# Supporting Cooperative Demand Fulfilment in Supply Networks Using Autonomous Control and Multi-Agent-Systems

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**Abstract:** Today, economic value creation is typically carried out in supply networks, which are temporal coalitions of independent partners. Each partner has its own decision competencies but the common objective of value creation requires a coordinated planning of the value creating processes. We show that the common decision making process can be understood as a combination of a Multi Agent System (MAS) and decision making according to the paradigm of autonomous control. This combination is an appropriate approach to coordinate the agents in the demand fulfilment process. We extract the advantages and deficiencies of autonomously controlled MAS. Our example of transport process planning combines the advantages of autonomous decision making by the agents and of a central coordination instance. This coordination instance may intervene only if the achievement of the common objective is severely endangered.

## 1 Introduction

Today's value creation is mainly based on a strict share of labour. Specialists providing particular services act on the market instead of companies offering complete value creation chains [Sch05]. As a consequence, the fulfilment of the supply network's demand requires the formation of temporal coalitions of the specialists in order to organize the required value creation chains. These coalitions are called supply networks or supply chains.

The coordination and planning of value creation activities in supply networks come along with several additional challenges compared to more traditional value creation systems. A major driver of the need for enhanced decision support is the fact that the involved partners want to maintain their own responsibilities, i.e. they want to decide autonomously about the activities that form their contribution to the coalition. Traditional models and decision mechanisms [Hal03] for supporting the decision making fail in supply chains because these models and mechanisms explicitly exploit a centralized decision making and coordination of all activities in a coalition [HW07]. Concepts developed for centralized process planning cannot be transferred. It is necessary to integrate planning concepts into the supply chain process planning that support decentralized decision making under the common roof of the rules agreed between the supply chain partners. Although, each partner is granted the right to decide on its own about selected parts of the supply chain processes, a supervising coordinator observes the acting of the partners. In case that the individual behaviour endangers the fulfillment of the supply chain goals, the coordinator is entitled to intervene and to overrule local decisions. Thus, the process planning in a supply chain is neither central nor decentralized but somewhere in between.

Autonomous Control (AC) is a decision making paradigm developed to cope with this special kind of heterarchically organized decision making processes [HW07]. Under this paradigm, planning concepts are collected that particularly address the mix of decentralized decision competence and central behaviour control. Multi-Agent-Systems (MAS) are promising candidates to model decision processes in heterarchically organized supply networks because they explicitly address the autonomy and the specific knowledge of the different decision making units but, at the same time, they are equipped to represent the coordinating opportunities of the supply chain coordinator. Together with the paradigm of AC, MAS open new perspectives for the decision support in supply networks.

This article aims at analyzing the potentials of MAS using AC (MAS-AC) as decision making and decision coordination paradigm. By means of the example of cross-enterprise transport process planning, we analyse the appropriateness of MAS-AC in a heterarchically structured decision situation.

Section 2 surveys the process of resource allocation in supply networks and extracts the challenges in the supply network's operations planning. Section 3 introduces MAS and the paradigm of AC and proposes a classification of different types of agents in the supply network. Section 4 introduces the decision making processes in transport planning in supply networks and links them with autonomously controlled agents. Section 5 analyzes the extension of the transport planning from individual supply networks to a cooperation of several networks. The cooperation extends the dispatching decision to the further option of so called operational transport collaboration.

## 2 Cooperation in Supply Networks: Concepts and Deficiencies

The acting participants in supply network-based value creation are depicted in Fig. 1. Several customers specify their demand of products provided by the supply network towards the supply network's coordinator. This coordinator derives the supply network's orders from the customer's demand. The supply network's orders are then to be fulfilled by the coalition partners, the so called service agencies. Each service agency offers a specific contribution to the supply network's products, i.e. a production service agency offers to produce semi-finished or finished goods and a storage service agency manages a warehouse. The task of generating supply network orders and their assignment to service agencies is referred to as *network capacity disposition*. The service agency receives the supply network orders and derives resource requests. Each generated request is then assigned to an appropriate resource in so called *service agency resource dispatching*. The

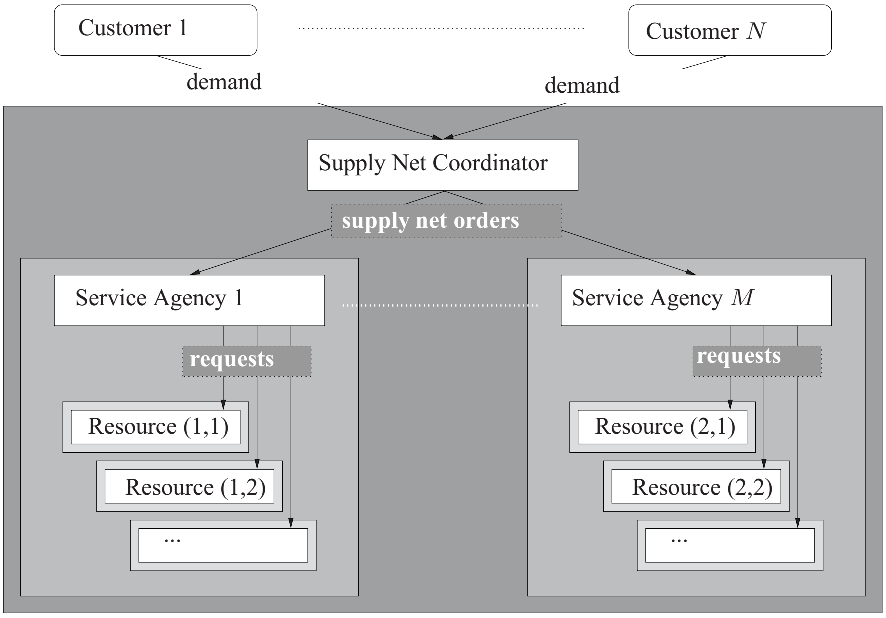


Figure 1: Semi-hierarchical structure of a supply network

service agency then fulfils the received requests.

The provision of resource capacity by the service agencies in response to a coordinator's call for resources is regulated in contracts agreed for a fixed period between the coalition's leader (the coordinator) and the participants (the service agencies). Incentives to be given to the service agencies to contribute the service agencies expenditures are fixed in the contracts.

The previously described stepwise allocation of resources in the supply network induces a natural kind of hierarchy in the supply network. The coordinator has global knowledge about demand and available service agents (depicted by the dark-grey shaded area surrounding all agents in Fig. 1). A service agency only knows about the orders received from the coordinator (depicted by the middle-grey shaded area surrounding the service and resource agents). Similarly, an information asymmetry is observed for the relationship between the service agency and the resource representative (the small, light-grey shaded area around it represents the knowledge of the resource representative). The service agency knows about the overall order(s) but the resource representative (e.g., a machine operator or a truck driver) only knows about the requests assigned to this resource.

Hierarchy in the traditional sense cannot be found in the supply network's structure. A superior actor (i.e. the coordinator) cannot intervene directly into the dispatching decisions of the subordinate service agencies. This fact is mainly based on the desire of each service agency to maintain its organizational and economic independence. Considering the differently coloured areas in Fig. 1, we can describe this independence as *areas of* *autonomy* as follows. Each coalition member can only influence (and sometimes even perceive) what happens in the area painted in its own colour. Thus, the supply network's coordinator knows only about the dark-grey shaded part of the supply network. A service agency knows only about the middle-grey shaded part and a resource representative can only recognize and understand information arising and affecting the light-grey shaded part of the supply network.

As a consequence, conflicts and mistrust between the coalition's partners occur from the aforementioned information asymmetry and endanger the efficiency of the supply network's business operation. The impacts of these disturbances in the cooperation between superior coalition members (the principal) and subordinate coalition members (the agents) are subject of the principal-agent-theory [Els91].

Kaluza et al. [KDM03] apply the principal-agent-theory to coordination and adjustment problems in supply chain and supply network scenarios. They point out two major sources of information asymmetry:

- The principal does not know how the agents will react after they have been instructed to fulfil a certain order (*hidden action*).
- The principal is not informed about all objectives of the agents when making a decision (*hidden intention*).

In a supply network setting we have two principal-agent interfaces. At first, the supply network's coordinator acts as the principal towards the service agencies who act as agents arranging the fulfilment of the supply network's orders. Secondly, a service agency plays the role of the principal towards the resources. In both principal-agent relations, mistrust and conflicts prevent the identification and realization of common decisions that lead to so-called pareto-optima representing the disposition or dispatching decisions that provide non-dominated solutions to the benefit of both, the principal and the agents.

The introduced supply network coalition represents some kind of vertical integration of (partially) autonomous decision making units. However, horizontal integration is also relevant in value creation. Unpredicted capacity-shortage of the resources endangers the performance of the supply network. In order to ensure that the supply network's demand is fulfilled to the customer's satisfaction despite of capacity shortcomings, external resources belonging to other supply networks are incorporated in the order fulfilment.

The coordination of decisions in a coalition is a quite sophisticated challenge because the autonomous areas of the coalition members have to be respected. If resources from another supply network have to be included into the value creation activities, the challenge becomes even more complicated. Coordination methods can be classified with respect to the decision making instances of centralized and decentralized control. Centralized control assumes a central planning instance with global knowledge and decision power. Decentralized control in contrast describes a system consisting of entities that decide independently and aim at optimizing their own objectives. To our understanding, both, centralized and decentralized control, are opposite elements on a continuum with realizations of planning systems being placed along this continuum. Examples for pure centralized control are found in the previously mentioned traditional models [Hal03], and an example of pure decentralized control is provided by [FMP96].

Fischer et al. [FMP96] do in fact describe a MAS transport system, which is similar to the one we will introduce in Section 5. However, their approach is entirely decentralized with no central control instance and focuses on the technical implementation of the MAS. We, in contrast, use a central control instance capable of intervention in case of performance collapses. Further, Fischer et al. grant the right to decide on order acceptance and route planning to individual trucks. Those rights are limited to the maximum of route planning in our approach since we believe that the organisational change required for the approach of Fischer et al. is not feasible. The intention of our approach is a supporting system preparing and recommending decisions to the human decision makers. As such our approach is located in the continuum between centralized and decentralized control.

AC is discussed as alternative to central planning systems in logistics systems. The basic idea behind AC is that due to their size, complexity and organisational restrictions the central planning of logistics systems cannot be executed any more. The definition of AC is then as follows.

> Autonomous control describes processes of decentralized decision-making in heterarchical structures. It presumes interacting elements in non-deterministic systems, which possess the capability and possibility to render decisions. The objective of autonomous control is the achievement of increased robustness and positive emergence of the total system due to distributed and flexible coping with dynamics and complexity [HW07].

Decentralized decision-making thereby implies that the system's elements, such as service or resource agents, have decision power and make those decisions independent of each other. Being responsible for those decisions, the element is said to be autonomous. However, autonomy does not imply economic independence since the elements form a larger system through their interaction having a joint purpose such as the operation of the supply network. In Fig 1, this is represented by the autonomous areas of superior elements including the smaller autonomous areas of subordinates. The system then changes with the decisions of its autonomous elements which can be made at any time as reaction to environmental or system internal changes. As such, the system is referred to as non-deterministic; the outcome of certain events cannot be predicted in advance. The objective of such a system is then a better reaction to the dynamic business environment compared to the situation under central, static planning; thereby ensuring robustness, i.e. future successful operation of the business.

As such, the concept of AC refers to a decentralized planning system. In contrast to centralized control, top-down planning cannot be found in systems with decentralized control. Thus, an alignment of the autonomous elements' objectives to the overall objectives of the system cannot be guaranteed. To overcome this impediment, we suggest a system including an instance that may influence the planning of the autonomous agents in order to rectify the overall situation. As such, our system moves back from pure decentralization and remains in the continuum between centralized and decentralized control.

## 3 Autonomous Control and Multi-Agent-Systems

The description of a system and its elements is very close to the idea of MAS in information technologies. MAS are analyzed in the field of Artificial Intelligence and are referred to as distributed Artificial Intelligence systems. The distribution of the problem solving capabilities for complex problems to smaller units can improve effectiveness and efficiency. This certainly contradicts classical game theoretic viewpoints, where the existence of several Nash equilibria may lead to suboptimal outcomes[Tim06].

If describing the autonomous system as MAS-AC, then the autonomous elements can also be referred to as 'agents'. When using the term agent we follow the definition of Timm et al. [TKKTG07] according to which agents are situated in an environment, act autonomously, and are able to sense and react to changes. In accordance with the definition of autonomous elements above, autonomous agents make decisions independent of each other always taking their currently perceived environment into account. As such, they act within an area of autonomy as part of a larger system. Depending on the scenario and modelling, the agents only have limited perception, i.e., they are not capable of seeing the overall system as in the theoretic case of perfect information, and as such optimize their own situation subject to uncertain environmental reactions and developments.

According to [Tim06], autonomous agents are characterized and distinguished by four features:

- **Non-deterministic action** of an agent describes the possibility that an agent might react differently in exactly the same situation occurring repeatedly.
- This may happen because of their **pro-active behaviour**, i.e. autonomous agents interpret their environment, reason about their goals and change those goals if required.
- Further, they can **communicate** and perceive each others behaviour which leads to interaction and
- **Emergence** leads to new system design and behaviour which may improve the overall solution compared to what the agents could achieve individually.

[TKKTG07] derive a mapping of levels of autonomy to agent types from [Tim06, RN03]. The authors distinguish four different types and related degrees of autonomy:

**Simple reflex agents** are best described by input-output functions, i.e. a certain external input leads to a deterministic output as specified by the agent designer. The simple reflex based agents' degree of autonomy is basically zero; they are strongly regulated. Their decisions are made in a deductive fashion, e.g. the agents act according to some simple rules. As such, the simple reflex based agents' decisions are entirely predictable. In an MAS-representation of a supply network scenario, the resources are represented by simplex reflex agents waiting for requests as input.

The **model-based reflex agents** possess an internal model that helps them to reflect on their behaviour and external developments. They base their decision on those forecasts.

Those agents do however not establish any structures that can be used again. As such, their autonomy is aligned to the operational level. On the operational level, problem solving has to be done repeatedly always based on current information and requires high communication efforts [Tim06]. The agents derive decisions inductively searching for the best possible alternative among all available alternatives. The alternatives are indirectly described by constraints representing the limits of the agents' acting. Compared to simple reflex agents, they are capable of making more complex decisions for which several alternative decisions are possible and have to be evaluated. The service agents in a supply network are model-based reflex agents. They maintain a decision model to determine their own decisions. The decision making is guided by optimizing their individual own objectives.

**Utility-based agents** can reflect on the environment and their actions and they can also assess how their actions and the environment influence each other. Further, utility-based agents evaluate possible actions by reflecting on their goals and deciding on the action that promises the highest achievement with regards to those goals. Therefore utility based agents remember past situations and consequences for their goal achievement and use this information to make decisions. This degree of autonomy is then defined as tactical with the agents deliberating on the consequences of their actions. A service agent falls into the category of utility-based agents if it is equipped with a memory and with detectors that enable it to recognize the impacts of his decisions with respect to the overall supply net but also with respect to particular resource agents.

Finally, **goal based agents** are additionally capable of reflecting on their goals and adjusting them where necessary. Goal adjustment happens on the level of strategic planning and as such goal based agents possess strategic autonomy by definition. The supply network coordinator is a representative of a goal based agent. Normally, the coordinator agent's acting is guided by the desire to maximize the efficiency of the supply network's operations ("accepting only profitable demand for network's capacity disposition"). However, the coordinator may desist temporarily from the achievement of this goal especially in temporary crises ("accepting temporarily unprofitable demand in order to keep the supply network alive").

## 4 Representation of Agents in Transport Networks

In transport networks, customers approach the company with varying transport demand. The demand ranges from more than-full-truckload jobs to less-than-truckload jobs and from packaged goods to bulk cargo. Further, the demand can be repeated frequently or can be one-off demand. However, most demand occurs on rather short notice and has to be incorporated into operative planning immediately after the demand has been accepted for completion.

The contact between the customers and the supply network is made by the transport network's coordination agent, who usually is the sales department of the freight forwarding company (Fig. 2). This coordination agent represents the highest level of the transport network. It decides on the acceptance of demand. If the coordination agent accepts a certain

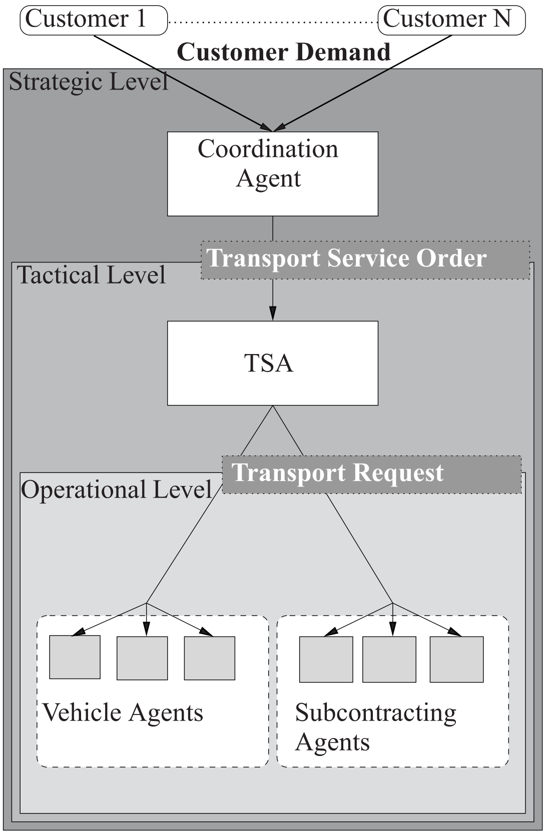


Figure 2: Structure of an Individual Transport Network

demand, it becomes responsible for the completion of it. In network capacity disposition the coordination agent then forwards the demand as transport service orders to the next level, the service agency. Since only the task of 'transport service' is considered here, only one service agency is required. We refer to this agency as Transport Service Agent (TSA). In service agency resource dispatching, the TSA receives transport service orders and converts them into executable transport requests. These transport requests are then forwarded to the resource agents. In contrast to an order, requests can be completely fulfilled by one of the resource agents.

In resource dispatching, the TSA faces two options: delegating the requests to own vehicles (vehicle agents) or to subcontractors (subcontracting agents). In order to delegate the requests, the TSA has to solve an integrated vehicle routing problem as described in [KK09] for example. By solving this problem, the TSA decides on the allocation of requests to available vehicle agents and to possible subcontracting agents. The TSA may further decide on the optimal sequence of requests for each vehicle agent that is the route to be driven. For subcontracting agents, the TSA can usually choose between agents with different features. The spectrum of subcontracting services ranges from long term contracts with trucks rented on a daily basis to single trips bought on an electronic freight exchange market. The TSA's decision has to incorporate those possible execution modes and find a solution matching the service requirements by the customers as well as the budget constraints. Budget constraints are created by the price resulting from the negotiations between the coordination agent and the customers. As such, the TSA can influence the profit margin by reducing costs.

The vehicle and subcontracting agents receive transport requests to be executed from the TSA. Relevant to those agents is the information on the loading and unloading locations, the size of the transport requests and the time windows they have to comply with. Further, the TSA might specify a sequence for execution or if not, the vehicle and subcontracting agents autonomously determine their best routes. These agents also have the autonomy to adjust their route planning in case of unforeseen events such as traffic jams [SK09].

The agents in the transport network can be classified according to the agent types of [TKKTG07] introduced in Section 3. This classification also provides the framework for the planning horizon and the extent for which individual agents make autonomous decisions. As such, the agents are assigned to the strategic, tactical and operational level and receive the respective decision power. Thus, the MAS is not entirely autonomous since a hierarchy results from the three different planning horizons: the strategic level creates a framework for both, tactical and operational level, and the tactical level creates a framework for the operational level but depends on the decisions of the superior strategic planning. These frameworks do limit the autonomy of decision making of the agents. The hierarchy is depicted in Figure 2 as arrows reaching from higher to lower levels and processing orders or requests. These orders or requests are commands that cannot be rejected or negotiated anymore.

The **coordination agent** is classified **as goal-based agent** since it operates in the market and is responsible for selling the transport network's services thereby ensuring future business operation. The coordination agent may negotiate the request fulfilment terms with customers and can adjust the transport network's offers to the market and demand situation. This means that during negotiations the coordination agent can change the goals of the entire supply network for example from cost minimal fulfilment to highest customer service.

The TSA operates within the framework created by the coordination agent. As such, it cannot adjust the systems goals anymore but can still optimize its own objectives. Those objectives might be in maximizing profit by minimizing operative cost, for example. As such, the TSA operates within tactical planning. In resource dispatching, the TSA has to decide on the splitting of transport orders into requests and then on the execution mode for all transport requests. When splitting transport orders, the TSA has to keep in mind, how the resulting requests can be aligned to the operative agents in the system. As such, the TSA has to be able to recognize the impact of its decisions on the system state and as such the **TSA** is represented **as utility-based reflex agent**.

On the operational level each transport network has several agents for physically executing the requests. Those agents might either be vehicle or subcontracting agents. The difference between both is in cost structure. Two ways for modelling those agents are thinkable and also found in practice. One option is to model these **vehicle and subcontracting agents as simple-reflex based agents** with the agents receiving their transport requests as route plans from the TSA and driving the routes as demanded by the TSA. When modelled as simple reflex agents, the vehicle and subcontracting agents possess no autonomy. The second option is, to grant the autonomy of deciding on their route to the **vehicle and subcontracting agents**, modelling them **as model-based reflex agents**. This means that the TSA only assigns a certain number of feasible transport requests to each agent and the agent decides on how to fulfil these requests. Further, the agents then have the ability to react to unforeseen events such as traffic jams and adjust their planning dynamically. However, the TSA's decision in this case is a challenge to the system-wide planning efficiency. This decision is usually based on planning feasibility with a certain number of transport requests and their specifications (such as time windows). Using model-based reflex agents on the level of operational planning might then lead to solving a similar problem twice which is certainly not desirable. As such and if modelling vehicle and subcontracting agents as model-based reflex agents this conflict has to be solved first.

Delegating decision power and responsibility to subordinates can lead the involved agents to use their information optimally. Contrarily, in central planning an information system for reporting this information to a central planner is required and the network members are required to report this information. This situation then neither induces truthful reporting nor creates trust in the central planner's abilities. The second argument for decentralized planning is the short planning horizon. Information reporting is time consuming - although supported by information systems - and the interpretation of this information, the decision making and communication by the central planner require even more time. As such, it might be beneficial to empower the subordinate transport network members by granting them larger areas of autonomy.

As such, a hierarchical structure exists in the transport networks, with the decisions of the coordination agent creating the framework for the TSA's decisions. The TSA's decisions in turn create a framework for the vehicle and subcontracting agents leaving them little to no autonomy. All decisions made in the transport supply network rely on the framework created by superior network members and on locally available information. The TSA's decision might be the best example for this, since the operational planning decision relies only on the number of requests and required capacity as specified by the coordination agent and on data related to the availability of execution agents (i.e. vehicle and subcontracting agents) and their related cost (which in turn depends on the number of requests assigned to this agent). Especially the required local information is an argument in favour of decentralized instead of centralized transport network planning. The availability of the information required by the decision makers is limited because of hidden action and intention of the respective subordinate agents.

However, each request or order processing requires feedback on completion. As such, each processing creates an informational flow pointing to the opposite direction. For the coordination agent further information is required. Since each coordination agent may decide on order acceptance and arrangements it needs information on capacity utilization, feasibility of individual orders and cost estimators. This information has to be provided by the TSA.

## 5 Extension to Transport Cooperations

Idle trips and low utilization rates in terms of truck load pose a challenge to operational planning in transport. Recent business trends to overcome those obstacles are the formation of transport cooperations and the usage of electronic freight exchange marketplaces. In research, a combination of both has been suggested in operational transport collaboration [KK06, BB08, GSV07]. In operational transport collaboration several individual transport networks cooperate with each other in their operational planning. Thus, they form larger systems.

The idea of operational transport collaboration is that freight forwarders might additionally cooperate with other freight forwarders and exchange some of the requests with the cooperation partners. The process of exchanging requests is referred to as collaboration. As such, operational transport collaboration extends the possible execution modes for the TSA's decision problem: For the classic option as described above, freight forwarders either use subcontractors or own vehicles on the operational level. Here, they may also choose the option of collaboration.

Two main benefits of this cooperation can be identified. The first is cost reduction since with limited capacities at the freight forwarders, collaboration is cheaper than using subcontractors [Sch05]. Second, the motivation is in increased capacity utilization of own vehicles, as might be done by collaborating in order to minimize idle trips. The purpose of the request re-allocation in operational transport collaboration can then be described as a levelling of capacity amongst the participating freight forwarders.

The cooperation between transport networks can be analyzed on two levels: strategic and operational. On the strategic level decisions on the formation and the design of the emerging system are made. On the operational level, only decisions within this design are made such as on which transport requests to exchange. The following discussion is limited to this operational level.

For the scenario, we assume the same structure for each freight forwarder, namely that of an individual transport network as introduced in the previous section. An exemplary cooperative transport network with the option of operational transport collaboration formed by two transport networks and including a separate collaboration system is depicted in Fig. 3. The individual transport networks are both structured as described in Section 4, with the TSAs additionally exchanging requests with each other by means of collaboration.

Each freight forwarder has a coordination agent who is again responsible for demand acquisition and negotiations with customers. The acquired demand is then forwarded to the TSA in network capacity disposition. The TSA is responsible for the service agency resource planning, that is operative transport planning. Thereby, the TSA now faces three options: assigning the transport requests to the own fleet, to subcontractors, or to the collaborative exchange mechanism. For all transport requests assigned to the own fleet the

TSA has to create operational plans such as assignment of requests to vehicle agents and route planning. We assume that all requests assigned to subcontracting agents are always accepted and fulfilled by those agents. Those transport requests assigned to the collaboration become visible to all other cooperation members and may be exchanged. We follow the assumption of [Sch05] that all requests not re-assigned are forwarded by the collaboration agent to subcontracting agents who then fulfil those requests. The collaborative exchange mechanism is represented as agent, namely the collaboration agent.

The TSAs at different freight forwarders all face the same decisions. All transport requests assigned to the collaboration agent are collected in a central pool, the market, and all information relevant for incorporating such requests into the transport planning of a freight forwarder's own fleet is revealed to all TSAs.

For the theoretical case of perfect information, the transport requests could then be traded as on a real market, i.e. with TSAs offering a certain price for the acquisition of one or several requests. However, in most cases, the information on terms negotiated with customers is private and will not be revealed. This case is referred to as informational asymmetry. The discussion here is oriented towards this second case. With informational asymmetry only limited information is reported to the collaboration agent. This information may include the loading and unloading location, the time windows and the quantity to be transported, for example. Further the submitting TSA then needs to specify the maximal remuneration for the execution of a certain transport request. The TSAs have the option to bid on transport requests in the market and the collaboration agent re-assigns the transport requests in the market to the freight forwarders. Depending on the exchange mechanism, the fulfilling freight forwarder then either receives exactly the offered remuneration or less. In this second case (as for example described in [KK06]), the remuneration is an information only known to the collaboration agent. Further, if the remuneration paid is less than originally offered, a profit of collaboration arises which is to be redistributed amongst the cooperation partners. In the example of [KK06], the cooperation partners bid their potential fulfilment cost. For the exchange, combinatorial auctions have been suggested [KK06, BB08, GSV07].

In terms of information, the TSAs have to report to the coordination agents. Further, they communicate with the collaboration system. The TSAs report available transport requests for exchange to the collaboration system and state their evaluations of such requests in the market. From the collaboration system, the TSA receive the information on transport requests available for exchange plus the results of the execution of the exchange mechanism. The decision on execution mode also involves the interaction with the collaboration agent. The TSAs have to evaluate the transport requests in the market and have to assess how their bidding and possible request acquisition renders the operative planning. As such, the area of autonomy (depicted as middle-grey shaded part in Fig. 1) of each of the TSAs is extended to areas outside the transport network.

The collaboration agent is a separate entity not integrated into the organizational structure of any of the freight forwarders. This agent is responsible for an optimal re-allocation of traded requests as well as for the determination of the transfer payments related to this exchange. The collaboration agent's decision problem thereby depends on the goals of the cooperation, such as cost minimal execution or high capacity utilization. The agent

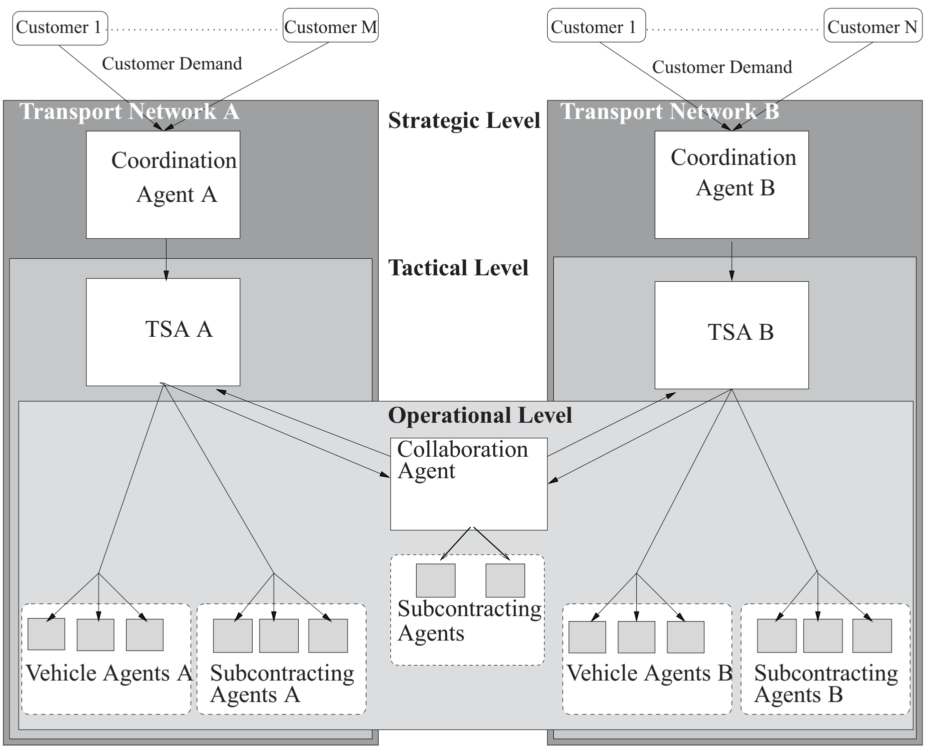


Figure 3: Structure of the exemplary cooperative transport network

therefore has to receive all relevant information from the TSAs. Since a freight forwarder's costs related to the execution of one or more of the requests in the market depend on the TSA's planning, this information is private. However, such cost data have to be used for finding an optimal re-allocation (cf. [KK06, KK09] for example). Thus, an exchange mechanism that induces truthful reporting to the collaboration agent has to be used.

The collaboration agent is also on the operational level, although it is outside of the hierarchical structure of any of the transport networks. The collaboration agent's decisions are the re-allocation of transport requests between cooperating transport networks and, if necessary, the redistribution of collaboration profits. This might seem a simple task for the example of Fig. 3 but the complexity of the re-allocation problem and of the profit sharing is increased significantly with more than two cooperating networks.

The **collaboration agent** might be modelled either **as simple reflex agent or as model-based reflex agent**. If modelled as simple reflex agent, it possesses a pre-specified allocation mechanism, with the same situation basically leading to the same redistribution and the redistribution being predictable. The benefit of such a setting is, that it is better accepted by the participants, since the mechanism is understood by everybody. However, with more cooperating transport networks, the complexity of the re-allocation problem increases. Conflicts may arise when two TSAs express exactly the same valuation for transport requests in the market. With a large number of possible transport requests, it is impossible to specify rules for solving such a conflict in advance. Granting the collaboration agent more autonomy could then mean that the agent creates different alternatives and evaluates those alternatives thereby achieving an acceptable solution to the conflict. In this case the collaboration agent is described as model-based reflex agent.

## 6 Conclusions

The discussion in the previous sections enables the conjecture that MAS are adequate to serve as a modelling base for decision processes in supply networks in general and in transport process planning in particular. AC as underlying coordination mechanism for supply network's process planning provides appropriate concepts to enable the cross-border decision making.

Transport planning has been identified as a representative example for such a decision making scenario. The main features of AC, pro-active behaviour, non-deterministic action, emergence and communication, are found in the scenario with its horizontally as well as vertically cooperating and interacting agents.

However, a certain hierarchy is retained in the transport planning scenario thus contradicting the idea of heterarchy in AC to a certain extent. This still holds for the cooperating transport networks, for which the traditional borders between networks open up. The hierarchy aims at binding the autonomous agents to a larger system, providing a joint purpose for their operation.

Further research on autonomy in transport networks will look closer into the decision making processes at individual agents. Simulations of different agent types and different underlying decision models may then aim at a more detailed evaluation of the AC paradigm.

## Acknowledgement

This research was supported by the German Research Foundation (DFG) as part of the Collaborative Research Centre 637 "Autonomous Cooperating Logistic Processes - A Paradigm Shift and its Limitations" (Subprojects B7, B9).

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