossible to establish a single centralized knowledge management system.

Therefore, we proposed a conceptual framework for distributed knowledge management in support of autonomous processes in dynamic environments such as the presented logistics domain. Our framework assumes a multiagent infrastructure with BDI-based agents. It emphasizes the importance of knowledge and its efficient management in agent interaction as well as within one agent. We propose a role concept which covers all relevant aspects of knowledge management, including knowledge acquisition, pro-active knowledge transfer, and knowledge maintenance.

The use of roles is motivated by a twofold advantage over common agent-based knowledge management approaches. An agent incorporating different roles may partition its knowledge base accordingly and hence reduce the complexity of its reasoning task, and secondly roles enable a much clearer modeling of the agents at design time.

Our framework provides the following important benefits:

1. It integrates the operational and knowledge management levels in decision-support applications through the allocation of roles.

2. It eliminates the need for a centralized knowledge repository whereas enabling the easy integration of existing KM infrastructures.

3. The use of the different BDI tiers to organize knowledge allows for a natural mapping to the organizational, strategic, and tactical information layers that exist in the real world.

4. It supports trans-organizational collaboration and coalition forming among agents while also allowing for competitive behavior.

As such we expect that our project, when fully implemented, will not only contribute to a better understanding of the use of autonomous agents in the logistics domain but also provide new theories and algorithms for the efficient management of knowledge in large-scale multiagent systems. Other important contributions include the development of a formal representation that is powerful enough to represent agents, their roles, and the underlying knowledge, as well as an efficient implementation of agents to allow experimental validation of the accuracy, precision, and promptness of autonomous decision-making in complex and dynamic environments.

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