

How autonomous control can improve the
performance of logistics networks
- a simulation experiment

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Declaration

I declare that this Doctorate of Business Administration thesis is my own work and that all sources literary and electronic have been properly acknowledged as and when they occur in the body of the text.

No material in this thesis has been submitted for any other degree or professional qualification.

Tim Preinl

June 7th, 2019

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Abstract

In this thesis the application of autonomous control concepts to logistics networks is studied by means of a simulation model. This simulation model is based on an actual outbound bulk product supply network of a commodity company.

Logistics planning and operation is facing growing challenges, such as increasing complexity and distribution, driven by Megatrends such as globalisation and integration. Decentralisation through autonomous control seems to offer to a promising approach to address these challenges.

The idea for the supply network at hand is therefore, to enable individual transportation units to autonomously take operational decisions, thus shifting control of the supply network from a central to a local perspective.

In surveying the literature and the academic discussion on autonomous control in logistics, software agents are identified as a suitable and well-studied approach to implement such a concept. Therefore, a multi-agent-based simulation model of the supply network is constructed to execute and test the solution. The model is built using data based on empirical observations and offers a full-scale simulation of the actual supply network.

In the model, software agents represent the individual transportation units, allowing them to communicate and interact autonomously, effectively decentralising operational control.

A comparative simulation experiment is designed and carried out, contrasting several different control scenarios.

The simulation results obtained show, that autonomous control can positively impact the performance of this supply network. Autonomous control scenarios require a lower number of trucks to achieve full order delivery and help to increase robustness of the supply network regarding the impact of environmental factors. Additionally, the more efficient use of transportation capacity may lead to a reduction in cost for transportation. The findings are verified with an industry subject matter expert and potential barriers on the path towards implementation are described.

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Abbreviation

ABM	Agent-based modelling
ABS	Agent-based simulation
AI	Artificial intelligence
APS	Advanced planning system
CAS	Complex adaptive systems
DDD	Directive Decision Devices
DES	Discreet event simulation
GIS	Geographic information system
GPS	Global positioning system
KPI	Key performance indicator
MAS	Multi-agent simulation
MRP	Material requirement planning
ODD	Overview, design concepts and details
OR	Operations research
PDP	Pickup and delivery problem
SCM	Supply chain management
SME	Subject matter expert
SUI	System under investigation
VRP	Vehicle routing problem

1. Introduction

1.1. Research Rationale

Global megatrend drivers such as globalisation and digitalisation drive the demand for transportation services and logistics (Kunze, 2016). Globalisation and the reduction of trade barriers allow production sites to be shifted to the location offering the best conditions (Gleißner & Femerling, 2008). At the same time, economic power shifts from mature to emerging economies, creating new markets (Jain, 2006).

Digitalisation has removed physical barriers and enabled the rise of e-commerce which, along with the trend to more individualised products and on-demand delivery (Klaus & Kille, 2008), increases the number of deliveries and requires different services and concepts. Both globalisation and digitalisation drive megatrends, such as mobility which subsumes a wide range of aspects from personal, to object as well as social mobility (Urry, 2012). In the context of transport research, it addresses the rising demand as well as the challenges for transport and traffic (Handke & Jonuschat, 2013). Similarly, other megatrends, such as the connected consumer or circular economies (Boumphrey & Brehmer, 2017), show the need for a new logistics ecosystem which are highly integrated and fully digitised (Chang, West, & Hadzic, 2006).

These ubiquitous trends (Horx, 2007) lead to an expected growth of the global logistics market from 54.6 billion tons in 2015 up to 92.1 billion tons in 2024 (Transparency Market Research, 2016).

Simply increasing the capacity of one's supply network may not be feasible, as the environmental conscience of consumers is growing and the public will not willingly tolerate growing environmental pollution and traffic (Bazzan & Klügl, 2014). Aside from the negative impact on sustainability (Abbasi & Nilsson, 2012) the further increase in traffic may negatively affect reliability and cost of delivery operations (Golob & Regan, 2002).

As a result, competition is shifting to the level of supply networks, with the ability to respond rapidly and flexibly to demand, or in other words the agility of the supply chain, becoming a key differentiator, to competing in the global market (Christopher, 2016). This is a challenge as decisions regarding planning and operating the supply chain need

to be taken under a high degree of uncertainty and with incomplete information (Fischer, Chaib-Draa, Muller, Pischel, & Gerber, 1999). Additionally, as the number of actors and services increases, integration and coordination activities rise, leading to more complex supply networks (Ellinger, Beuermann, & Leisten, 2013). Established methods of planning and controlling supply chains such as combinatorial mathematical and heuristic methods seem to have reached their limit, particularly with regard to execution speed and application in practice (Skobelev, Budaev, Laruhin, Levin, & Mayorov, 2014). The growing dynamic and the high uncertainty, as not all individual constraints are known, lead to constant adaptations and re-planning.

While the above observations and challenges are true for most supply chains, they particularly affect bulk supply networks. For bulk products, transportation costs are a significant factor, often accounting for up to 25% of the product cost, caused by the relation to the typically low product price itself (UNCTAD, 2015). Additionally, return transport vehicles are often empty due to the unidirectional design of the transport network, further increasing the cost burden (Prentice, 1998).

At the same time, demand for bulk transportation is constantly rising, in line with the global bulk seaborne market, which has increased from 448 Mio. tons in 1970 to 3172 Mio. tons in 2016 (Statista, 2018). While bulk transportation is often associated with sea or train freight, Mehmman & Teuteberg (2016) point out, using an example from the German agricultural sector, that as much as 76% of bulk products are transported by lorry trucks. This combination of large quantities with a high number of individual transport vehicles while operating at low margins, shows how bulk supply networks are in need for innovative solutions, helping them to address the challenges faced in planning and controlling their operations (Kunze, 2016).

In the search for such innovative solutions, autonomous control seems to be an interesting approach. Based on concepts of self-organisation observed in nature, such as ant hills or bee hives (Hölldobler & Wilson, 2009), autonomous control offers benefits for distribution and complex systems (Prigogine, Stengers, & Prigogine, 1984). In the mobility context, autonomous control is being applied to a wide range of topics, enabling autonomous spatial mobility (Kellerman, 2018). Autonomous control for example, improves urban traffic control (Roozmond, 1999), manages traffic lights and

traffic flow at intersections (Campos, Falcone, Hult, Wymeersch, & Sjöberg, 2017) or autonomously manages the coordination of mobility on demand services and public transport (Salazar, Rossi, Schiffer, Onder, & Pavone, 2018).

Looking at logistics, autonomous control seems to provide benefits for the planning and operation of supply networks as well. One of the central aspects of autonomous control which can be brought to logistics, is the decentralisation of decision-making (Windt & Hülsmann, 2007). As decisions are shifted to the level of the individual logistical entities (Freitag, Herzog, & Scholz-Reiter, 2004), the flow of information can be simplified, removing central control instances that may act as bottlenecks (Freitag et al., 2004). Additionally, by delegating decisions to local entities, global problems are decomposed into local subproblems, thus reducing their complexity substantially (Windt, 2008). This decomposition may introduce faster problem solving to logistics planning and increase the flexibility of the supply chain (Fischer et al., 1999).

While these concepts seem promising to address the challenges faced by supply networks as described above, the question remains as to how autonomous control can improve the performance of logistics networks over conventional control methods.

1.2. Research Area

1.2.1. Simulation

To achieve the research aim stated above, a simulation experiment, which compares different control methods using a model of an actual bulk supply network, is conducted. Simulation offers a wide range of benefits, most notably the ability to address the “what if” question (Happach & Tilebein, 2015, p. 249). Further, simulation can be described as a computational laboratory (Davis, Eisenhardt, & Bingham, 2007) which allows experimentation on a computer model of a system (Pidd, 2004). This allows to safely test changes or configuration which might disrupt business operations or otherwise pose a risk to the system (Greasley, 2008). In addition, simulation allows time to be compressed by simulating “weeks, month or years in seconds of computer time” (Pidd, 2004, p. 9). Simulation further offers the flexibility to repeat experiments with different settings of control variables in the same environment (Berends & Romme, 1999). This is particularly useful when aiming to compare the effects of different configurations on a

system as in the simulation experiment at hand. Simulation and the underlying model can also serve as a communication tool (Greasley, 2008). Having visual representations of systems and results greatly contributes to comprehensibility and facilitates the communication across disciplines and with non-experts (Happach & Tilebein, 2015).

1.2.2. System Under Investigation

The simulation experiment in this study will be conducted by creating a model of a real-world supply chain. The logistics network under investigation is the outbound supply chain of a company that is producing and distributing fertiliser products. The system is a good representation of a bulk supply network as it is facing similar challenges as listed before. Transportation in the network is primarily outbound from plants to ports with no significant return transports. As most products are shipped via sea freight, the network constitutes a business-critical part of the company's supply chain. While rail service is available to one port, the majority of the transport is carried out by lorry trucks. This results in a high number of individual transportation units which operate independently. Accordingly, transportation capacity is fluctuating and information flow on available capacity and transportation status back to planners is poor. At the same time, demand is growing while transportation lead times are shrinking as competition intensifies. As a result, the cost of transportation is rising due to frequent short-term re-planning and inefficiencies, causing an operational risk for the company under study.

Taking a closer look at how planning and control of the supply network is executed, further underlines the need for innovation. Currently, most of the planning tasks are done manually on paper and spreadsheets, relying on the tacit knowledge and experience of the planner (Nonaka, 2008). Previous implementation efforts of an Advanced Planning System and similar IT systems have failed. This situation has been witnessed by the author across many production companies. Transportation is often only understood as a cost generating necessity. Outside of the major freight forwarding companies, very little system-based distribution and transportation planning is done. Where there is system support, trust in the results obtained is often not very high and results are adjusted manually afterwards.

The observed implementation gap has been described in literature as well. Bell, Bradley, Fugate, & Hazen (2014) point out, that while investing in IT solutions for supply chain management, many companies fail to benefit from their investment, creating a significant business risk. While several reasons can be identified for this, a lack of understanding and a missing process focus do play a significant role (Fawcett, Wallin, Allred, Fawcett, & Magnan, 2011).

These observations further highlight the need for innovative solutions that help to address the complexity and the challenges bulk supply networks face.

1.2.3. Software Agents and Innovation

When looking for ways to implement autonomous control, software agents seem to offer a promising approach. Software agents have been applied to a wide range of problems from the mobility domain, most notably to traffic control and transportation planning (Azevedo et al., 2016). Chen & Cheng (2010) provide a survey study of application in that area.

Looking at software agents in logistics, agents are used to represent logistical entities in a software system and act on its behalf (Schuldt, 2011). These entities can be individual delivery trucks (Fischer et al., 1999) or tug trains in production supply (Borucki, Pawlewski, & Chowanski, 2014) but also entire logistics functions such as an order agent (Mishra, Kumar, & Chan, 2012). Software agents can bring significant benefits for systems that are geographically distributed, exist in dynamic environments and where their subsystems need to interact flexibly with on another (Adler & Blue, 2002). This list of properties closely describes logistics networks and their challenges. Therefore, software agents seem to offer a promising approach to addressing planning and control of logistics networks.

While software agents have been used to address a wide range of topics, the survey studies by Davidsson, Henesey, Ramstedt, Törnquist, & Wernstedt, (2005) and Louis & Giannakis (2016) show, that the area of bulk transportation networks has not been covered. This thesis aims to close this gap by demonstrating how software agents can be applied to and used to plan and control transportation in an outbound bulk supply network on truck level.

Software agents may seem to be a dated technology in the light of the current discussion around the benefits of the internet of things and blockchain for logistics (Meinel, Gayvoronskaya, & Schnjakin, 2017). Looking at these technologies in the context of innovation helps to put them into perspective. The latest priority matrix for supply chain execution technology published by Gartner (2018) provides the necessary framework for this.

Priority Matrix for Supply Chain Execution Technologies, 2018

benefit	years to mainstream adoption			
	less than 2 years	2 to 5 years	5 to 10 years	more than 10 years
transformational			Autonomous Mobile Robots Supply Chain Execution Predictive Analytics	Autonomous Trucks Blockchain in Supply Chain Supply Chain Convergence Transportation Forecasting Ubiquitous Independent Logistics Grid Warehouse (Humanoid) Robots
high	RFID for Logistics and Transportation	Commercial UAVs (Drones) DOM PAT Track-and-Trace and Serialization	3D Printing in Supply Chain Warehouse Labor Forecasting Warehouse Resource Planning and Scheduling	
moderate		Global Logistics Visibility Information Hubs for SCM Mobile Technology — Supply Chain Execution Real-Time Dynamic Route Optimization Slotting Optimization Transportation Benchmarking Services Warehouse Control Systems	Freight Capacity Platforms (Road) Real-Time Visibility Platforms Web-Based Logistics Portals	Warehouse Execution Systems Wearables in Logistics
low		Carrier/Supplier Appointment Scheduling		

Figure 1.1 - Priority Matrix Supply Chain Execution Technology (Gartner, 2018)

The matrix indicates mainstream adoption for blockchain in logistics to be more than 10 years out. While there are interesting use cases that apply blockchain to supply chains (Gonzalez Aces & Kleeberger, 2018) or global trade (IBM & Maersk, 2018), again there is a significant implementation gap. In the same time range, the topics supply chain convergence and transport forecasting are placed. These topics best capture the issues to

be addressed in this thesis, improving planning and resource allocation in the supply network.

All these technologies are clearly radical innovations requiring new technological competences (Pisano, 2015). Putting this into context with the observed implementation gap regarding supply chain planning and control systems, both in the client example and across the industry, these innovations harbour considerable risk.

Software agents, while still being a technological innovation (Tidd, Bessant, & Pavitt, 2005), can help to incrementally improve existing processes. Such incremental or routine innovations are central in creating and capturing value (Pisano, 2015) and to sustain business success, particularly in the logistics sector (Flint, Larsson, Gammelgaard, & Mentzer, 2005).

This thesis will show how software agents can help to achieve these long-term technological goals, while realising more attainable short-term targets. By improving logistics visibility and offering an easy implementation for mobile technologies, software agents pave the road towards more ambitious supply chain technologies, narrowing the implementation gap for IT solutions in supply chain management.

1.3. Aim and Objectives

As explained in the research rationale, the aim of this study is to investigate how autonomous control can improve the performance of logistics networks when compared to conventional control methods.

To better understand the steps necessary to achieve this aim, it is helpful to break them down into individual research objectives. To understand the developments and challenges to logistics as well as the resulting need for innovative control methods, such as autonomous control, a critical investigation of the literature is required. Therefore, the first objective will be:

Objective 1: Understand the challenges of logistics networks and the need for autonomous control

Having established the need for autonomous control in logistics, an investigation by which means it can be applied, will follow. Therefore, the second research objective is:

Objective 2: Investigate how autonomous control can be applied to bulk transportation networks

To move from the theoretical realm towards implementation, an agent-based model will be created to demonstrate the application of autonomous control to the bulk truck transportation network under investigation. Therefore, the next objective is:

Objective 3: Create an agent-based simulation model of a bulk truck transportation network

To understand the effect autonomous control has on this supply network, the simulation model is then used to execute a simulation experiment comparing autonomous control with the currently used control method. Consequently, the final research objective is:

Objective 4: Conduct a simulation experiment to compare the performance of autonomous control over existing control methods

The research aim and the four objectives required to achieve it are documented in Figure 1.2. The figure will be completed with the missing information throughout the course of this thesis, portraying its underlying research structure.

Research Aim	Research Objectives	Literature Gaps	Research Questions	Results
<p>Aim: The aim is to investigate how autonomous control can improve the performance of logistics networks over conventional control methods</p>	<p>Objective 1: Understand the challenges of logistics networks and the need for autonomous control</p> <p>Objective 2: Investigate how autonomous control can be applied to bulk transportation networks</p> <p>Objective 3: Create an agent-based simulation model of a bulk truck transportation network</p> <p>Objective 4: Conduct a simulation experiment to compare the performance of autonomous control over existing control methods</p>	<p><i>Defined through literature review in chapter 2</i></p>	<p><i>Defined in chapter 2</i></p>	<p><i>Defined through the findings in chapter 6</i></p>

Figure 1.2 - Research Structure

Regarding the contribution to knowledge, this thesis demonstrates how autonomous control can improve the performance and robustness of a bulk supply network when compared to conventional control methods. As a means to do so, a comparative simulation experiment will be conducted, using an agent-based model of an actual bulk

supply network. This will provide a showcase of how autonomous control can be applied on level of individual transportation unit in a bulk supply chain using software agents. Such a showcase can help narrow the gap regarding the implementation of software in supply chain planning and operation.

This aspect is also relevant from a practical point of view, as this lack of system support was observed in the client example at hand and across the industry.

Further, practitioners will benefit from having a full-scale simulation study which can serve as a proof of concept and demonstration for other clients as well as application areas. Finally, a reusable agent-based simulation model will be available for use by other practitioners, contributing to easier access to and faster deployment of agent technology.

1.4. Methodology

The thesis applies a quantitative research design which has its roots in the author's positivistic worldview and is influenced by the research area, the author's experience as an industry consultant and opinions and views of stakeholders (Creswell, 2014).

Following this quantitative approach, an experimental research design is applied in the thesis to address the research aim and objectives.

The research method enabling the experiment is simulation. Simulation has been defined as a method in which computer software is used to model real-world processes, systems or events (Law & Kelton, 1991). Several benefits of simulation have been listed above. Most notably, the use of simulation enables the comparative study as simulation runs can be repeated in the same environment using different variables (Berends & Romme, 1999). This allows a comparison of the performance of autonomous control with the existing conventional control methods using a model of the actual supply chain.

While there are many types of simulation available, agent-based simulation has been selected for this simulation experiment for a variety of reasons. Agent-based simulation models are uniquely equipped to model decentral control structures (Siebers, Macal, Garnett, Buxton, & Pidd, 2010) such as the proposed autonomous control approach. The research problem at hand further shows a natural division into agents (Macal & North, 2014). Each truck can be represented as an agent which acts as an independent and self-directed entity (Bernhardt, 2007). This bottom up approach, allows a more natural description of the system under observation by focusing on the individual units instead

of aggregated system behaviour (Bonabeau, 2002). The individual actions of agents and their interactions may lead to emergent behaviour (Bernhardt, 2007), allowing insights into the system beyond the sum of its parts (Bonabeau, 2002).

This again shows how agent-based simulation is uniquely suited to enable the simulation experiment intended for this thesis, enabling the autonomous control approach under investigation.

1.5. Structure of the Thesis

This thesis consists of seven main chapters. This introduction provides a general overview of the thesis, laying out the research context, followed by the aims and objectives.

Chapter two explores the literature relevant to the research area and develops the research questions. The chapter starts by providing an overview of the logistics and supply chain management domain along with current challenges before looking at autonomous control in logistics, followed by an in-depth examination of software agents in logistics and gaps identified before closing with the research questions.

The research methodology followed in this thesis is addressed in chapter three. Based on the philosophical view it develops the research design, before explaining simulation as a research method and locating agent-based simulation. It closes with the description of the approach to formatting and testing this agent-based simulation model.

Chapter four is dedicated to the design of the simulation model used. It offers insight into the system under investigation before describing the model entities and the relevant process flows in detail. It closes with explications on the test process for the model and the simulation tool used.

Chapter five explains the simulation experiment, starting with an overview of the different scenarios, followed by a listing of the performance indicators, the experiment setup and the data obtained.

Chapter six contains the discussion of the findings from the simulation runs. It offers insight into limitations and validation of the model and described in detail the relevant findings from the main simulation experiment.

Chapter seven provides the conclusion of this thesis. The findings are reflected in the context of the literature and their practical relevance is evaluated. Recommendations for future research are offered.

Having established the research rational by describing the research problem and the academic context, this introduction has provided an explanation of the aims and objectives of this thesis along with the methodology chosen. As mentioned in the structure overview, the next chapter will start with a discussion of the relevant literature for this thesis.

2. Literature Review

2.1. Overview Logistics and Supply Chain Management

The following section will provide relevant definitions from the logistics domain and structure the main concepts. Section 2.1.2 will examine the primary logistical functions as necessary building blocks of any supply network in detail. The setup of supply networks and their main actors will be analysed in section 2.1.3, followed by current developments and trends impacting logistics networks and the resulting challenges.

2.1.1. Defining and Structuring Logistics

Logistics is commonly defined by its main objective, namely “providing the right quantity of the right objects in the right place at the right time in the right quality for the right price” (Jünemann, 1989, p. 18). Mallik (2010) further added “...in the right condition to the right customer” (p. 146) accounting for new demands and additional complexity is what logistics is faced with today. Together these objectives form what is often referred to as the “seven R’s” as depicted in Figure 1 (Gleißner & Femerling, 2008, p. 5).

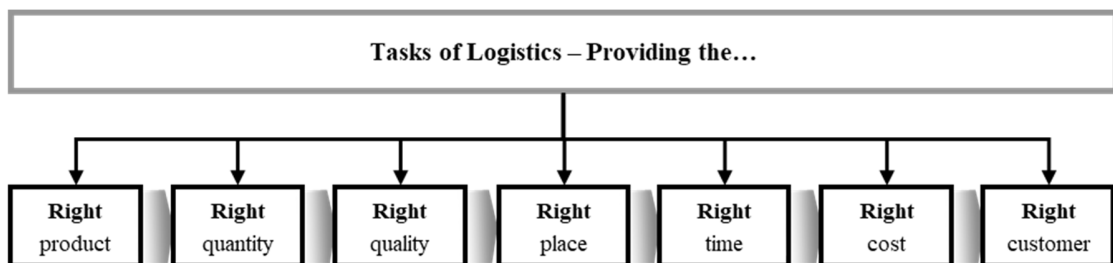


Figure 2.1 - 7 R's of logistics (Gleißner & Femerling, 2008, p. 5)

Offering another angle in defining logistics, Fleischmann (2008) states, that “logistics is the composition of logistical systems and the control of the logistical processes within them” (p. 3). Examining this definition, it is evident that it can be divided into two major parts. The first part, logistical systems can itself be categorised into macrologistics, micrologistics and metalogistics (Gleißner & Femerling, 2008). Macrologistics is concerned with the infrastructure that supports logistics such as, for example, traffic networks or waterways on a national or even global scale (Gudehus, 2012b).

Micrologistics, on the other hand, looks at the different processes and steps within the

supply chain of a particular enterprise. A company's supply chain can be subdivided into different types of logistics: procurement logistics, production logistics, distribution logistics and reverse logistics (Martin, 2006). While Fleischmann (2008) argues, that this division into subcategories is contrary to the idea of a holistic view on logistics, he admits that it can be helpful, as each category focuses on different objects and directions of material flow. For example, procurement logistics is concerned with procuring and receiving raw materials, looking at the inbound flow where in contrast, distribution logistics is concerned with outbound shipments of final products. Further, production logistics is concerned with internal movements between warehouses and the production line. Lastly reverse logistics has a different direction of movement altogether, bringing material from the customer back for recycling or refurbishment (Fernie & Sparks, 2014). The linear supply chain as described above and depicted in Figure 2 (Fleischmann, 2008, p. 5) is disappearing more and more as complex supply networks with large number of participants are formed.

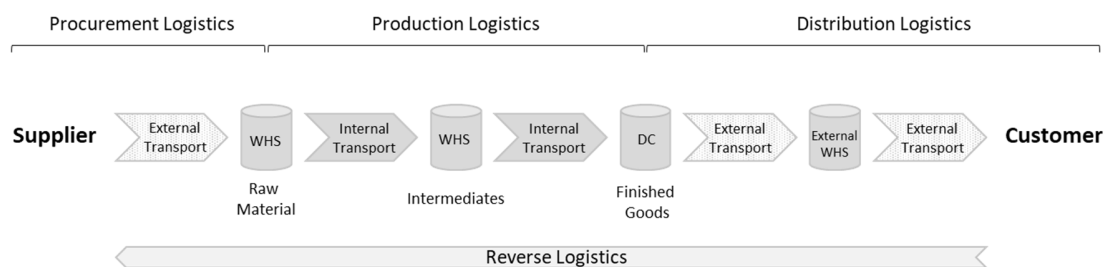


Figure 2.2- Linear supply chain adapted from (Fleischmann, 2008, p. 5)

As these supply networks reach across the borders of individual enterprises and integrate different logistical objects (types of goods), subjects (companies, clients, logistics service provider) and modes of transport (train, ship, etc.) they form what can be considered as metalogistical systems (Gleißner & Femerling, 2008).

Coming back to the definition of logistics offered above by Fleischmann, its second part focuses on control of logistical processes. Shifting the focus of logistics from executing operations to planning and controlling processes (Fleischmann, 2008), lead to the development of the term Supply Chain Management. First introduced by Oliver, Webber & others (1982) supply chain management has the task of combining and executing the relevant physical and informational transactions efficiently, to fulfil the logistical requirement at minimal cost (Gleißner & Femerling, 2008). Following Christopher

(2016), supply chain management is a wider concept than logistics, linking and coordinating processes between suppliers, customers and the organisation itself.

The aim in any case “is to ensure an optimal flow of cargo” (Schuldt, 2011, p. 13).

Within this thesis, the term cargo will focus on material logistics, leaving out persons or information logistics (Fleischmann, 2008). Within the area of material logistics, further distinction is necessary.

Firstly, again material can be classified with regard to its position within the supply chain, separating raw materials from semi-finished and finished goods corresponding to purchasing, production or distribution logistics (Aberle, 2003). Reverse logistics in relation to refurbished or scrapped goods will be mentioned here to complete this list.

The second distinction, that is commonly applied to categorise material in this context, is related to its physical properties. Material can be in a state of solid, liquid or gas having different requirements with regard to logistical operations (Martin, 2006). Looking at solid material, even further distinction between general cargo and bulk cargo can be made. General cargo is handled in pieces or packing units, whereas bulk cargo can be poured, pumped or shovelled during logistical handling. Commonly known examples are ore, coal, grain or waste (Martin, 2006). The distinct properties lead to different requirements and limitations in processing through the required logistical functions.

2.1.2. Primary Logistics Functions

Looking at the main objective of logistics stated above, another deconstruction helps to better understand the components of supply chains. To achieve the aforementioned objective, logistics carries out certain transformation operations with regard to materials, for example bridging of time and space (Schuldt, 2011). These main transformations can be represented on an operational level by logistical functions. Gudehus (2012a) identifies a set of four primary logistical functions, to which all logistical transformations can be reduced. These primary functions are:

- Transport
- Handling
- Storage
- Picking

These primary logistical functions constitute the building block of any supply chain and will therefore be examined in greater detail in the following sections.

2.1.2.1. Transport

Transport is required where supply and demand are physically distributed (Arnold, 2008) bridging the spatial distance between sources and sinks.

As this distances can vary greatly, a distinction between internal and external logistics is made (Gleißner & Femerling, 2008). Internal or intralogistics as it sometimes called, connects sources and sinks within one production site (Gudehus, 2012a), while external logistics is concerned with the transport between different physical sites and legal entities.

Transport consists of the transport object and the means of transport (Gleißner & Femerling, 2008). Means of transport can be categorised according to the mode of transport they serve, typically road, rail, air, water, and pipeline are distinguished (Lambert & Stock, 1993). Each mode of transport offers particular advantages and disadvantages. For example, air transport is considerably faster than sea transport. However due to the weight of the cargo being a limiting factor and the resulting high shipping cost, typically only critical and valuable goods are shipped via air freight (Jünemann, 1989). Comparing train and truck transport, trains can move larger quantities of material at a lower price than trucks (Vastag, 2008). They are however restricted to certain routes due to their need for tracks. Trucks on the other side, can provide door-to-door services, offering higher flexibility for the additional cost (Aberle, 2003). To combine the advantages of different modes of transportation, such as the cost-benefit of trains with the flexible last mile transport of trucks, intermodal transport could be a solution (Vahrenkamp, 2007). Looking at transport in the context of bulk supply chains, it is noteworthy that the material flow is often only unidirectional whereas in other application areas return transport means have to be considered, impacting complexity and cost (Prentice, 1998).

2.1.2.2. Handling

As transport covers the physical movement (Gleißner & Femerling, 2008) all tasks that alter the transportation object or are required to change the means of transport are subsumed as handling (ten Hompel, Sadowsky, & Beck, 2011). An example for this is unloading a container and distributing its content to different delivery trucks (Bretzke, 2010).

The handling operations involved, such as unloading, unpacking and reloading incur cost from resources needed, such as forklifts or trolleys and the personnel required (Fleischmann, 2008). Additionally, the holdup time of the transportation equipment which is being loaded or unloaded adds cost, which can be a significant factor, when for example, looking at berthing times for ships (Lun, Lai, & Cheng, 2010).

To carry out handling operations as efficiently as possible (Fleischmann, 2008), automation is increased and operations are centralised (Gudehus, 2012a). Another common approach is to standardise packaging materials and sizes to increase handling efficiency (Lange, 2008) such as using standard sea freight containers

2.1.2.3. Storage

While transport is used to overcome spatial gaps in the material flow, storage is used to bridge temporal gaps (Gleißner & Femerling, 2008). Such gaps occur whenever inbound and outbound material flows are not synchronised (Schmidt & Schneider, 2008). Even though storage is typically not seen as a value adding function, it is required for a variety of reasons (ten Hompel et al., 2011) as it provides a buffering function, helps to increase utilisation of production equipment and is essential in avoiding shortages of raw material and ensures the ability to deliver customer orders (Martin, 2006).

These storage functions are carried out in a storage system or warehouse (Schmidt & Schneider, 2008). Warehouses are typically categorised by the type of storage they provide or by their position in the supply chain. Gleißner & Femerling (2008) and ten Hompel et al., (2011) provide an extensive overview.

2.1.2.4. Picking

Picking can be defined as the task of combining goods from a provided range of articles according to defined orders (Gudehus, 2012b). It can be further understood as the interface from storage to consumption of material (ten Hompel et al., 2011). Picking describes the switch from sorted storage in the warehouse to unsorted storage and handling by creating individual shipping or sale units (Gleißner & Femerling, 2008).

A good illustration is the distribution process in a mail ordering business, where out of a wide product range, relatively small orders for individual customers have to be compiled (ten Hompel et al., 2011). However, picking is also used in internal logistical processes, such as supply of goods to production lines (Martin, 2006).

Picking involves several steps, namely the provisioning of the goods, the movement of the picker followed by the removal of goods and the disposal of the picked goods (Martin, 2006) forming a picking system.

The implementation of such a picking system varies greatly across industries and companies (Gleißner & Femerling, 2008; ten Hompel et al., 2011) as each network requires a combination of the primary logistical functions in different ways.

2.1.3. Supply Chain Setup and Actors

While the previous section offered a functional segmentation of the supply chain, when looking for influence factors driving supply network complexity, the organisational perspective has to be considered as well.

The starting point is the simplest scenario in which a company has the capability to execute all relevant primary logistical functions by itself. For example, operating the company's own warehouses and delivery trucks as required. With the trend that started in the 1990s, by focusing on a company's core competencies (Prahalad & Hamel, 2006) this traditional logistical operation model started to disappear. Even though Bretzke (2010) cites a few examples where self-supplied logistics provided economic or strategic advantages, the trend to outsource logistical activities is unbroken.

As a result, the first level of integration is to procure individual logistical services, such as transportation or warehousing services from so-called second-party logistics providers (2PL) (Gudehus, 2012b). 2PL can be defined by their ability to carry out primary

logistical function without invoking services by other companies (Scholz-Reiter, Toonen, & Windt, 2008). This definition serves as distinction to the third-party logistical providers (3PL) which represent the next level of integration. 3PL, or system providers, can take over defined parts or the complete supply chain of companies (Gudehus, 2012b). They offer a wide range of logistical services, either with their own resources or by integrating additional service providers into their network, making most 3PL providers 2PL at the same time (Vahrenkamp, 2007). Good examples of this are freight forwarding companies in retail industry, which operate the complete distribution network, from warehousing to commissioning and transportation to and from the individual stores (Bretzke, 2010). By making logistics their core competency, 3PL benefit from cost effects due to economies of scale and higher specialisation but also sector arbitrage, due to lower labour cost in the logistics sector (Gleißner & Femerling, 2008).

As differentiation and, particularly, vertical integration continue to grow, the next level of service providers, named 4PL or lead logistics service providers can be identified (Klaus & Kille, 2008). 4PL are typically described as pure integrators, not possessing any logistics resources themselves, but rather procuring and combining logistical services acquired on the market (Gudehus, 2012b). While the integration can be observed, the term 4PL is discussed somewhat controversial. In practice, many companies claiming to be 4PL are often well established 3PL companies, owning logistical resources and offering additional services. Similarly, in literature, Scholz-Reiter et al., (2008) note that serving customers without owning logistical resources may become a challenge, particularly with regard to the strategic design and leadership of a supply chain. Additionally, Gudehus (2012b) doubts the logistics competence of companies that do not offer any logistical services themselves and have no experience on an operational level.

Nevertheless, the continued differentiation and the growing demand for integration clearly illustrate the increasing complexity within supply networks highlighting the need for advanced control methods. This is further aggravated by the trends and developments discussed in the following section.

2.1.4. Current Developments and Underlying Trends in Logistics

The increase in number of participants in modern supply chains and the resulting demand for integration as described above, can be considered a result of certain effects or trends affecting supply networks. Klaus & Kille (2008) identified a total of eight megatrends, four of which affect the demand for logistics. They overlap to a considerable extent with a list of effects proposed by Aberle (2003) and will be evaluated in detail below.

The first megatrend is the ongoing globalisation which allows companies to build global production and value-adding networks by allocating production steps freely to locations with the best conditions (Gleißner & Femerling, 2008; Klaus & Kille, 2008). This, together with easier access to customers in foreign markets, leads to an increase in demand for transportation as supply chains are spread out across the globe. Aberle (2003) describes this as integration effect and cites the continuing market expansion in the European Union as an example of the increase in logistical demand due to economic integration. To address this increase in complexity and dynamics new approaches and technologies for logistics are required (Fischer et al., 1999).

The second megatrend affecting logistics, is the shift to a post-industrial society (Klaus & Kille, 2008). This shift entails a change in type and properties of goods consumed and can therefore also be described as goods structure effect (Aberle, 2003). In industrial societies there is a high demand for bulk transports of raw materials driven by mass production. These transports could be well served with train or inland waterway moving large quantities of similar goods. With increasing demand for individualisation served by mass customisation and the shift from a vendor to a buyer market, the number of shipments increases rapidly while volumes per shipment decline (ten Hompel et al., 2011). This new demand structure requires different logistical capabilities which lead to a shift from bulk freight transports towards parcel and express services (Vahrenkamp, 2007).

The third observed megatrend can be described as on-demand logistics (Klaus & Kille, 2008) or simply as logistics effect (Aberle, 2003). It describes a rising expectation of the availability of products and a decreasing tolerance for lead times. It goes hand in hand with the aforementioned trend of mass customisation. Customers demand individual

products and expect them to be available right away. To be successful in such market conditions, companies must show what is described as a temporary advantage (Fine, 2010). To achieve this advantage, more flexible logistics processes and a better coordination of logistical activities are key. In a way, one might say that the high availability and quality of logistical services today create additional demand for logistics (Schuldt, 2011).

Concerning the fourth trend, the previously mentioned authors take different points of view. Abele (2003) describes a substitution effect, due to an ongoing individualisation of transports, which leads to a shift in the transport modal split. Aside from the increase of road freight traffic, due to the aforementioned good structure effect, it can be observed that transports which were previously carried out by train or barge are increasingly switched to truck transports as well. This can be attributed to the particular properties associated with road freight traffic, namely flexibility and end-to-end transport capabilities (Gleißner & Femerling, 2008). The down side to road transportation, namely the negative environmental impact (Eisenkopf, 2008) is at the centre of the fourth megatrend described by Klaus & Kille (2008).

These authors describe the increasing environmental awareness as the fourth megatrend which impacts logistics (Klaus & Kille, 2008). With an growing public awareness around environmental issues, increasing pollution and traffic caused by logistics will not be tolerated by the public anymore, requiring logistics to provide new solution approaches to, for example city logistics (Wittenbrink, 1995) or last mile deliveries. At the same time, this situation offers new opportunities as recycling businesses and closed loop supply chains require elaborate logistical solutions, further driving demand and complexity.

In summary, all these factors increase the challenges faced by supply networks and logistics operations.

2.1.5. Resulting Challenges for Logistics

As Fischer et al., (1999) observe, the logistics domain is generally described as highly dynamic, as decisions often have to be made under condition in which there is a high degree of uncertainty and incompleteness. The trends described in the previous section

further aggravate these properties. Together with the increasing number of actors, they provide significant challenges to planning and controlling supply chain operations. Orchestrating the combination of the primary functions across all participants in the supply chain is vital for its success (Ellinger et al., 2013). This endeavour is, nevertheless, challenging as logistical processes typically demonstrate the following three properties (Schuldt, 2011):

- Complexity
- Dynamics
- Distribution

The impact of these properties and the limits imposed will be discussed in the following subsections.

2.1.5.1. Complexity

As previously mentioned, supply networks are increasingly complex as they consist of many actors that carry out different logistical functions. Aligning and coordinating them is a demanding task. Conventional approaches to model supply networks and to compute optimal configurations include approaches from operations research or mathematical models such as mixed integer programming (Ellinger et al., 2013). While analytical methods offer useful results, they often rely on major simplifications to account for the complexity of the problem (Nikolopoulou & Ierapetritou, 2012). Complexity in this context refers to the computational complexity of an algorithm and the computational effort required to solve it. Complexity as a property of an algorithm is measured by the relation of the input and the computational effort required under a worst-case scenario (Arora & Barak, 2009). To allow comparison they are typically assigned to complexity classes (Saake & Sattler, 2013). Commonly known complexity classes are logarithmic, quadratic, exponential or factorial complexity. A good example for logarithmic complexity is binary search. When doubling the number of entries in an array, the effort to find a given value will only increase by one iteration. For an algorithm with quadratic complexity computational effort increases quadratic, for a logarithmic algorithm however, it increases logarithmic with each input.

To understand the computational demands of complex logistics networks, it helps to look at simpler standard problems first.

For example, a classical standard logistical problem, the transport problem, deals with allocating transports to particular transport lanes between suppliers and consumers (Hitchcock, 1941). It describes a scenario where suppliers provide, and consumers demand an item, asking how to completely satisfy demand while minimising total cost. The transport problem can be solved by the simplex algorithm (Dantzig, 2016). When compared to real life logistical problems, the transportation problem is quite simply structured, placing no restrictions on delivery time and considering only a single type of goods to be delivered. However, the complexity of the simplex algorithm is exponential, meaning that by adding one more consumer the complexity rises exponentially.

Another classical logistical problem is the travelling salesman problem (Lawler, Lenstra, Kan, & Shmoys, 1985). It describes a combinatorial problem finding the optimal route through a transport network. The selected example for this problem is a salesman who must visit several customer locations and subsequently return to a home location. The question is, how to choose the order of his visits to minimise the distance travelled. Even though the question seems simple at first glance, the problem is complex due to the number of permutations of the locations being $(n - 1)$ (Applegate, Bixby, Chvatal, & Cook, 2007). This means that with each additional location the effort to solve the equations is multiplied, making this problem highly demanding regarding computational effort.

These two basic logistical problems help to gain an understanding, why mathematical solution of planning questions in logistics networks quickly reach limitations regarding complexity.

2.1.5.2. Dynamics

As described above, planning for logistical networks can be very complex and solving the required equations can be very costly in computational time. This is especially relevant as calculations for logistical processes often need to be carried out frequently. A good example is material requirement planning (MRP), which considers all requirements for raw materials, planning production and procurements activities for a given time

horizon. As the task is quite complex, the calculations are mostly executed overnight, providing a daily plan. This is sufficient in an optimal case; nonetheless disruptions, such as breakdowns or delays, requiring deviations from the plan, are inherent to logistical processes (Bearzotti, Salomone, & Chiotti, 2012). For example, a delay in delivery by one supplier may lead to further delays downstream in the supply chain as, in turn, announced production and delivery dates cannot be met (Bretzke, 2010). This leads to a need to reschedule e.g. execute another planning run with the changed parameters. As calculations are time consuming, such a delay would not be reflected until the next day. It can be argued that daily planning is acceptable and sufficient, however, leaving out of consideration the possibilities offered by dynamic re-planning. Or in other words, "...being competitive in logistics and transport means increasingly being able to use information more intelligently, and with less latency." (Dullaert et al., 2009, p. 10281).

To give an example, delays in delivery may be compensated by switching modes of transport, from sea to air for parts of a shipment. Or, it may be advantageous to participate in spot markets for transportation services where prices might be significantly lower, as carriers try to fill vessels prior to departure.

In short, it would be beneficial to act dynamically at any point in time on changes and opportunities within the supply network. The question as to whether this is possible is again closely connected to the complexity of logistical problems and the computational time associated. High complexity makes frequent recalculations impossible, leading to situations where results may already be obsolete the moment they are obtained, as parameters have changed during the time of calculation. Bretzke (2010) notes in this context, that not only frequency but also scope of the planning may prove challenging. This thought provides an interesting path forward, hinting that conventional, centralised planning might not be the solution for the required dynamics in logistics planning.

2.1.5.3. Distribution

As noted before, logistics networks are often widely distributed, both spatially and across legal entities (Schuldt, 2011). The main impact on supply chain control resulting from this fact, concerns the flow of information. To control such a supply chain from a

central point requires all information to be transmitted to this control instance and instructions to be distributed back. This is expensive and at times inefficient as such a central control unit poses a bottleneck and introduces a potential single point of failure. The second impact on supply chain planning and control results from distribution across legal entities. As explained above, it is common to outsource tasks within the supply chain to logistics service providers. The exchange of data across company boundaries, however, is not without challenges. Technical impacts such as communication protocols etc., may be addressed by using industry and global standards (EDIFACT, VDA etc.). More importantly though, confidential business data needs to be protected (Cardeneo, 2008), particularly when logistical service providers, offer similar services to competitors. As a consequence, not all information necessary to obtain a globally optimal result may be available for central planning and control. Bretzke (2010) even states, that to obtain a global optimum within a given supply network, it is necessary for that supply network to have sharp boundaries. Sharp boundaries in this context means, that a particular company can only pertain to a specific supply network and to no other (Schuldt, 2011). In reality there are very few supply networks with sharp boundaries as most logistics service providers serve several companies. If, nevertheless, partners in a supply chain are reluctant to share data among each other, centralised modelling and planning of that supply chain becomes effectively impossible (Stadtler, 2005). As most advanced planning systems (APS) available today require information to be centrally available, this challenge of modern logistics networks provides an opportunity for autonomous control.

2.2. Autonomous Control in Logistics

Complexity in supply networks is increasing, driven by the growing number of actors and further fuelled by the megatrends described in section 2.1.4. As a result, modern supply networks are characterised by frequent dynamic changes and high uncertainty, as not all individual constraints are known, and constant adaptations of planning are required.

These properties illustrate why simply adding transportation capacity to supply networks will not address the challenges that logistics is facing. Adding, for example, more

transportation units will further increase complexity instead of reducing it (Golob & Regan, 2002). Considering the economic, environmental and social impact that further increases of transportation capacity would entail, such as increasing traffic volume and pollution, this may be hard to justify (Bazzan & Klügl, 2014). A solution must, rather, make better use of existing capacity and infrastructure, planning and allocating resources more efficiently.

These requirements for modern logistics show the demand for new approaches to planning and controlling supply networks. Considering the properties previously outlined, more self-reliant and distributed control methods seem to offer interesting possibilities and potential.

Described in the next section are approaches to autonomous control in logistics, establishing first the necessary definitions before looking into the opportunities offered and discussing limitations.

2.2.1. Defining Autonomous Control in Logistics

Autonomous control is based on the concept of self-organisation. Self-organisation “refers to the fact that a system’s structure or organisation appears without explicit control or constraints from outside the system” (Di Marzo Serugendo et al., 2004, p. 2). Structure in a self-organising system arises, therefore, intrinsically from the interaction between local components (Bartholdi III, Eisenstein, & Lim, 2010). A popular example for self-organising systems are colonies of social insects, such as ants or bees (Hölldobler & Wilson, 2009). Autonomous control has been successfully applied in the mobility area to topics such as traffic control (Campos et al., 2017) or the coordination of mobility on demand services (Salazar et al., 2018).

Applied to logistics, self-organisation is understood as autonomous control which can be defined as: “processes of decentralised decision-making in heterarchical structures. It presumes interacting elements in non-deterministic systems which possess the capability and possibility to render decisions” (Windt & Hülsmann, 2007, p. 8).

In simpler terms, the idea behind autonomous control is to enable logistical entities to take decisions individually. Logistical entities in that context can be understood as all materials and facilities that provide or consume logistical services (Freitag et al., 2004).

Depending on the application scenario, a logistical entity can be anything from an individual sales unit, a whole container or even the provision of an entire service. According to the concept of autonomous control, every logistical entity in a supply network is responsible for achieving its individual logistical objective. To achieve this it is necessary to allow communication and cooperation between the individual entities (Hellenschmidt & Wichert, 2007). An example of this can be a sea freight container, which, based on outside conditions, determines to change its shipping route (Schuldt, 2011) or a part in production, which feeds back information on the production process to the following units (Armbruster, de Beer, Freitag, Jagalski, & Ringhofer, 2006). The definition above further states, that logistical entities interact in a heterarchical environment. That means, that no hierarchy or structure between the logistical entities has been predefined (Freitag et al., 2004) or the structure can change at runtime. Importantly, this implies that no central instance is required to control execution of the logistical tasks.

2.2.2. Opportunities through Autonomous Control

The most promising opportunity autonomous control offers for logistics, is the decentralisation of control. In a centrally controlled network, all relevant information has to be provided to the central entity that makes the decision which, in turn, has to be communicated back to the entities (Freitag et al., 2004). This does not correspond well to the distributed structures naturally found in logistical networks. Autonomous control allows passing the decision-making process to the individual logistical entities (Freitag et al., 2004). The approach follows concepts from self-organisation and can be observed in other distributed systems in nature (Prigogine et al., 1984). Decentralising control does not only make the decision process more efficient and the network more robust, it also helps to reduce complexity.

The observed increase in complexity of organisations and systems makes it “” (Fischer et al., 1999, p. 531) This holds particularly true for logistical systems and supply networks which can benefit from the “power of decentralisation” (Van Dyke Parunak, 1999, p. 379). By delegating decisions to local entities, autonomous control significantly reduce complexity by decomposing global problems into local subproblems (Windt,

2008). With a reduced number of input parameters to be considered, computational complexity of the algorithm necessary to solve the particular subproblem is greatly reduced. This reduction in computational complexity may introduce faster problem solving and the ability to react rapidly and with more flexibility to supply networks (Fischer et al., 1999).

As only local input data is considered, the distributed approach also helps to address the privacy issues mentioned above. With decisions being taken by local entities, data does not have to be distributed across the global network, thereby better addressing concerns of data privacy and confidentiality.

Finally, through decentralisation autonomous control may also help to address the increase in dynamics logistics networks face. As complexity of decisions is reduced, the time required to compute solutions also reduces, thus making more frequent re-planning feasible. This in turn helps, to address the challenges in ever more dynamic and distributed logistical networks.

The main criticism to the concept of autonomous control results from the problem decomposition. Local entities will try to find a locally optimal solution for the logistical problem they are facing, using the input parameters available to them.

Nonwithstanding, these various local optima may, in summary, not result in a globally optimal solution. This is a natural consequence of distributed decision-making (Ellinger et al., 2013). However, to address the challenges mentioned it seems reasonable to work with obtainable local optima instead of failing to find a global optimum.

2.2.3. Limitations of Autonomous Control

While the concept of passing the decision-making process to the individual logistics units (Freitag et al., 2004) seems promising from a planning and controlling point of view, the implementation still holds some challenges.

To take decisions locally, the individual logistics units need to be equipped with computing and communication functions. At first glance, this seems to be a feasible task, as technologies such as RFID are becoming cheaper and readily available (Lampe, Flörkemeier, & Haller, 2005). With computing power still following Moore's law, and doubling roughly every 18 to 24 months (Moore, 1998) the reduction in size of

microprocessors and circuit boards is digitising increasingly more areas of life, making the internet of things a reality (Bullinger & ten Hompel, 2007).

However, while these technologies can help to enable autonomous control in logistics, they are subject to technological, economical and legal limitations (Schuldt, 2011).

The most relevant technological limitation relates to power consumption. While low-power hardware designs (Flynn, Aitken, Gibbons, & Shi, 2007) have become available, energy consumption is a limiting factor for embedded systems in logistical entities. As battery development is not progressing at the same rate as processing power (Mattern, 2005), electrical energy is a scarce commodity for embedded systems. This limits processing power and operating time of such devices and also affects communication, as particularly transmitting activities consume considerable power (Kopetz, 2011).

Communication functions and protocols therefore need to be carefully tailored towards implementation scenarios, using for example, passive RFID tags, which only transmit data when activated by a receiver's magnetic field, over active, battery powered tags (Franke & Dangelmaier, 2006).

Looking at economical limitations, finding the right level of granularity (Windt, 2008) when implementing autonomous control, is most relevant. The question regarding which logistical entities need to be capable of autonomous control (Schuldt, 2011) is necessary to consider, as prices for hardware required, such as RFID transmitters, are a relevant cost factor (Franke & Dangelmaier, 2006).

Aside from cost for devices, IT infrastructure and implementation costs for software need to be considered as well (Kim & Sohn, 2009). When looking at operation cost, the aspect of how much autonomy is granted to the logistical entities should also be considered. The economic impact becomes clear when looking at the example offered by Schuldt (2011), who describes a shipping container representing an autonomous logistical entity that realises it may arrive late at its final destination. Consequently, it might consider changing its mode of transport from sea to air. However, the cost incurred with this change is significant, therefore, its autonomy may have to be restricted in this case, requiring alerting a human dispatcher first.

The question on the level of autonomy leads right to legal limitations which have to be regarded. As logistical entities are granted freedom in their decision, questions arise

whether these decisions and the resulting contracts are legally binding (Nitschke, 2006). Additionally, questions on data security and privacy need to be addressed, clarifying liability in case of misconduct (Weber & Weber, 2010).

As this section has shown, while holding much promise, the implementation of autonomous control in logistics still must overcome certain limitations.

2.3. Implementing Autonomous Control in Logistics

The question as to how concepts of autonomous control can be implemented in logistical networks links directly into the limitations described before. As there still are certain technological, economical and legal constraints to overcome, it may not be feasible to equip each logistical entity with the required hardware. However, the concepts of autonomous control still can be implemented by abstracting away from the physical devices. A promising approach seems to be software agents, that represent individual logistical entities in a software system, and act on its behalf (Schuldt, 2011).

This section provides an overview of applications of software agents in logistics, along with necessary definitions and limitations of the technology.

2.3.1. Definitions of Software Agents

There is no universally accepted definition of the term software agent as discussions in the literature show (Nwana & Wooldridge, 1997). However, there are several definitions available that offer different perspectives on what seems to define a software agent. In an early definition Bradshaw, Dutfield, Benoit, & Woolley (1997) describe agents as “objects with attitudes” (p. 382). They aim to contrast agents in their agent-based system architecture with objects from the realm of object-oriented programming in computer science. What they refer to as attitude can be understood as characteristic and properties that are attributed to the software agent. Consequently, most definitions available today describe software agents by their characteristics.

A frequently cited definition stems from Wooldridge (2009), who describes a software agent as “...a computer system that is situated in some environment, and that is capable of autonomous action in this environment in order to meet its design objectives.” (p. 21). This definition highlights autonomy as a key characteristic of an agent.

Autonomy is understood as the agent's ability to operate without direct intervention and to control its actions and internal states (Wooldridge & Jennings, 1995). Macal & North (2014) describe an agent as autonomous, when it is self-directed and functions independently in its environment. Besides autonomy, they further list modularity, sociality and conditionality as defining characteristics for software agents.

Modularity in this context means that an agent is an identifiable, discreet and self-contained entity with clear boundaries. In other words, it is clearly defined as to which agent a certain functionality or property belongs.

These discreet entities interact socially with each other, meaning they communicate, exchange information or influence one another, called sociality in this context.

The final characteristic, conditionality, refers to agents having different states that can change over time. A simple example can be an activity or loading status of a transport unit.

There are several similar definitions available, listing different characteristics or properties. Stadtler (2005), for example, describes agents as "...self-interested, autonomous, rational entities having their own objective(s) and being in charge of a certain sub-task of an overall decision problem. To solve their sub-tasks, agents have to communicate and to coordinate their decisions." (p. 584).

Adding a purpose-based view to the discussion, he describes agent as self-interested and being responsible for a certain sub-task. This definition is interesting in the context of this work, as it describes the delegation and decomposition of tasks and responsibilities to individual entities, which constitutes one of the key concepts of this thesis.

Dullaert et al., (2009) offer yet another point of view, as they list 'intelligent' along with the aforementioned key properties 'autonomous' and 'communicative' for agents (p. 10283). This additional characteristic raises the question of what intelligence in the context of software agents means and whether it is a mandatory property. To answer this, the relation of the two academic fields of multi-agent systems and artificial intelligence (AI) must be considered. To illustrate the ongoing debate on differentiating these fields, two quotes will be used. Representing the multi-agent side, Etzioni (1996) states that "Intelligent agents are ninety-nine percent computer science and one percent AI" (p. 1323). Examining this from the artificial intelligence side, Poole, Mackworth &

Goebel (1998) define computational intelligence as "...the study of the design of intelligent agents" (p.1).

The two quotes make clear that there certainly is an overlap between these two research areas, though there may be disagreement on the extent of the same. Coming back to the question on how intelligence is defined for an agent and whether it is a mandatory property, Dullaert et al., (2009) understand this as the agent having some form of 'business intelligence' (p. 10283). They cite an example of a transportation unit that knows its maximum capacity and uses that information to decide whether to accept new orders. Looking at this explanation from an AI point of view, it does not necessarily constitute intelligence. AI requires an intelligent agent to display rationality, learning and autonomy (Russell & Norvig, 2003). Following that definition, learning is a mandatory requirement for an intelligent agent. Russel et al., even question whether an agent can be really autonomous when it lacks the ability to learn and adapt its behaviour accordingly (Russell & Norvig, 2003). The author would rather follow a conditional approach as suggested by Macal & North (2014): "An agent **may** have the ability to learn and adapt its behaviours based on its experiences." (p. 9).

To summarise this section, agents are defined by their characteristics, with the most relevant being autonomy, modularity, sociality, conditionality. They are further self-interested, responsible for a particular sub task and can be intelligent.

2.3.2. Benefits of Software Agents

Software agents as described above seem to offer great potential to address a variety of research problems from computer science and beyond. They have been described by some as "the most important new paradigm for software development since object-oriented design" (Luck, 2004, p. 199).

Software agents have been applied to wide range of research domains from economics (Bookstaber, 2012) to social sciences (Smith & Conrey, 2007) and biomedical research (Folcik, An, & Orosz, 2007), and also to model air traffic controllers (Conway, 2006), to create MRP controllers (Turgay, Kubat, & Taskin, 2007) or to support crime analysis (Malleon & Birkin, 2012). Macal and North (2010) offer a broad overview of areas where software agent-based approaches have been investigated.

Even though software agents are not constrained to a certain scientific domain, agent-based solutions seem to be suitable for a distinct group of problems.

Agent-based computing seems to be particularly suited for the development of complex and distributed systems (Zambonelli & Van Dyke Parunak, 2003). This can be seen as a result of their own inherent distribution and decomposition into individual entities. The agent-based problem decomposition offers an effective way of partitioning the problem space of a complex problem (Jennings, 2001). Van Dyke Parunak (1999) further mentions, that applications which are modular, decentralised, changeable, ill-structured or complex benefit from agent technology. The property ill-structured refers to, that at the time of design of a system not all information, particularly not with regard to interfaces and information sharing between entities, is available (Davidsson et al., 2005). Such a system, where properties and connections arise out of the interaction of the individual entities is also described as showing emergent properties (Axelrod & Tesfatsion, 2006). Software agents are particularly useful in addressing the design challenges such systems present.

Taking a slightly different angle, Adler & Blue (2002) propose the following three conditions under which agent technology can significantly aid in the design and analysis of problem domains:

1. The problem domain is geographically distributed
2. The subsystems exist in a dynamic environment
3. The subsystems need to interact with each other more flexibly (p.441)

This list of properties is particularly interesting as it closely resembles the list of the challenges to logistics defined in section 2.1.5. As established there, logistics networks are often widely geographically distributed. They face growing complexity and reside in dynamically changing environments, making them an ideal candidate for agent-based solutions (Chen & Cheng, 2010).

Bazzan & Klügl (2014) see it as “well established that agent-based approaches suit traffic and transportation management” (p. 375). This can be extended to most areas of logistics as they profit similarly from the autonomy, collaboration, and reactivity of agents as well as their ability to operate without direct human intervention (Chen & Cheng, 2010). As mentioned before, the natural decomposition (Jennings, 2001) of

complex problems and the “local perspective” (Bazzan & Klügl, 2014, p. 376) to problem-solving are strong arguments for the use of agent-based solutions in logistics.

2.3.3. Limitations of Software Agents

As with any technology, certain limitations apply to software agents and their application to logistics. Similar to the criticism on autonomous control, the local perspective offered by agents Kikuchi, Rhee, & Teodorović (2002) may not contribute to reaching a global optimum. However, the author would follow Bernhardt (2007) who states, that this can be understood as a strength of and a reason to use agent technology. Being able to calculate local optima and thus gain a better understand of a system may be preferable to forever trying to approximate an impossible-to-reach global optimum. Bernhardt (2007) himself lists a few more limitations for agent-based modelling, mentioning that agent-based models may require substantial amounts of data and be computationally intensive. In terms of data, Bernhardt examines behavioural data, to explain the decisions of individuals. While the author agrees, that such data may be hard to obtain, he would argue that this holds true for any kind of model, if the same degree of accuracy is to be achieved. Regarding the computational demands, simulating large numbers of individual agents may indeed increase the calculation time required. Notwithstanding, as this thesis will show, the available computer power is, in the meantime, sufficient to model and simulate agent networks of real world scale even on desktop computers.

This last limitation ties into what Bonabeau (2002) described as finding “the right level of description” (p. 7287) for any agent-based model. When trying to identify the required level of detail to produce the results intended, available computational power may be factored into the decision.

A final limitation raised by Bernhardt (2007) addresses the emerging behaviour agents may demonstrate. In the previous section this has been described as agent intelligence (Dullaert et al., 2009) or agent learning (Russell & Norvig, 2003). These properties may lead to agents showing unplanned or unpredicted behaviour. As discussed before, whether this is desirable or not depends on the implementation scenario. Bernhardt (2007) makes the point, that agent-based models showing emergent behaviour may be

hard to validate, as pre-established rules or performance indicator may not account for such behaviour. This is indeed a factor to consider when choosing agent-based modelling and learning agents. However, this limitation, applies to the whole area of artificial intelligence and needs to be balanced against the potential insights that can be gained by intelligent agents.

2.3.4. Agents in Complex Adaptive Systems

When discussing agents and their application, the area of complex adaptive systems should be mentioned as well. Complex adaptive systems (CAS) can be defined as “systems that have large numbers of components that interact and adapt or learn” (Holland, 2006, p. 1).

CAS operations has been observed in a wide range of examples from nature such as prebiotic chemical reactions, the immune system or the flocking behaviour of animals (Gell-Mann, 1994). Meanwhile, complex adaptive theory has been applied to a wide range of research areas, ranging from economics (Tesfatsion, 2003) to organisational change (Dooley, 1997) to socio-ecology (Levin et al., 2013). Pathak, Day, Nair, Sawaya, & Kristal (2007) provide a recent overview.

Looking closer at complex adaptive systems, the components that constitution a CAS are frequently described as agents (Holland, 2006). The concept of agency in complex adaptive systems differs however from software agents, as described in the previous sections (Niazi, 2013). Complex adaptive systems are characterised by emergence, meaning that new and unexpected patterns, properties or processes emerge as the system evolve (Goldstein, 2008). This emergence is driven by the interaction of the individual components of the CAS (Gershenson & Niazi, 2013). The components or agents have the ability to change and reorganise to adapt to their surroundings (Holland, 1992). CAS may even change the boundaries of the system as they evolve by including or excluding agents (Choi, Dooley, & Rungtusanatham, 2001).

In order to enable this behaviour, agents in CAS must possess certain properties, most importantly modularity along with adaption and evolution (Holland, 2006). Modularity in this context, refers to the ability of an agent to freely recombine existing subroutines within its own set of operations to address new problems. Adaption and evolution refers

to the ability of an agent “to produce new rules that are plausible in terms of the agent’s experience” (Holland, 2006, p. 2).

Linking back to the discussion on intelligent agents in section 2.3.1, both the aforementioned properties make it evident that agents in CAS must be intelligent agents as defined by Russel & Norvig (2003). To enable the emergent properties desired on system level in a CAS, the individual agents must be able to adapt and learn.

As mentioned before, the agents used in this study are currently not equipped with learning functionality, leaving the application of complex adaptive theory for further research.

Looking at existing research in this area, supply networks can be understood as complex adaptive systems (Choi et al., 2001). Supply chain management can benefit from a complex adaptive systems perspective, particularly when taking a macro level view (Pathak et al., 2007). CAS, therefore, may, in the context of the theoretical problem of this thesis, offer an approach to applying concepts of autonomous control at the level of mobility problems, providing another opportunity for further research.

2.3.5. Literature on Agents in Logistics

2.3.5.1. Survey Studies

There seems to be agreement that the use of agent technology can bring benefits to logistics. This section will provide an overview of the research work done in that area. As a starting point, four papers offering literature surveys have been identified. The first three pertain to the traffic and transportation domain, which is closely related to logistics, particularly to the transportation functions which play a central role in this thesis. The fourth study provides an overview on agents in supply chain management. No study on agents across all logistics functions has been effected so far.

Davidsson et al., (2005) focused on logistics and freight transportation, creating a framework to organise the existing literature according to various dimensions. These dimensions include, among others, the domain, the mode of transport along with the control method and the agent attitude. This allowed several papers to be identified with a

focus on research areas relevant to this thesis, such as the transport domain and road-based traffic.

Another important criteria Davidson et al., (2005) introduced into their framework is a maturity indicator. The indicator is based on an earlier approach by Van Dyke Parunak (2000) categorising research work in the agent field with regards to its implementation status, from purely conceptual work up to actually deployed systems hinting at the significant implementation gap in this area.

The second literature survey was undertaken by Chen & Cheng (2010) focusing on the application of agent technology to traffic and transportation systems. Even though the authors indicate a split between traffic and transportation and offer chapters on both areas, there is clearly a focus on the traffic subdomain. The study provides an overview on agent-based traffic control and management systems before looking at traffic modelling and simulation. Traffic modelling and simulation includes research papers on topics such as modelling driver behaviour (Burmeister, Doormann, & Matylis, 1997), route guidance systems (Adler, Satapathy, Manikonda, Bowles, & Blue, 2005), lane-change model (Hidas, 2002, 2005), demand bus simulation (Liu, Ishida, & Sheng, 2005) or pedestrian flow (Kukla, Kerridge, Willis, & Hine, 2001).

From the transportation side, systems for roadway and railway transportation are examined. While there is some relevant work on the railway transportation side, such as transportation scheduling (Burckert, Fischer, & Vierke, 1998; Lind & Fischer, 1999) and one paper on freight train traffic management (Cuppari, Guida, Martelli, Mascardi, & Zini, 1999), when looking at the roadway transportation side, again the traffic topics dominate. The studies listed include agent-based approaches to urban traffic signal control (Chen, Chen, & Lin, 2005), bus fleet management (Belmonte, Pérez-de-la-Cruz, Triguero, & Fernández, 2005) or holistic solutions for urban public transportation management (Balbo & Pinson, 2001). The majority of the studies do not offer any relevant insight for the scope of this thesis. Aside from general ideas and concepts, there are only a few selected findings, for example different agent platforms such as the Matisim traffic simulator (MATSim, n.d.) and the AGENDA tool used by Fischer et al., (1999).

When looking at the third literature survey, a similar picture emerges. While contributing some insights to the logistics domain, the paper created by Bazzan & Klügl (2014) focuses primarily on agent-based traffic and transportation simulation. The authors divide their work into two areas, showing that agent technology can be used both for modelling and simulation as well as on the operational side, for control and management of traffic. This operational aspect is another important argument for the selection of software agents for this thesis. Bazzan & Klügel (2014) stress again, how agents are uniquely suited for modelling and simulation in the traffic area, as they inherently address topics such as emergence, spatial distribution and heterogeneous populations. The survey on traffic modelling and simulation shows how agents are used to reproduce human decision-making and behaviour such as route choice (Chmura & Pitz, 2007), intersection behaviour (Doniec, Mandiau, Piechowiak, & Espié, 2008) or traffic flow simulation (Nagel & Schreckenberg, 1992).

The survey on control and management offers some interesting ideas on distributed control and decision-making. However, the focus of the work analysed is again on the traffic domains. Concepts such as controlling traffic lights by self-organising networks (Oliveira & Bazzan, 2009) are described, moving on to collaborative driving (Desjardins, Laumônier, & Chaib-draa, 2009) where agents represent live vehicles and eventually influence them in their behaviour (Wang, 2008).

The fourth survey identified is significantly shorter. Louis & Giannakis (2016) list agent-based approaches to supply chain management. The focus of the individual studies is on strategic planning and decision making. Agents are primarily used to functionally decompose supply chains, with each agent representing one particular function (Mishra et al., 2012), such as an order agent or a scheduling agent (Fox, Barbuceanu, & Teigen, 2001). Other studies in the survey focus on collaboration and information sharing (Kwon, Im, & Lee, 2007) or price negotiations (Li & Sheng, 2011). While these studies do demonstrate the relevance and applicability of software agents to supply networks and logistics, they do not address the level of detail investigated in this thesis. Only Mattia (2012, p. 2) describes agents representing individual logistical units, calling them “Directive Decision Devices (DDD)” (p. 2) that can take decisions

autonomously on an operational level. However, no implementation or simulation is conducted, leaving room for further investigation.

The following section will examine literature related to the core research problem, allowing for a more detailed analysis on the state of research in that area.

2.3.5.2. Agents in Freight and Logistics

The transportation subdomain can be further divided into research related to transportation of humans such as public transportation and transportation of freight and cargo, with the latter one being the most relevant to address the research problem at hand.

Sandholm (1993) focused on the negotiation between agents for load assignment by an improved version of the contract net protocol. The contract net protocol is a protocol developed for the communication and negotiation between nodes in distributed problem solving such as in sensor networks (Smith, 1980). In Sandholm's (1993) implementation, agents represent delivery centres, each aiming to optimise their own delivery schedule. His contribution is to allow agents to exchange or trade orders, as their responsibility areas overlap. Sandholm (1993) is able to show that a reduction in transportation cost can be achieved by following the agent-based approach.

The focus of this research paper is clearly on the negotiation process and its implementation. Some interesting insights regarding communication between agents can be taken, as the concept of passing orders on to other agents is relevant for the simulation in this thesis as well. From an application point of view, this paper does, however, fall short, as order allocation within one delivery centre relies on static algorithms only, not making use of agent technology. While the cited constraints in computing power and the TRACONET framework were certainly valid at the time of publication, later research by, for example, Skobelev et al., (2014) was able to overcome them.

A second paper identified is by Fischer et al., (1999) describing a multi-agent simulation (MAS) approach for a road delivery scenario. These authors model a road transportation network constituted out of several shipping companies and trucks. Both companies and

trucks are implemented as agents, dynamically receiving transport orders and planning and executing transports.

This study is highly relevant as it contains several central ideas, applied to this thesis. First and foremost, it shows the general applicability of MAS for the freight transport domain and highlights the benefit of multi-agent simulation. On the design side, it presents the idea to represent trucks by individual software agents. This is done with similar intentions, as mentioned above, e.g., moving planning and scheduling from a central instance to the local entity. The result of this can be summarised as “one very complex plan is replaced by several smaller and simpler plans, allowing one to react quickly and without global re-planning to unforeseen events” (Fischer et al., 1999, p. 534).

On the implementation side, simulations are carried out for a comparatively small number of orders only, placing the focus clearly on theoretical approaches to optimisation. While the ideas presented in this paper are of valuable input and the concepts are sound, the focus on the negotiation aspect, along with a very particular software testbed consisting of AGENDA and MARS, leaves room for additional investigation.

Schuldt (2011) addresses these shortcomings by offering a comparative simulation to describe an agent-based approach to logistics. He uses software agents to represent shipping containers and selected logistical entities such as ports and warehouses. Additionally, a case study to demonstrate effectiveness of the proposed autonomous control approach is presented. The case study models the inbound supply chain of a consumer products company, representing their sea freight container-based import business from port of origin to their distribution centres.

Even though the industry and the logistical units differ from those in this thesis, the study provides significant insight into to designing and modelling a multi-agent network. Despite being an inbound supply chain, there are certain similarities such as a comparatively small number of transportation lanes and fixed logistical entities, such as ports and warehouses. At the same time, a high number of individual units frequent these transport lanes -in Schuldt's (2011) study these units are containers - in this thesis they are trucks.

As mentioned, Schuldt (2011) offers a comparison between multi-agent simulation and the current centralised process control. He shows that the agent based, autonomous control approach can perform better than the centralised human controlled approach regarding speed of decisions, reliability and adherence to logistical objectives. Schuldt (2011) proposes several advanced concepts, such as team formation between agents with similar properties which is intended to reduce coordination effort. These ideas may be relevant for future implementations of the simulation model at hand.

Looking closer at the implementation side, the papers by Hoffa & Pawlewski (2014) and Borucki, Pawlewski, & Chowanski (2014) offer relevant input. Both show how agent-based simulation (ABS) and discrete event simulation (DES) can be combined in one simulation model. While the distinct properties of these simulation types will be discussed in greater detail in section 3.4, both studies offer a new perspective on agent technology in logistics.

Hoffa & Pawlewski (2014) use agents to model disturbances in supply chains. They model both individual transportation units as agents as well as a disturbance itself. This allows the enhancement of disturbances with properties, such as the duration of a road closure or the area impacted by a thunderstorm. These disturbance agents can communicate with a truck agent to announce themselves. The remainder of the model such as the unloading and loading is modelled as a classic discrete event simulation model. While this is another interesting application of agent-based technology to logistics, aside from the representation of transportation units as agents, little more is relevant for the problem modelled in this thesis.

Borucki et al., (2014) describe a simulation model of a production supply scenario in an automotive plant. They represent tug trains that carry out replenishment deliveries to the production line as agents along with a central control agent. Control remains with the central agents which push orders to the tug trains. The tug train agents control their activities such as loading, unloading or waiting for new orders via internal states. The approach is interesting as it shows how agent-based modelling can also be applied to internal logistics. The technical implementation of agents representing transport units and the usage of state transition models to represent the inner processes of one agent are close to what is being implemented in the simulation model of this thesis. However,

from a control scenario point of view, no decentralisation can be observed, leaving great parts of the potential of the agent technology unused.

2.3.5.3. Agents in Vehicle Routing Problems

Looking for studies that apply multi-agent technology to the logistics domain, several papers addressing the vehicle routing problem can be found. Vehicle routing problems (VRP) can be described as “the problem of designing optimal delivery or collection routes from one or several depots to a number of geographically scattered cities or customers” (Laporte, 1992, p. 345). The VRP is typically modelled and solved using methods from operations research (OR). As it is of the NP-hard type, exact methods are limited with regard to the size of the network. However, there is a large number of metaheuristic approaches available (Kumar & Panneerselvam, 2012). As it was first described as a truck dispatching problem (Dantzig & Ramser, 1959) it naturally bears some resemblance to the logistical problem described in this thesis. Looking at the subsets of the vehicle routing problems, the so-called pickup and delivery problems, seem to correspond best to the supply network at hand.

Pickup and delivery problems (PDP) can be described as a “class of vehicle routing problems in which objects or people have to be transported between an origin and a destination” (Berbeglia, Cordeau, & Laporte, 2010, p. 8). An example of a PDP is the dial-a-ride-problem, where the door-to-door transport for elderly or disabled people must be arranged (Cordeau & Laporte, 2007). There are different subtypes of the PDP available, such as one-to-many and one-to-one PDP.

The supply network under examination in this study could be modelled as a dynamic one-to-one PDP. It is important to point out the distinction between static and dynamic routing problems. A routing problem is considered static, if all information on demand and supply is known before start of execution (Berbeglia et al., 2010). Even though a large share of the available algorithms and heuristics only consider static VRP, this constraint cannot be satisfied in most practical implementations (Skobelev et al., 2014). Particularly for open dynamic scheduling problems and in the presence of uncertainty, classic algorithms from operations research and centralised approaches have failed (Bouzd, 2003).

As a result, there have been several studies on addressing VRP and related problems with agent-based approaches.

The most relevant ones are listed below, starting with Kohout, Erol, & Robert (1999) who describe an agent based online optimisation system for a vehicle routing problem. They model and simulate an airport pickup & delivery service with the intention of using agents to address the shortcoming of OR algorithms for this dynamic VRP. This study is interesting for two reasons: firstly, it again uses agents to represent the individual transportation units, effectively decentralising control of the system. Secondly, the study is designed as a comparative simulation, contrasting an established, central control algorithm with the newly devised agent-based approach, similar to what is intended for this thesis. In their study, Kohout et al. (1999) are able to show that, under certain conditions, the agent based approach can outperform the central control algorithm.

Even though this study gives additional validity to the approach chosen for this thesis, the study itself cannot be applied directly to the problem at hand. Aside from the different scenario and industry certain problems, such as time slotting for example, are not relevant for the model at hand, limiting the applicability of the study described.

Looking at further applications of agent technology to VRP, Sitek, Wikarek, & Grzybowska (2014) describe a multi-agent modelling approach for a multi-echelon vehicle routing problem. Multi echelon vehicle routing problems are an extension of the classical vehicle routing problem. They describe routing for cases where the transport is not directly executed from a depot to the customer but is routed through distribution centres, requiring planning for each leg of the journey. The research project is described as an optimisation problem using an integrated approach of constraint programming and mixed integer programming. Agents are used to reduce the combinatorial problem.

According to the computational tests provided, this contributes to faster solution times for complex problems and improves modelling of constraints.

Even though this study offers another beneficial application of multi-agent technology to the logistics domain, in the context of this thesis it has only limited relevance. The first limiting factor is the layout of the supply network itself. The network under investigation in this thesis does not require any multi-echelon routing as all relevant

transports are carried out as “direct shipping” (Sitek et al., 2014, p. 123) which is a quite common setup for bulk transports. The second factor is related to what has been called identifying “the right level of description” (Bonabeau, 2002, p. 7287). The agents employed in the study by Sitek et al., (2014) do not represent the individual transportation units as intended in this thesis, offering only limited applicability to the problem at hand.

Sawamoto, Tsuji, & Koizumi (2002) look at the delivery scheduling problem, which is closely related to the previously described vehicle routing problem. The practical example they provide is creating schedules and assigning orders to a fleet of delivery trucks. They propose an agent-based approach as existing algorithms fall short, particularly when integrating dynamic rescheduling. They make use of problem decomposition and the local perspective offered by agents, dividing the delivery area into subsections and assigning a separate agent to each area. A mobile component is added as delivery trucks can report back on road conditions and disturbances. The model is simulated in a proving system, showing that the proposed approach produces meaningful results.

Reviewing this study in the context of this thesis, the question arises as to why the decomposition was not carried out to the fullest extent, meaning modelling the individual trucks as independent agents. The way the agents are proposed to be implemented by Sawamoto et al., (2002), it could be argued, still constitutes a central control approach as all information is fed back to central control agents. Hence no decentralised, “bottom up” (Skobelev et al., 2014, p. 3) decision-making is implemented, leaving room for the simulation model proposed in this thesis.

Continuing to look at agent-based approaches for scheduling problems, Bouzid (2003) describes an approach to online transportation scheduling using agents. Transport scheduling can be viewed as a partial problem of the above mentioned VRP. The interesting aspect from this study is the concept, that trucks evaluate their own location relative to the order pickup and delivery location, calculating its utility in accepting an order. Parts of the order allocation function implemented later in this thesis will build on that concept. The paper describes only a theoretical model and does not offer any actual implementation or application results.

The final study addressing scheduling problems was conducted by Skobelev et al., (2014) showing an adaptive scheduling solution by applying a multi-agent approach. They equip each agent with an individual cost function, which the agent wants to optimise e.g., either reduce cost or avoid penalties, for example. Agents can interact with each other, forming effectively a virtual market where they offer their services or buy other agents' services. This generalised approach allows application of the multi-agent technology to a variety of scheduling or resource allocation problems.

The concept of the cost function, or more abstract equipping agents with measurable goals, is picked up for the model used in this thesis. Agents will aim to maximise their own utility function, deciding for each interaction whether it is beneficial to them.

2.4. The Research Questions

2.4.1. Key Literature Overview

This section serves to provide an overview of the key literature discussed in the previous sections. Table 2.1 lists the key papers identified in the literature review along with a short summary and the main insights which have contributed to the progress of this study. Further, the papers are linked to the relevant literature gaps which will be discussed in the section below.

Authors	Title	Summary	Key Insights	Gap identified
Davidsson, Henesey, Ramstedt, Törnquist & Wernstedt, 2005	An analysis of agent-based approaches to transport logistics	Survey study on agent-based simulation with focus on logistics and transportation	Several relevant papers identified. Implementation of maturity index	Objective gap, Implementation gap
Fischer, Chaib-Draa, Muller, Pischel, & Gerber, 1999	A simulation approach based on negotiation and cooperation between agents: a case study	Order allocation and route optimisation for road delivery scenario	Agents represent delivery trucks and other logistics functions	Simulation gap
Sitek, Wikarek, & Grzybowska, 2014	A multi-agent approach to the multi-echelon capacitated vehicle routing problem	Agent based approach to multi echelon VRP. Dispatching multi-customer deliveries out of central delivery centres	Complexity reduction through problem decomposition by using agents	Objective gap, Simulation gap, Implementation gap
Schuldt, 2011	Multiagent coordination enabling autonomous logistics	Coordination of inbound supply chain of retail business	Agents represent sea freight containers; Comparative simulation	Objective gap
Kohout, Erol, & Robert, 1999	In-time agent-based vehicle routing with a stochastic improvement heuristic	Agent based optimisation system for VRP. Model based on airport pickup & delivery service company	Comparative simulation, contrasting agent-based with established, central control approach	Objective gap, Implementation gap

Table 2.1 - Key Literature Overview

2.4.2. Literature Gaps

To identify the relevant gaps in literature, it is helpful to look back at the research objectives as stated in chapter 1 and shown again in Figure 2.3.

Research Aim	Research Objectives	Literature Gaps	Research Questions	Results
<p>Aim: The aim is to investigate how autonomous control can improve the performance of logistics networks over conventional control methods</p>	<p>Objective 1: Understand the challenges of logistics networks and the need for autonomous control</p> <p>Objective 2: Investigate how autonomous control can be applied to bulk transportation networks</p> <p>Objective 3: Create an agent-based simulation model of a bulk truck transportation network</p> <p>Objective 4: Conduct a simulation experiment to compare the performance of autonomous control over existing control methods</p>	<p>G1: Objective gap</p> <p>G2: Simulation gap</p> <p>G3: Implementation gap</p>	<p><i>Defined in chapter 2</i></p>	<p><i>Defined through the findings in chapter 6</i></p>

Figure 2.3 - Research Structure

The first objective, to understand the challenges to logistics networks and the need for autonomous control was clearly evident in the literature and the relevant factors were explained above. Considering the second objective, software agents were identified as a suitable and accepted way to apply autonomous control to logistics networks. A wide overview of studies applying agent technology to the logistics and transportation area was provided, addressing this objective.

Looking however more closely at the research area, as done for **Objective 3**, the first gap in literature, the objective gap can be identified.

To further explain the research objective gap, it helps to look at the detailed view of studies provided in the previous chapter. Even though the studies presented in the previous sections provide good general examples of how agent technology can be applied to logistics and transportation, they fail to address the problem at hand. Several of the papers look at entirely different industries, such as Borucki et al., (2014) showing an application from internal logistics or Kohout et al., (1999) demonstrating their approach to an airport shuttle problem.

Others such as Sitek et al., (2014) or Fischer et al., (1999) apply agent technology to road freight transportation. However, the subject of their studies is to optimise routes and dispatching of multi-customer deliveries out of central delivery centres. No study has been identified that applies agent technology to a bulk transportation scenario.

Hence, the particularities of that industry, such as high-volume shipments and short-term substitutions such as for train transports, for example, are not addressed.

As the industry differs, the problem addressed also varies. Several studies around vehicle routing and delivery scheduling have been identified, such as Bouzid (2003) and Sawamoto et al., (2002). However, most offer little input to optimise order and resource allocation as required for the problem at hand. Skobelev et al., (2014) and their approach based on individual cost functions looks promising, however, again no application to logistics has been provided so far.

Hence, the gap regarding the research objective includes lacking the industry and problem focus. However, it is important to include “the right level of description” (Bonabeau, 2002, p. 7287) as well, which, as pointed out before, is critical when building simulation models. The level of description varies greatly in the papers examined, ranging from agents representing whole delivery centres (Sandholm, 1993) to individual transport units. As this thesis aims to examine the shift of control to individual units, the last level seems to be the ‘right’ level for this purpose. Given that most studies listed did not create models at this level of detail, it is important to highlight the two studies that did. Schuldt (2011) uses agents to represent individual sea freight containers while Fischer et al., (1999) modelled delivery trucks as software agents. While both studies prove that the chosen approach is feasible, again they leave enough room for the thesis at hand, as they do not address the bulk load and decentralised control aspect of the supply network under investigation.

Summarising the research objective gap, none of the studies presented before addresses the right problem, in the right industry context using the right level of description at the same time.

The second gap identified, the simulation gap, results from the fourth objective.

Objective 4 does not only aim to conduct a simulation experiment but also to compare the results side by side to the currently applied control methods in order to validate the performance gain. Looking again at the studies listed before, not all of the studies ran simulations to apply and verify their concepts. Out of those that did, only two offered comparative simulation experiments. A comparative simulation was executed by Kohout et al., (1999) and Schuldt (2011). Even while addressing a vehicle routing problem,

Kohout et al., (1999) focus on an application out of the public transportation domain by simulating an airport pickup and delivery service. Schuldt (2011) offers an example from the logistics by simulating inbound container transports. However, this inbound supply chain differs significantly from the outbound bulk shipping scenario under investigation in this thesis. This leaves room for a comparative simulation of the outbound bulk supply network investigated.

The simulation gap links right to the third and largest gap observed, the implementation gap and is connected to both objectives listed before. The gap has been observed by several authors of the previously cited studies. Chen and Cheng (2010) for example, observed “Most agent-based applications, however, focus on modelling and simulation. Few real-world applications are implemented and deployed.” (p.494). Davidsson et al., (2005) highlighted a lack of implementation and maturity in their study. They considered this important enough to develop a maturity index to rate agent-based studies with reference to their implementation status. The maturity index is based on work by Van Dyke Parunak (2000) and was extended by Davidsson et al., (2005) to include the four categories shown below.

Maturity level	Data quality	Implementation scale
1. Conceptual proposal		
2. Simulation experiment	2.1 Artificial data	2.1.1 Limited scale
		2.2.2 Full scale
	2.2 Real Data	2.2.1 Limited scale
		2.2.2 Full scale
3. Field experiment		3.1 Limited scale
		3.2 Full scale
4. Deployed system		

Table 2.2 - Maturity level index by Davidsson et al., (2005).

According to this definition, a deployed system is understood as an agent-based system that is used in a productive environment. A field experiment is distinguished from a simulation experiment by the fact that it has been deployed and executed in the actual environment where the application is meant to be implemented.

Applying this index to the papers analysed before in detail, none of the studies has reached actual level 3 or 4. For the survey study conducted by Davidsson et al., (2005) 4 out of 56 papers analysed achieved such a status, representing 7.1%. Simulation studies based on actual data and full-scale account for about 10.7%.

These numbers help to point out how large the implementation gap in the area of agent technology is and how much a study based on real-world structure and data can contribute to the further advancement and understanding of that technology.

Looking beyond agent-based modelling, Taylor, Eldabi, Riley, Paul, & Pidd (2009) report similar findings for simulation studies overall. Conducting a survey study in the logistics and manufacturing sector, only 6.8% of all papers are motivated by real-world problems and 5% demonstrate a benefit if they are implemented. These numbers further stress the need for simulation studies with a practical connection and contribution.

Having identified three gaps in the relevant literature, namely the objective, the simulation and the implementation gap, the following section will present the resulting research questions required to achieve the aim of this study.

2.4.3. Research Questions

To achieve the research aim stated in chapter 1, a total of four objectives were identified. As shown in the previous section, the first two objective could be achieved by analysing the literature presented. At the same time three gaps were identified, relating to the two remaining research objectives. The identified gaps lead to the formulation of two research questions which are provided below.

The objective gap concluded, that considering the supply network under observation, no study was addressing the right problem, in the right industry context using the right level of description at the same time. Therefore, the first research question to be answered in this study is as follows:

RQ1: Can agent-based modelling be used to apply autonomous control to an actual bulk truck transportation network?

The first research question will at the same time help to reduce the identified implementation gap by creating a simulation model using data from an actual supply network and enabling a full-scale simulation experiment.

The second research question relates directly to the fourth research objective and the underlying research aim, intending to show that autonomous control can improve the performance of logistics networks. The second research question is therefore:

RQ2: Can autonomous control improve the performance of bulk supply networks over existing approaches?

To evaluate the performance, a comparison between autonomous control and the currently used control methods is essential. This comparison will address the final gap listed above. The simulation gap stated, that very few studies were identified in literature, that offered a comparative simulation approach, allowing a grounded understanding of the performance of autonomous control in logistics.

The following chapters will aim to answer these research questions, starting by describing the underlying research methodology.

Research Aim	Research Objectives	Literature Gaps	Research Questions	Results
<p>Aim: The aim is to investigate how autonomous control can improve the performance of logistics networks over conventional control methods</p>	<p>Objective 1: Understand the challenges of logistics networks and the need for autonomous control</p> <p>Objective 2: Investigate how autonomous control can be applied to bulk transportation networks</p> <p>Objective 3: Create an agent-based simulation model of a bulk truck transportation network</p> <p>Objective 4: Conduct a simulation experiment to compare the performance of autonomous control over existing control methods</p>	<p>G1: Objective gap</p> <p>G2: Simulation gap</p> <p>G3: Implementation gap</p>	<p>RQ1: Can agent-based modelling be used to apply autonomous control to a bulk truck transportation network?</p> <p>RQ2: Can autonomous control improve the performance of bulk supply networks over existing control approaches?</p>	<p><i>Defined through the findings in chapter 6</i></p>

Figure 2.4 - Research Structure incl. Research Questions

3. Research Methodology

3.1. Philosophical View

The intent of this chapter is to explain and justify the research methodology chosen for this DBA work. According to Creswell (2014), the research methodology or research approach can be broken down into three main components: the philosophical worldview, the research design and the research method. Following this division, this first section provides insight on the philosophical viewpoint of the author and this research work. The philosophical viewpoint or epistemology (Crotty, 1998) can be described as “a basic set of beliefs that guide action” (Guba, 1990, p. 17). As this hidden philosophical idea (Slife & Williams, 1995) influences the research work it should be openly discussed to put the research in context of the philosophical underpinning. The author’s philosophical viewpoint is shaped by the research area, the authors own experience as well as opinions from advisors, mentors and similar stakeholders in the research (Creswell, 2014). The research area of logistics and transportation planning does not dictate or favour a particular research approach and underlying philosophy. Looking at the previously cited survey study on agent-based models in logistics, both quantitative and qualitative studies can be found. However when looking for studies addressing or measuring performance, a strong tendency towards quantitative research can be reported (Davidsson et al., 2005). Along with the authors professional background and actual and assumed expectations, this has had an influence on the philosophical viewpoint adopted in this thesis. Coming from a world of facts and figures, the positivistic research philosophy feels natural to the author to a considerable extent. Statements such as scientific knowledge being the only valid form of knowledge (Larrain, 1979) and facts being the only possible objects of knowledge (Egan, 1997) resonate well with the author. Positivism is rooted in the empirical approach of the natural sciences. It is based on a realist and foundationalist epistemology (Guba & Lincoln, 1994), viewing the world as existing independently of our knowledge of it (Grix, 2010). This objectivity leads to the concept that truth can only consist of what can be observed and experienced. This notion leads to a focus on quantitative methods, aiming to measure and explain phenomena with numerical data. This philosophical position is clearly reflected in the research approach chosen for this thesis. As laid out above, the research questions at hand revolve around measuring and

improving performance of logistical networks, which suggest a quantitative design rooted in a positivistic worldview.

However, there are aspects of a purely positivistic viewpoint, such as the above described concept of truth that conflict with the research approach at hand. Looking at the complete research string, the author is clearly rooted in an objectivistic ontology, believing that there is an absolute truth which can be obtained by observation and empirical methods. Applied to the logistical models described before, this signifies that there is an optimal configuration for each control method and scenario, maximising overall network performance. However, finding this optimal solution for a given network configuration may be arguably infinitely complex based on currently available methods and their limitations such as lacking computational power. Asking the question 'what can be known' leads to a slightly different philosophical viewpoint. Post-positivism acknowledges that reality can never be fully known and efforts to understand it are limited by the capabilities of human beings (Guba, 1990). Post-positivism developed as a response to the challenges arising from positivism, particularly the focus on knowledge to be erected on an absolute secure foundation. By assuming an objective reality but at the same time recognising that it is imperfect (Dias & Hassard, 2001) post-positivism provides an answer to the previously mentioned dilemma, that there is an optimal solution but it cannot be found with the current methods or resources. Post-positivism would also accept that, as knowledge evolves, there will be new solutions available and old ones will potentially be rejected. Therefore, the post-positivistic stance would recommend to continue researching and testing (Phillips & Burbules, 2000). In other words, post-positivistic research accepts the researcher's fallibility, meaning that it is possible to approximate but the researchers may never fully know reality (Trochim & Donnelly, 2001).

Another interesting aspect of post-positivism is, that unlike under a pure positivistic research philosophy, observations made do not have to directly support a particular theory (Grix, 2010). This approach is beneficial for this research work as software-agents may show emergent behaviour as mentioned above (Bernhardt, 2007; Macal & North, 2014). This holds true for the whole area of artificial intelligence and machine learning, where unplanned or unpredicted behaviour is not only a possibility but rather a

desired outcome of the autonomous data analysis. Results may yield the desired benefits and are reproducible; however, the mechanisms behind these results are not completely understood. These data-driven discoveries (Waller & Fawcett, 2013) are, however, vital to advance knowledge and understanding of this research area and should not be dismissed just because they currently cannot be explained by natural science in a positivistic sense. Hence post-positivism offers some opportunities for the thesis at hand. The research approach for this thesis is clearly rooted in an objectivistic ontology, adapting the above-mentioned aspects of a post-positivistic worldview to widen the philosophical horizon of the research approach while addressing key areas of the underlying research topic.

3.2. Research Approach & Design

Having explained the philosophical viewpoint underlying this thesis, the research design and methods will be discussed next in order to formulate the research approach (Creswell, 2014). Considering the strong objectivistic tendency in the researcher's philosophical worldview, it will not come as a surprise that a quantitative research design was chosen to conduct this thesis. The thesis applies an experimental research design to answer the proposed research questions. The experiment compares the effect of different control strategies on the supply network at hand. The control method will thus represent an independent variable, influencing several dependent variables, such as the rate of order completion or the reliability of the service provided (Creswell, 2014). The research method enabling this experiment is a simulation. As simulation allows to execute the experiment several times with the exact same parameters, hence enabling randomisation and providing complete control over all variables, the research design fulfils the criteria for a true experiment (Walliman, 2006).

While for the main part of the study a quantitative research approach has been chosen, elements and methods from qualitative research are applied when required. For example, interviews were being conducted with subject matter expert from the client side. These interviews helped to establish face validity by asking, whether the model and its behaviour are reasonable (Sargent, 2013). Close interaction with the client and SME is

vital to a successful simulation study, be it to transfer knowledge and data (Robinson, 2008b) or to ensure understanding and acceptance of results (Robinson & Bhatia, 1995). The qualitative means, such as interviews and workshops used to enable this communication do not, however, shift the research approach towards the qualitative end of the continuum (Newman & Benz, 1998) but are rather a part of a sound quantitative design (Robinson, 2008b).

3.3. Simulation as Research Method

Simulation can be described as a virtual experiment (Carley, 2001), allowing “experimentation on a computer-based model of some system” (Pidd, 2004, p. 10). In this study, simulation enables the experiment to compare the effect of different control methods on the supply network at hand. Simulation has been defined as a method to use computer software to model real-world processes, systems or events (Law & Kelton, 1991). Highlighting further the execution aspect of simulations, Bratley, Fox, & Schrage (2011) describe simulation as “Driving the model with certain inputs and observing the corresponding outputs” (p. 2). This execution is controlled by variables that can be manipulated (Berends & Romme, 1999). Birta & Arbez (2013) help to better define the relationship between modelling and simulation, calling the model an object which serves as a vehicle for experimentation. This experimentation is the simulation activity, which makes simulation a suitable method for experimental research.

Simulation as a research method has been chosen for a variety of reasons. One of the primary motivations was its ability to generate data, which can be analysed subsequently (Axelrod, 1997). The company serving as real-world example did not have an integrated IT system, when the study was conducted. As a result, no end-to-end empirical data model of the supply chain was available for analysis.

In such situations, where sufficient empirical data is hard to acquire, simulations can offer significant benefits (Happach & Tilebein, 2015). Along with this ability comes the flexibility to repeat experiments with different settings of control variables in the same environment (Berends & Romme, 1999). This would be difficult in a real-world environment as each change may disrupt actual business operations (Greasley, 2008), posing a potential economic risk for the organisation. Simulation experiments provide

benefit whenever experimentation with the actual system is too dangerous, too disruptive, too costly or irreversible (Birta & Arbez, 2013). Additionally, input parameters and environmental factors would inevitably vary between individual experiment runs, impacting the comparability of results obtained (Axelrod, 1997). Davis, Eisenhardt, & Bingham (2007) describe simulation as a computational laboratory, which allows for the study of the effect of certain variables on the output. The flexibility simulation offers in manipulating input parameters and control variables paves the road to the “what if” (Happach & Tilebein, 2015, p. 249) question. This ability to not only explore new configurations but also test existing ones (Schultz, 1974) represents a significant and distinct benefit to scientific investigation and business. Axelrod (1997) even claims that simulation can be seen as a third research method besides induction and deduction. On the application side, the ability to validate existing control concepts and associated assumptions provides substantial benefit as documented in the subject matter expert interview in section 7.3 shows. Closely associated with the ability to experiment is the simple fact that simulation allows to compress time (Cohen, 1960; Shubik, 1960). As shown in this thesis, processes that take several weeks to execute can be simulated within minutes, given there is enough computational capacity available. In addition, Cohen (1960) describes how simulation can help to facilitate communication between different research areas by providing a common and easily accessible language. It helps to abstract underlying theoretical concepts and improve the transparency thereof (Serman, 2000). The author would like to add that this is particularly true for the communication with stakeholders outside academia, such as in the case of this DBA thesis, the business partners involved. Having visual representations and graphs from simulation (Happach & Tilebein, 2015) greatly contributes to comprehensibility of communication between these groups.

As with any research method, simulation faces certain challenges and shows distinct weaknesses that need to be addressed. Happach & Tilebein (2015) offer a list, naming data validation, parameter estimation, the need for assumptions and the precision in formulation as the most important ones. As most of these challenges need to be accounted for during the design phase of the simulation model, the details and necessary countermeasures in this simulation study will be laid out in sections 4.1 and 4.4.

To summarise, simulation emerges as a research method for the research problem at hand, as it manages to address the issue of limited data availability while providing the ability to execute comparable experiments.

3.4. Types of Simulation

3.4.1. Classification of Simulation Types

When trying to categorise simulation, the structured overview introduced by (Berends & Romme (1999, p. 578) provides a good starting point:

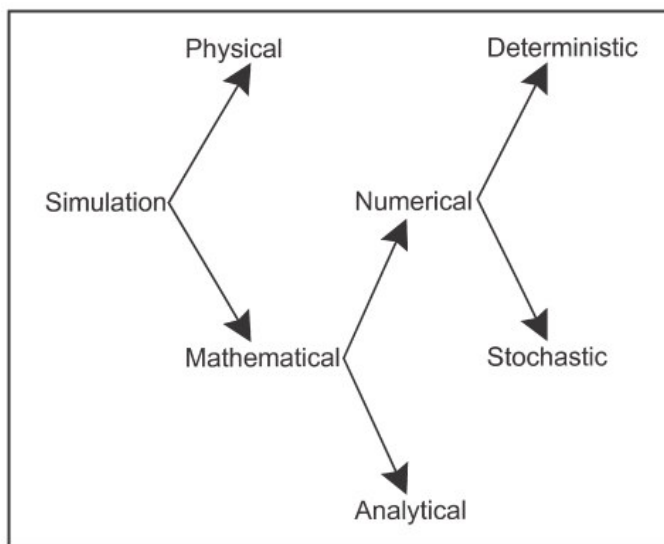


Figure 3.1 - Simulation categories (Berends & Romme, 1999, p. 578)

Figure 3.1 depicts the evolution of simulation. The first distinction is between physical and mathematical simulations, where physical simulations refers to experimentation with real objects (Berends & Romme, 1999). An area where this is quite common is with simulators, where at least a part of the physical system is replicated to enhance realism (Birta & Arbez, 2013). Mathematical simulation models, on the other hand, describe the simulation model using mathematical equations (Banks, Carson II, Nelson, & Nicol, 2005). These equations can be classified into analytical and numerical formulas. Analytical simulation models aim to provide single optimal solutions whereas numerical models focus on describing system behaviour (Forrester, 1971). As Banks et al., (2005) point out, analytical models use mathematical reasoning to solve the model whereas

simulation models employing numerical methods are not solved but ‘run’ using computational procedures.

Deterministic models have a known set of input variables which lead to a unique set of outputs (Banks et al., 2005). Unlike stochastic simulation models, no random aspects, such as random interarrival or service times are considered (Birta & Arbez, 2013). Due to these random events, outputs from stochastic simulation models must be treated as statistical estimates (Banks et al., 2005), meaning that simulations experiments need to be carried out several times in order to collect and aggregate sufficient data to arrive at meaningful results (Birta & Arbez, 2013).

Aside from the above introduced classification, there are other approaches to categorising models or systems. Some are not particularly relevant for simulation models, such as the distinction between linear and non-linear systems, as the simplifications based on the mathematical property of linearity have no consequence in simulation (Birta & Arbez, 2013). The distinction between static and dynamic models, on the other hand, is interesting. Static models do not evolve over time (Birta & Arbez, 2013) whereas time is a central aspect in dynamic models. While both static and dynamic models can be found in simulation, the majority and, particularly, the simulation model built for this thesis are dynamic models.

A far more important distinction between types of simulation models is the classification into discrete and continuous models. Discrete event simulation (DES) models are described as models of systems where the state variables change only at discrete points in time (Banks et al., 2005). In these simulation models time advances in discrete intervals which are unequal (Birta & Arbez, 2013). As random phenomena play a central role in discrete event models (Birta & Arbez, 2013), a very common field of application are queuing models with random interarrival times, such as the model of a service counter in a store, where new customers arrive in random intervals. The state of this model would then change each time a customer arrives or leaves the queue to be served for example.

In continuous time dynamic models on the other hand, the state changes occur continuously (Birta & Arbez, 2013).

It is important to point out, that when looking at real-world systems, this distinction is not clear cut. Most systems show properties of both discrete and continuous behaviour, however, typically one will dominate, allowing the proposed classification (Law & Kelton, 1991). In that context, system dynamics has to be mentioned as another approach to simulation modelling. System dynamics focuses on the interaction of elements that form a system over time (Forrester, 1971). Relying on mechanisms such as feedback loops, stocks and flows, it is particularly suited to model continuous and non-linear systems (Sweetser, 1999). However, as Ossimitz & Mroczek (2008) point out, even though system dynamics is commonly associated with continuous time, it can be applied to both discrete and continuous system.

Similarly, there are simulation models that apply and combine both discrete and continuous elements in the same model (Birta & Arbez, 2013).

While system dynamics has been used in logistics and supply chain modelling (Tako & Robinson, 2012), it is often associated with strategic level decision making by taking a holistic view of the enterprise (Rabelo, Helal, Jones, & Min, 2005). Looking at the research problem at hand, the local perspective of the individual transportation units, along with their behaviour, is the focus of this simulation model. For this level of low abstraction, system dynamics is not considered the best choice as confirmed by Borshchev & Filippov (2004).

The following section will introduce agent-based simulation and list its advantages over DES for the simulation model build in this thesis.

3.4.2. Agent-Based Simulation

During the 1990s, a third type of simulation emerged alongside discrete event and continuous time simulation, named agent-based simulation (ABS) (Siebers et al., 2010). Agent based simulation can be understood as “a modelling and computational framework for simulating dynamic processes that involve autonomous agents” (Macal & North, 2014, p. 6).

Siebers et al., (2010) offer another definition, highlighting the relationship between ABS and agent-based modelling (ABM): “ABS is the process of designing an ABM of a real system and conducting experiments with this model” (p. 206). ABM and ABS have

gained widespread popularity across a variety of scientific areas and practical applications (Bonabeau, 2002; Macal & North, 2007), as they have the ability to effectively address the increasing complexity and distributed character of systems and organisations (Fischer et al., 1999). Macal and North (2007) add, that with increase in computing power and availability of micro-level data, ABM allows problems to be addressed that could not have been modelled with previous methods. Picking up on that micro-level argument, Bonabeau (2002) argues, that “ABM is a mindset more than a technology” (p. 7280), meaning the concept to model a system from the perspective of its units, applying a bottom-up point of view. This approach allows a more natural description of systems, describing the behaviour of individual entities, such as employees or shoppers directly instead of relying on equations or averages to abstract behaviour (Bonabeau, 2002). At the same time it allows to capture the complexity arising from the interactions of these entities (Siebers et al., 2010). The ability of the agents to take individual actions and interact with one another when appropriate may lead to emergent behaviour (Bernhardt, 2007). This is another benefit offered by ABS, which offer an inductive approach (Axelrod, 1997) by allowing insights into and knowledge about the system, beyond the sum of its parts (Bonabeau, 2002). As a result, ABM are frequently used to model decision-making and social and organisational behaviour.

Finally, ABS offer a high degree of flexibility, due to its setup of individual agents, which can quite easily be extended or modified (Van Dyke Parunak, 1999). This, together with an “ease of implementation” (Bonabeau, 2002, p. 7280) provides good reasons to use ABS and contributes to its increasing popularity. The benefits and limitations of ABS correspond to a large extent to the list provided for individual agents in section 2.3.2.

As with any new approach there is discussion about the delineation from existing approaches and potential overlaps. For ABS the discussion is particularly strong with the DES research community, some of which go as far as to claim that ABS may be redundant to DES modelling (Siebers et al., 2010). While there certainly is some overlap, Siebers et al., (2010) provide a quite comprehensive list of differences between DES and ABS modelling. The most relevant aspects are the difference in focus. DES

focuses on top-down modelling of the system, while ABS are able to model individual entities and their interactions. Another difference is in the level of control, with DES being commonly being organised in a central control thread, while ABS models enable decentralised control which resides with each agent. The entities in DES models are typically passive, while “something is done to them” (Siebers et al., 2010, p. 207) whereas in ABS the agents, possess intelligence and take actions themselves.

Having explained the benefits of agent-based simulation in detail, the question remains as to why ABS was selected for this thesis.

Following “good modelling practice” (Siebers et al., 2010, p. 206) the research method, or more precisely the type of simulation, was chosen with the research questions in mind. Looking at the research questions, the two key phrases influencing model selection are “autonomous control” and its application to a “logistics network”. As indicated before, agent-based simulation models are uniquely equipped to model decentral control structures (Siebers et al., 2010), with each agent acting as independent, self-directed entity showing complex behaviour (Bernhardt, 2007). By representing the trucks entities, the research problem shows a natural division into agents (Macal & North, 2014). Beyond that, ABS are particularly suited for spatially distributed problems (Axtell, 2000) where the location of agents is not fixed (Bonabeau, 2002) which is clearly the case for the truck agents. Van Dyke Parunak, Savit, & Riolo (1998) refer to both the physical space as well as the interaction space, which refers to the agent’s ability to communicate across distance. This includes all the remaining agents in the network at hand, which all interact across distances, forming dynamic relationships (Macal & North, 2014). These interactions are complex, non-linear and discreet, fulfilling another requirement for ABS (Bernhardt, 2007).

The benefits of software agents for logistics have been extensively discussed above. When looking for applications for ABS, Siebers et al., (2010) list once more explicitly supply chains as natural application areas for ABS particularly for their ability model dynamic processes and adapt quickly to changing requirements. Bernhardt (2007) mentions in this context disaggregated systems such as transportation systems benefit from ABS.

This list of characteristics shows the “intimate connection” between the model and the nature of the problem which is to be solved (Birta & Arbez, 2013, p. 4). Hence in this case, the capabilities of agent-based models, make it a perfect match for the system under investigation.

3.5. Formatting and Testing an Agent-Based Simulation Model

3.5.1. How to Build a Simulation Model

The process of creating and testing agent-based simulation models follows the general steps of model creation with the addition of some agent-related activities (Macal & North, 2014).

First the general steps to create a simulation model will be outlined, before focusing on the particularities of agent-based models. There are several approaches and guides available on how to create a simulation model, such as Shannon (1975), Law & Kelton (1991), Banks et al., (2005) and Birta & Arbez (2013). As Robinson (1997) points out, there is much similarity across these approaches, with each one describing a series of steps to be executed in some logical sequence. There is a level of agreement that not all steps must be carried out strictly sequentially and that iterations are required (Robinson & Pidd, 1998). Exemplarily for the individual approaches, Figure 3.2 shows a frequently cited model by Law (2003) which is used to explain the basic steps and contrast relevant differences.

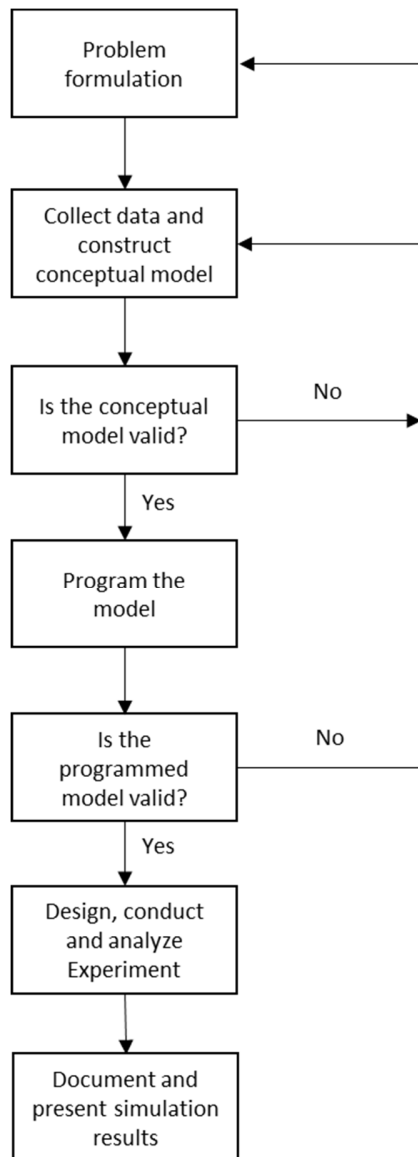


Figure 3.2 - Seven step approach for conducting a successful simulation study (Law, 2003)

The first step is to formulate the problem that is to be addressed by the simulation model. Also described as project description, this initial step helps to set the scope (Law, 2003) and provide the objectives for the simulation project at hand (Banks et al., 2005). This activity is highly relevant, as “it is not meaningful to undertake any modelling study without a clear understanding of the purpose for which the model will be used” (Birta & Arbez, 2013, p. 7). It is important to mention that this step may require considerable work, as the initially stated problem descriptions by project sponsors or SME may lack the clarity and precision required to create a meaningful model (Law,

2003). Additionally, the problem and the understanding of it may change during the course of the simulation study, highlighting the importance of an iterative approach to simulation modelling (Robinson, 2008b). In this thesis, the research questions serve as problem formulation.

For the second step some authors choose to separate the tasks of data collection and model conceptualisation (Banks et al., 2005) while other follow Law's example and combine them. Data collection and building the conceptual model are closely interlinked (Shannon, 1975), both depending on and influencing one another throughout the construction phase of a model. For both activities, close interaction with the client is vital. The data and information required to create the conceptual model is collected from subject matter experts on the client side (Robinson, 2008a). Ideally, this is an iterative process with the conceptual model serving as a means of communication between the modeler and the client (Pace, 2002). The conceptual model can be understood as a formalised and abstracted version of the system under investigation (SUI) (Birta & Arbez, 2013). Constructing any model of a system is sometimes characterised "as much art as science" (Banks et al., 2005, p. 14). With a model being defined by Shannon (1975) as "a representation of an object, system or idea in some form other than itself" (p. 7), the challenge arises on the right level of detail of the representation. As a consequence, Law (2003) states, that "a simulation model should be a simplification or abstraction of the real system, with just enough detail to answer the questions of interest" (p.68). The reason for this focus on the level of detail is that too much detail increases complexity while not enough detail may render the simulation useless with regard to the effects to be demonstrated (Birta & Arbez, 2013). While there is no silver bullet to achieve the right level of detail, it is important to keep the goal of the simulation study in mind (Birta & Arbez, 2013) when collecting data and involve model users and experts early on to verify the model (Banks et al., 2005).

This leads directly to the third step in the diagram above, which describes the validation of the conceptual model before moving on to program the simulation model in the next step. As validation and verification are two essential tasks in any model design it is important to clearly distinguish these tasks. Verification asks whether the conceptual model has been correctly translated into the simulation model, e.g., if the software

product was built right (Sargent, 2013). Whereas validation asks the question, whether the right product has been built or, in other words, whether the model is an appropriate representation of the SUI (Law, 2003). Again, these questions can only be answered in the context of the simulation study's objective as no model has "universal applicability" (Birta & Arbez, 2013, p. 49). Validation and verification should therefore happen as early as possible in the simulation study and continue as a reoccurring activity, to ensure the model's accuracy (Banks et al., 2005). Both verification and validation build the client's confidence in the model (Greasley, 2008) and thus help to establish the credibility of the model (Birta & Arbez, 2013). Credibility can be understood as validity of the model from the perspective of the client (Robinson, 2008a). It indicates whether the results of the simulation are accepted by SME or sponsors of the simulation study (Law, 2003). It is important to point out that a credible model may still be invalid, while on the other hand a valid model may not be considered credible.

Once credibility is established and both the modeller and the client are satisfied that the model is valid, experimentation may begin (Robinson & Bhatia, 1995). The results from experimentation are documented and presented to the client. To consider the simulation study successful, the results should be understood and accepted by the client (Robinson & Pidd, 1998).

Taking a look at the overall simulation model creation process, two aspects can be observed. The first one is that the process contains several feedback loops which make it necessary to acknowledge that iteration is a natural and required element of simulation modelling (Robinson & Bhatia, 1995).

The second aspect is the central role of the client in the modelling and simulation process. The client can be understood as "people for whom the project is performed" (Robinson & Pidd, 1998, p. 200). These people may take on different roles, from sponsor to subject matter expert to model user (Greasley, 2008). They are required throughout the course of the project as they provide information and serve to validate the model.

Engaging them early and frequently in the model creation and simulation process helps to increase confidence in the model and its results (Greasley, 2008).

These observations are true for any simulation study, even while the individual steps may vary, as the next section on agent-based simulation modelling will show.

3.5.2. Approach to Agent-Based Simulation Modelling

While the general steps in creating a simulation model are similar, tasks on agent design and agent behaviour need to be considered. While the list of approaches and development models is considerably shorter, two approaches will be highlighted here. The first is the approach by Macal & North (2014) who offer a development process for agent based models, that accounts for agent related activities, as shown in Figure 3.3.

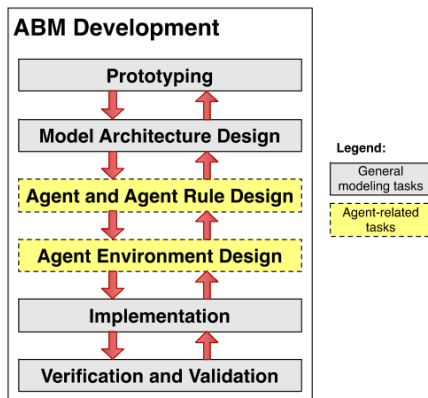


Figure 3.3 - Agent based model development process (Macal & North, 2014)

While differing significantly from the previously described approach, it offers two aspects, that the author believes serve well in the context of this thesis. First, the process starts at a prototype, which is in line with the approach chosen for this simulation study and reflects well the current state of art in software and product development (Schwaber & Beedle, 2002). Secondly, the development process is iterative, looping from the prototype across all relevant activities to the validation and verification tasks and back again. This highlights the previously mentioned need for constant validation and close interconnection to users and SME of the model.

The second design approach is the ODD protocol proposed by Grimm et al., (2010). The ODD (Overview, Design concepts and Details) protocol was introduced to provide a standardised and more complete way to describe agent-based models (Grimm et al., 2010). While the standardisation effort and its success are not within the scope of this

thesis, the protocol offers a valid framework of steps to describe and build agent-based models. The main elements of the protocol are:

1. Purpose
2. Entities, state variables, scales
3. Process overview and scheduling
4. Design concepts
5. Initialisation
6. Input data
7. Sub-models

An in-depth analysis of the framework can be found in Grimm et al., (2010). Looking at the sequence of steps, certain similarities to the general approach to modelling can be found. Again, the first step highlights the importance of clearly identifying the problem at hand (Grimm et al., 2010). The next step targets the particularities of agent-based models, addressing the identification and description of entities in the model. This explicitly includes both agents and the environment along with spatial units followed by a dedicated step describing the processes and scheduling mechanisms used in the model (Grimm et al., 2010).

These steps together with ideas from the previously shown approaches led to the model creation approach depicted below in Figure 3.4. The approach is based on the seven steps approach shown earlier while incorporating central elements relevant for the creation of agent-based models. This approach is followed in the creation of the simulation model for this thesis.

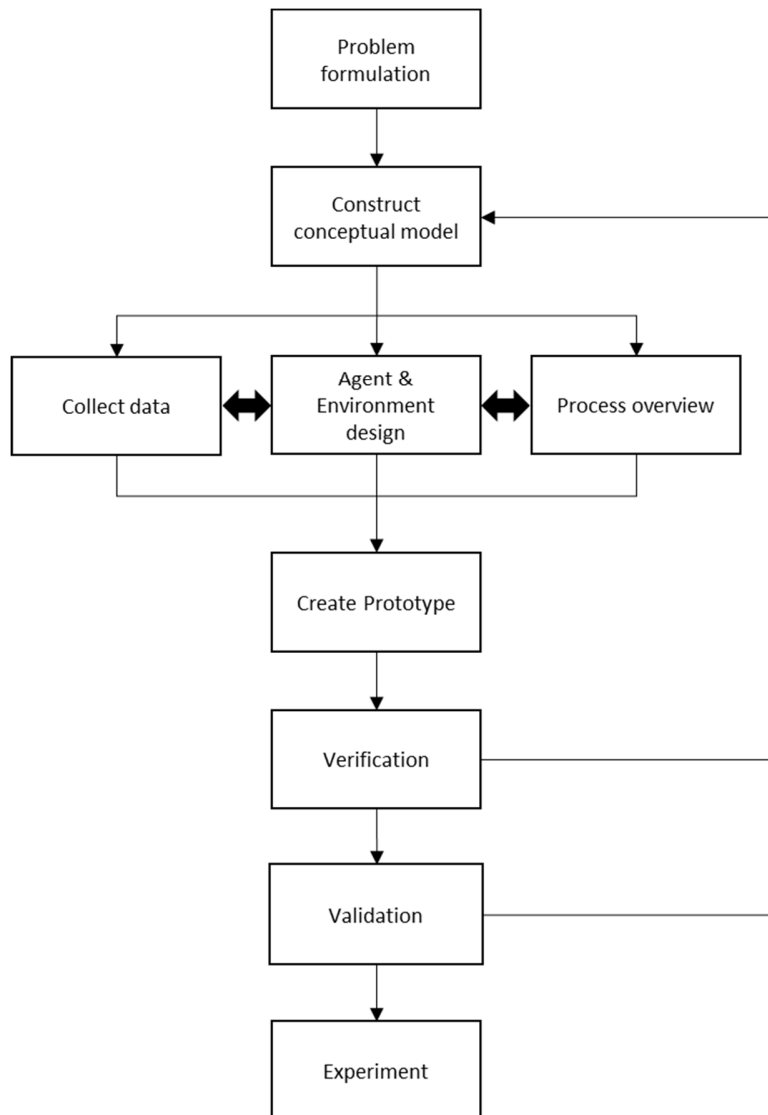


Figure 3.4 - Integrated simulation model creation approach

The approach starts again with a clear formulation of the model’s purpose and objectives, which is reflected in this thesis by the research questions. Next, a conceptual model as abstraction of the system under investigation (Birta & Arbez, 2013) is created. The difference to the approach described before lies in the tasks required to create this conceptual model. The three tasks, data collection, agent and environment design and process overview are closely linked in a feedback loop. The tasks can and will happen in parallel with the outcomes of one task influencing the others. Data collection being a key task for the reasons listed before. The second task, agent & environment design is unique to agent-based simulation models. As agents play a central role in ABS models,

identifying the entities which are to be represented as agents in the model is crucial (Macal & North, 2014). This task is closely related to the level of granularity chosen for the model. While this is important in any model, it is even more critical in agent-based models. Agents act as decision makers in an ABS model (Macal & North, 2014) driving models by their behaviour and interactions. Therefore, not having the right level of detail (Bonabeau, 2002) may render a model useless for its purpose. Along with the agents, the environment in which they reside, and its properties need to be defined. This can be physical representations such as GIS models but also populations or organisations and their boundaries (Grimm et al., 2010). The third important task in creating and refining the conceptual model is the process overview. This task aims to answer the question “which entity does what and in what order” (Grimm et al., 2010, p. 2764). Again, the process flow is relevant in any simulation. In a DES model for example, the process is explicitly built into the model. In an ABS model, agents are allowed a range of behaviour. The individual agent may then decide how to interact leading to emergent behaviour, e.g. behaviour that was not explicitly built into the model. This is a strength of ABS but makes it even more important to clearly describe and test the desired processes when creating a model.

Testing is an important aspect of building any model. Therefore, the next step after having built a conceptual model is to create a prototype. In the approaches above this step is described as translating the conceptual model (Banks et al., 2005). The author chose to name the task ‘create prototype’ instead, to emphasise the temporary and iterative nature of the activity. The prototype is developed based on the conceptual model and then verified against the SUI. As indicated by the arrows in the figure above, findings from verification and validation activities are fed back into the conceptual model, improving the model and leading to a refined version of the prototype. This loop is carried out until the prototype has the desired quality and represents adequately the system under investigation. Only then has this prototype become the model to be used in the simulation experiments designed.

The next chapter will therefore describe the creation and validation of the simulation model using the approach described above. It will start with the data collection on the system under investigation, followed by the agents and the environment before offering

an overview on the processes. The prototype created and the verification of the same will complete the chapter.

4. The Simulation Model

4.1. Data Collection on the System Under Investigation

According to Greasley (2008) data collection is “one of the most important and challenging aspects of the simulation modelling process”(p.39). While simulations may be able to generate data from simulation runs, they do require input data to build the simulation model and output data to validate it (Robinson & Bhatia, 1995).

For the system under investigation, data collection was particularly challenging. The company under investigation did not have an integrated IT system at that point in time, meaning that data was highly compartmentalised and distributed in information silos. Data was stored in individual spreadsheets and databases across different departments and functional areas. As very little data was readily available in a reusable format, the author needed to collect much of the required information first hand from a wide range of data sources (Greasley, 2008). This included expert interviews, observations on-site and through participation in meetings, as well as disaggregation and analysis of historical data. Fortunately, as this thesis was being created alongside the author’s work as a consultant, access to both logistics sites and personnel was provided frequently. To give an example, the author took part in weekly transportation planning meetings held by the client, allowing first hand insight into the order allocation process and validation of quantity structures.

However, as much data was gathered through interviews and interactions with subject matter experts, data validation was a critical factor in the data collection process. Deviations are to be expected when interviewing SME, as each expert may have a different view of a particular process or problem (Robinson, 2008b). Therefore, data was tested for plausibility and accuracy by cross referencing it with other sources and validating it with other experts, particularly for extreme values or outliers (Sargent, 2013). For example, the loading and unloading times at the plants are based on discussions with plant managers and were validated against first hand observations during site visits. Nevertheless, during validation of the prototype modelled, significant deviations were observed by other SMEs. That led to another round of interviews, during which a legacy database from one of the weighing systems was identified. This

historical data could be used to further validate and adjust the distributions employed for the model, leading to credible results.

This demonstrates that data collection, again, was an iterative process, as data requirements and understanding changed as the model evolved (Greasley, 2008).

A positive aspect that can be derived from the extensive data collection and validation process for this model, is the resulting close interaction with a wide range of SMEs and stakeholders from the client side. The need for close collaboration and frequent exchange of information led to the establishment of structures and forums where the author presented his progress and collect valuable feedback, such as, for example, a bi-weekly simulation status meeting. The close cooperation between client experts and the author in the role of modeler, not only facilitated the validation process as described in section 4.4, it also helped to achieve credibility of the simulation model and its results (Greasley, 2008).

4.1.1. Supply Network Structure

The simulation model created for this research project is based on a real-world example. The system under investigation is the outbound supply chain of a company that is producing and distributing fertiliser products. The supply chain for the distribution of these final products can be divided into three major parts, commonly referred to as transportation legs: land transport from production plant to the port of export, ocean transport to destination harbour and onward land transport to the final customer. The company produces and distributes three main product groups, namely dry bulk material, liquid bulk material and packed material which is transported in standard sea freight containers. The dry bulk materials are both directly sold to customers as well as being used in several downstream products manufactured by the company itself.

For this thesis the focus is on the first leg of the supply network, the inland transportation from the production plant to the ports of export as this part seems to offer the greatest potential for improvement by autonomous control.

The inland transports are executed using both road and rail transport capacities. Rail transportation is preferred over truck transports as it offers greater volumes at a significantly lower price. However, at the same time the dependency on train transports

constitutes a large part of the problem at hand. The execution of the train service is highly unreliable, as a result causing massive fluctuation in the demand for truck transports, which are used to substitute missing train capacity.

Hence the primary area of interest for this thesis will be the road transports carried out by lorry trucks. There are a large number of individual transport units that can and need to be coordinated. In the current setup in the real world, trucks are ordered and dispatched centrally according to a given production plan. This constitutes a classical central control setup, which will be modelled as a reference and serves as baseline to compare performance of the autonomous control methods.

The idea for implementing autonomous control in this context is that each truck constitutes an individual logistical unit. Each logistical unit can make decision, such as which transport order to accept or which route to take. The trucks as logistical transportation units will be represented as individual software agents in the simulation model. As laid out during literature review, this concept has been successfully applied to the logistics area (Fischer et al., 1999).

Only dry bulk transports will be studied. Transports for liquid bulk are not considered as they constitute only a comparatively small portion of the overall transport volume.

Further, the transport medium used (both train and truck) require specific liquid chemical containers, offering very little potential for interchangeability of transport units and thus limited room for improvement through autonomous control.

Container transports are ignored in the model as well for the following two reasons.

Again, the volume is significantly smaller when compared to the bulk business, signifying that business impact of an optimisation here is comparatively smaller. The second reason considers the contribution of this thesis to theory. Autonomous control in container transport scenarios has been extensively studied by Schuldt (2011), for example.

Hence the simulation model reflects the inland part of the outbound supply chain, which is tasked with moving finished goods from the production sites to the port locations. As dry bulk products have a low unit price, they need to be moved in large quantities to allow sale on level of vessel loads.

Most products shipped are non-toxic and not susceptible to weather conditions such as rain or exposure to sun light. Therefore, the inland transport is carried out by regular lorry trucks or bulk train cars not requiring special or custom transportation equipment. These properties positively affect the other primary logistical functions (Gudehus, 2012a) as well. For example, storage of the product on the production sites is not a major concern as sufficient space is available and material can be stored in the open or in large covered bulk warehouses. At the port facilities, however, warehouse capacity is limited as the space requirement for storing significant amounts of the products together with the high land cost at most commercial ports create a significant constraint.

The demand situation typical to commodity markets represents a further challenge to the supply network. Even though long-term framework contract exists, fluctuating market prices and spot markets (Seifert, Thonemann, & Hausman, 2004) lead to frequent last minute order closures. This is aggravated by the fact that bulk sea freight relies largely on so called tramp transports, meaning that individual contracts for each port to port connection are negotiated (Lun et al., 2010). In this market, large last-minute discounts are often granted to avoid unused capacities on vessels. From a supply chain point of view, these two properties of the bulk shipping market, reduce lead times and increase pressure on planning accuracy.

This planning effort is frequently foiled by fluctuation in transport capacity caused by unreliable train services putting additional strain on the inland transportation network. In the context of the unique properties of this supply chain, most importantly, the limited port storage together with short-term demand situations and fluctuating transport capacity, providing the right quantity of the products at the right place in the right time becomes a challenge. Effectively addressing this challenge is vital to the enterprise under investigation as this outbound inland supply network is at the very core of its operations.

4.1.2. Supply Network Layout

The geographical layout of the supply chain modelled for this study is shown in Figure 4.1. To comply with demands regarding confidentiality of business information of the company examined here, the plant and port locations shown on the map below do not

correspond to the actual locations. The model itself has been built using the exact locations and distances from the real-world example, ensuring the highest possible fit and level of accuracy. Only the graphical representation generated by the simulation tool has been modified to protect critical business information.

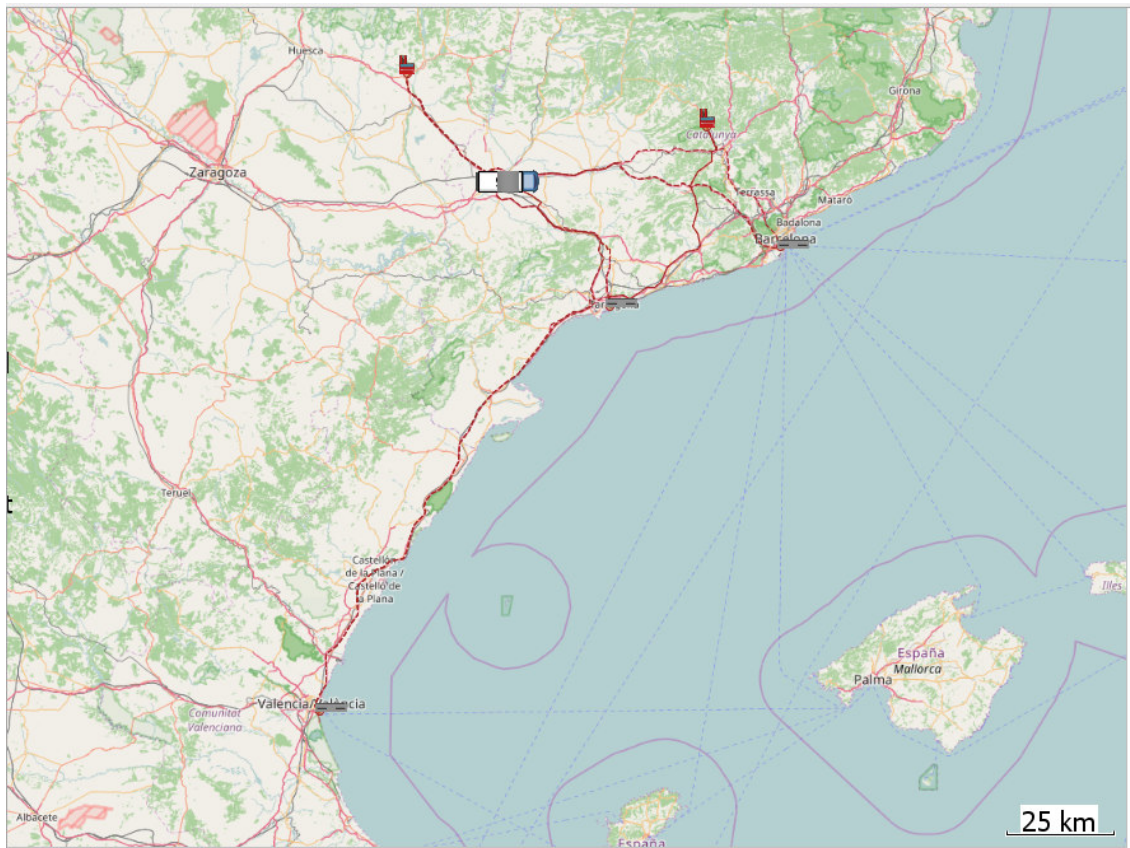


Figure 4.1 - Geographical model layout

The supply network consists of two production plants and three port locations. One of the port locations is connected via train lines to both the production plants. The remaining ports can only be served by truck. Both truck and trains are loaded at the plant using automated loading equipment. Weighing is required before and after loading to determine the actual quantity loaded and avoid overloading of the transportation units. This weighing task and malfunctions of the loading equipment used can cause waiting times for both truck and rail cars at the plants. The train cars are typically loaded overnight and are scheduled to leave once a day from each plant location. Trucks are loaded around the clock at both plants and move from the plant directly to the port. The trucks have a central depot location where they are dispatched from and return for

maintenance. As observed in reality, only full truck loads are shipped as everything else is not economically viable in this large quantity bulk business.

Product flows only in one direction through the network, meaning that the trucks deliver material to the ports and return empty. Occasionally return transports are encountered by the trucks but the occurrence is very rare as the region where the business is situated primarily exports bulk material with most import happening in containers, creating a large discrepancy between required outbound and inbound bulk truck capacity. For the model at hand, return transports are therefore ignored.

When comparing truck to train transports, trains generally offer significantly lower cost per ton and provide larger overall transport capacity (Heidmeier & Siegmann, 2008). However, as mentioned early, trains are less flexible than trucks as they are destined to a particular port only and have to adhere to an exact schedule. In addition, in this case, trains are unreliable as a consequence of trains sharing railway tracks with passenger trains which are prioritised over freight trains. This is not uncommon but has severe impact on the reliability of the freight train schedule in this case. Additionally, the train cars and engines used have a high failure rate, so while cost of train transports are low, they often need to be substituted or supported by unplanned truck transports, demonstrating the aforementioned substitution effect (Aberle, 2003) in reality. As the capacity difference is significant (a train carries about 1800 tons compared to 20 tons for a single truck) this has high impact on the number of trucks required and is a significant challenge to capacity planning of the supply network.

4.1.3. Quantity Structure

For the supply network under investigation, most transport planning is done on a weekly basis and this timeframe also serves as baseline for the numbers provided. The total capacity of the supply network for a week is deduced from the number of ships to be loaded. This number was given to be between 2 and 3 ships each week, with each ship being considered to carry 30000 tons of load. This would suggest a total average transport capacity of between 60000 and 90000 tons per week. Observation shows, however, that the range is smaller, varying between 50,000 and 70,000 tons per week, equalling from 1.7 to 2.3 ships a week. The reason for this being primarily, that during

the observed period not all ships required the full 30,000-ton load, as there were mixed cargo ships being loaded as well. Therefore, the observed weekly capacity will be used for this study. To supply the required quantity of material, a total of 12 train transports are scheduled each week. Each train provides a maximum loading capacity of 1,800 tons due to length restrictions allowing maximum number of 30 rail cars each carrying 60 tons. As mentioned before, the train transport is as vital as unreliable in this supply network, hence instead of the theoretical weekly capacity of 21,600 tons, the observed train capacity ranged between 17,000 and 20,000 tons. This equals 9.4 to 11.1 trains per week, underlining the perceived fluctuations in availability of this transport medium. As truck transports are used to partially compensate the shortfall in train transports, the number of these transports varies accordingly. The observed values range from 1,900 to 2,200 individual transports per week. The initially reported values indicated an even wider range of 1,500 to 2,500 truck transports to correspond with the overall quantity levels. However, the study will assume the observed range as baseline for the later verification of the model. An overview of the values is provided in the table below.

		Transports	Tonnage
Ships	<i>Reported</i>	3 - 4	60,000 - 90,000
	<i>Observed</i>	1.7 - 2.3	50,000 - 70,000
Train	<i>Reported</i>	12	21,600
	<i>Observed</i>	9.4 - 11.1	17,000 - 20,000
Truck	<i>Reported</i>	1500 - 2500	30,000 - 50,000
	<i>Observed</i>	1900 - 2200	38,000 - 44,000

Table 4.1 - Supply Network Quantity Structure

The observed numbers of transport and associated tonnage were used as input for the simulation model at hand. The model was constructed to replicate observed values as accurately as possible, using random distributions to account for fluctuations in order levels and timing. The implementation is described below in the section on model entities and the order process respectively. Further, the model is built to allow the user to influence number of transports at runtime.

4.1.4. Assumptions and Constraints

As pointed out by Law (2003) a simulation model will always be a simplification and abstraction of the real-world system. While these simplifications are necessary to reduce

complexity and make the task of model creation feasible, they entail certain constraints and assumptions creating boundaries for the model. To maintain the credibility and applicability of the model, it is, however, vital to make these assumptions and constraints transparent and clearly document them (Birta & Arbez, 2013).

Therefore, this section serves to document the differences between the system under investigation and the model at hand, capturing the assumptions and constraints necessary to depict the supply network described in the simulation model.

The model only considers the dry bulk supply network and container and liquid bulk shipments are omitted, as the number of transports required is significantly lower.

Further, in the real-world system, between two and six different dry bulk products are produced and transported simultaneously using the same network. The difference between the products is mostly related to purity and chemical characteristics, hence there is no cleaning or setup time when loading vehicles with different products. In the model, this differentiation between products of the dry bulk product group is not considered.

The demands for the product groups are combined and, in this way, the total transport capacity of the supply network is being used. The reason being, that the focus is on optimising the supply network performance overall instead of production planning and scheduling. No substitution effects in the plants supply planning need to be considered, avoiding competitive planning scenarios. Capacity at the plant is also not an issue considered in this model. As mentioned before, even in reality the plants have significant storage capacity. By further eliminating the interdependencies caused by different products, the assumption is that the plants can always satisfy the demand created by the orders in the model. Therefore, the only constraint to delivery capacity is the transportation network itself, which is at the centre of this investigation.

In the real-world example, orders are received on a vessel basis, meaning that at intervals, orders for ship size quantities are received. These orders are placed at a port which then, in turn, will place orders with the plants considering its own stock situation. The plants will subsequently integrate the order into their respective demand plan and allocate it to individual transport units. In the model, the actual vessel order is not modelled. Instead, the orders are placed directly from the port to the plant in truck size units. The allocation to individual transport units happens at the plants, taking into

consideration the different control methods for each scenario. Again, as the focus is on the inland transportation and allocation of orders, the ports' own supply and demand planning operation are not modelled explicitly, setting a clear limit to the model.

The trucks operate on a 24/7 basis in the model. While the around-the-clock operation is accurate, certain restrictions to truck availability, such as national holidays, apply. As this is only applicable on a very small number of days each year, it was decided to account for that variation by choosing a timespan for observation with no holiday and, additionally, calculate performances on a daily basis to compare the simulation results. Breakdowns and planned maintenance are modelled via distributions in the model at hand, using historical availability rates obtained from sample data available.

Both in the model, as in reality, each truck carries same quantity as the trailers used are similar in size, aiming to maximise loading capacity under the given legal limits. Small differences in weight due to overloading or loss that occur in reality are, however, not accounted for in the model, the reason being, that they cannot be planned. In reality, a slightly larger material quantity is supplied to the port to ensure full delivery of the required order quantity. For the overall performance of the network these small deviations are regarded as unimportant. As they would, however, increase modelling complexity, they are not considered for the simulation model used in this research project. Less than full trucks were only observed in exceptional cases and are, therefore, not considered in the model either.

Loading and unloading capacity at the plants is modelled via delay times (varying via distributions) that it takes for the loading to complete.

The trucks choose and follow their own route across the GIS space of the supply network both in reality and the model. For simulation purposes however, fixed route alternatives have been established. Real time traffic is available for the model but is not considered due to a strong negative impact on model runtime. Traffic jams and detours are, therefore, accounted for via the average truck speed, which is recalculated for each journey individually.

4.2. Model Entities and Estimation of Empirical Variables

Following the previously described approach to agent-based modelling, all relevant entities in this model are represented as agents (Siebers et al., 2010). This includes stationary agents, representing physical locations, such as plants or ports, as well as mobile agents, representing the transport units or even agents that represent abstract objects, such as an order. As it is one of the central benefits of agent based models, all agents have the ability to interact (Bonabeau, 2002). Based on these interactions, different topographies can be defined (Macal & North, 2014). The model pertains to the group of geographic information systems (GIS) where agents move or interact with realistic geo-spatial landscapes. Agents have an actual location (e.g. geospatial coordinates) in that landscape. The GIS space is vital to the functionality of the model at hand, as it provides the ability for the truck agents to move from point to point using road network information and even traffic data. This functionality allows for the accurate simulation of transportation tasks as required for this study. However, not all agents are linked to a physical location, hence to a certain degree the model at hand can also be categorised in the group of network-based topologies. In this topology, agents are defined by their role and linkage to other agents. For example, the order agent ‘travels’ along edges from port to plant to truck nodes, without physically moving through GIS space at that moment in time. Accordingly, the model described here can be understood as being a hybrid with regard to agents’ social interactions, applying both concepts from GIS and network topologies.

All individual agents and their respective functions are described in detail in the following sections. The detailed code for each agent is provided in the appendix.

4.2.1. Port Agent

Each port is represented by an agent. The main functionality of the port agent is to create orders that transfer the demand for material to the plant agents. For that purpose, the port agents are equipped with an event that triggers the *createOrder()* function in intervals. This interval is influenced by a Poisson distribution, reflecting the random placement interval of orders in reality. The lambda values are dependent on the order level chosen and can be controlled via parameters for each simulation run. The order levels used in

the experiment are described in greater detail in section 6.1.1.2. Each port generates random orders for each plant, indicating the loading plant in the order. This is done to reflect the transport demand situation of the network accurately, where certain orders are allocated to a particular plant, depending on factors, such as availability or plant capacity.

4.2.2. Order Agent

The ports generate orders reflecting their demand for material. These orders are represented by an agent in the model. Each order agent is sent as a message from the port to the plant agent, as described in the process flow below.

The following parameters are stored in each order agent:

- *Order ID* (a unique identifier)
- *Destination Port* (the name of the port that placed the order)
- *Loading plant* (name of the plant the order is addressed to)
- *Order rate* (price offered per km for transport of the order)

The order rate is determined during order generation by the port agent. The rate reflects the price that is paid to the carrier for transportation of the product from the production plant to the port. As in the customer example, the rate is set on a per km basis to account for different distances to the different ports. From a model point of view the order rate reflects to a certain extent the different price levels paid by customers for orders. More importantly the fluctuating rates try to capture the differences in price resulting from the priority of deliveries. Delivery times demanded by customers leave often very little lead time for inland transportation, requiring quite frequent shifts of priorities. The unreliable train connection aggravates that situation even more. Typically higher prices are paid for such rush orders, to compensate carriers for the change in plan or to attract additional capacity. For the model an exponential distribution was found to depict the fluctuation in order rate.

$$rate = \exp(2, 0.2)$$

The order rate serves as an important element to simulate fluctuation in demands for transportation. Orders are not only placed at random intervals but are also of varying economic interest for the carriers, creating the demand side of the market in the model.

The order agent contains additional variables for *order value* and *trip length*. They are initialised on order creation by the port and will be filled by the plant agent upon order arrival.

4.2.3. Plant Agent

The orders generated are sent as message to the plant agent specified in the loading plant parameter. Like the system under investigation, the model contains two production plants, hence two plant agents are active in the model at runtime. Both plants are able to produce the single product in sufficient quantities.

In reality, loading capacity is limited by availability of loading equipment. This is modelled as delay in the loading process step and is described in greater detail in the delivery process flow below. The plant has two main functions in the model. It first calculates for each received order the order value variable. The formula used in the model is the order rate multiplied with the distance from loading plant to destination port in kilometres. This formula could be adjusted to cover more complex customer scenarios in future implementations of the model. The second central function executed by the plant agent is the allocation of orders to trains. Both plant locations are connected via train lines to port B. As mentioned, train transport is the preferred option for all orders that are destined to go to port B. Therefore, the plant has a functionality to check train availability for all relevant orders. That includes both the train operational status and its capacity. If the train is operating and has free capacity, the order is allocated to the next free train. If the train availability check returns with negative result, the order is forwarded to the central order registry. The same is true for all orders on routes where there is no train service available.

4.2.4. Truck Depot Agent

The order registry is one core function of the truck depot agent. It contains an unsorted list of all orders placed by all destination ports and to all loading plants. The central registry is a technical requirement for the model function. For reasons related to program architecture, it was placed in the truck depot agent. The technical realisation of the order registry has no impact on the control scenario. It both supports central and decentral

control scenarios. In decentral control scenarios trucks poll the order registry for a new order and then decide whether to accept the order offered or not. In the central control scenarios, such as the scenario currently used in the SUI, the orders are assigned by the plant agents to their trucks, using the order registry as backlog. The process of order allocation is described in section 4.3.1.

The truck depot agent serves as a start and return location for the trucks in the model. Therefore, the truck depot has a physical location on the GIS map in the model. Trucks without orders will return to the truck depot as will trucks that require maintenance. This closely reflects behaviour in reality, where trucks use central dispatch points in close vicinity of the plants to wait for orders. Trucks will not always start their trip from there and return to this lot. As these trips are not compensated by the company and do not affect planning they are not considered in the model.

4.2.5. Train Agent

The model offers two transport mediums for the orders received: trains and trucks. Both are modelled as agents in the simulation model at hand. They are, however, implemented differently to account for their role in the model.

There are two train agents available, each one representing one train connection from plant to port. Each train has a parameter to indicate their operation status and a capacity counter. The maximal capacity can be set for each simulation run from the simulation control screen. Each train agent further has an event that is triggered periodically, setting the train's operational status. In the simulation model this event uses a random distribution to determine the running status of the train. The probability value can be set from the simulation control screen via the train breakdown probability parameter.

In a potential operational implementation of the model, this event would constitute a suitable spot for an interface to an online service of the train company, providing availability information directly to the agent environment. This possibility to connect outside or legacy software into a simulation model, by “wrapping” its functionality in an agent is another advantage offered by multi-agent environments (Bazzan & Klügl, 2014, p. 376).

In this model, trains are not modelled individually as, unlike trucks, they are not to be controlled on an individual unit level.

4.2.6. Truck Agent

Trucks are modelled individually as agents. They form a population of agents sharing similar functionalities and parameters. As the truck agents are at the core of this simulation model, they contain a wide range of functions and controlling parameters. The most important parameters are listed below:

- *Cost rate driving (cd)*
- *Cost rate waiting (cw)*
- *Markup factor (mf)*

In all but the fixed assignment scenarios, a market is formed between the transport demand and the transport services offered by the transportation units. It is assumed that all market participants aim to maximise their economic utility in that market. Therefore, the truck agents have not only parameters representing their cost rates for driving and waiting, but also a markup factor that reflects their intended profit margin (Bouzid, 2003). All three parameters are individually determined for each truck agent via distributions on model start-up. Both cost rates are approximated in the model using truncated exponential distributions. The formulas are as follows:

$$cd = \exp(0.2, 0.5, 0, 1)$$

$$cw = \exp(0.03, 0.1, 0, 0.05)$$

The markup factor is dependent on a general markup parameter that can be set via the simulation control screen. Based on that markup parameter an individual markup factor for each truck is determined using a truncated normal distribution with the following formula:

$$mf = \text{normal}(mv - 10, mv + 10, mv, 10)$$

Truck cost parameters and markup factor are essential for the truck agents' *CalculateUtility()* function. It is among the list of the central functions each truck agent incorporates:

- *FindNextOrder()*

- *CalculateUtility()*
- *ClosestTruck()*

In the autonomous control scenarios the *FindNextOrder()* function is essential in the process of order allocation. It will request a new order from the central order registry whenever the truck is in an idle state and ready to accept new orders. The different states of the trucks agent are described the section covering the delivery process. Upon receipt of an order the *CalculateUtility()* function is invoked to decide whether to accept the order or request a new one. The *CalculateUtility()* function determines in a first step, the variable cost incurred for this order using the cost parameter mentioned above based on this formula:

$$cv = tripLength * cd + distance * cd$$

Trip length being a variable of the order agent providing the distance via road from the loading plant to the destination port. This value is filled for each order by the plant agent as described earlier. The distance variable is calculated by the truck agent in real time and indicates the distance via road from the truck's current physical location to the loading plant.

In the next step, the *CalculateUtility()* function will determine the price p the truck is willing to accept by applying the markup factor using the following formula:

$$p = cv + cv * mf$$

Finally, the *CalculateUtility()* function will compare price p to the order value offered by the current order. If the value is equal or higher, it will accept the order.

If cooperation is active in the scenario, the *ClosestTruck()* function will be called before accepting the order. Its primary responsibility is to determine whether there is a truck that is better positioned and willing to accept the order. The idea behind this function is to improve overall performance, trying to move from locally optimal solutions to a global optimum, addressing the concern, that agents may not be able to achieve a globally optimal solution, but rather only find local optima (Kikuchi et al., 2002). In order to achieve this, the *ClosestTruck()* function will act as a temporary broker for this order. It polls all trucks to determine whether they are in a state that allows them to accept an order. All trucks on this list are asked for their current distance to the loading plant. All trucks that have a shorter distance than the truck agent acting as broker are

considered. If no truck is closer than the truck agent itself, the *closestTruck()* function terminates and the truck itself starts delivery execution. If there are trucks that have a smaller distance to the loading plant, these trucks are polled for their price. That means that all these truck agents in turn run their own *calculateUtility()* function to determine their offer price. If there is a truck that asks a price lower or equal than the order value, the order is sent as a message to this truck. In case there is more than one truck, the first truck agent to respond will receive the order. As this situation only occurs in rare instances, no further optimisation to find the optimal price was implemented here. If there is no truck that is willing to accept the order value offered, the truck agent executing the *closestTruck()* function will carry out the delivery itself. Allocating the order to the closest truck may fall short with respect to achieving a global optimum with regard to the cost incurred (Bouzid, 2003). As implemented, the *closestTruck()* function may select a truck which is better located, but charging a higher price. However, this behaviour is accepted, as the focus of this model is rather on better usage of the transportation capacities available, than on cost minimisation. Additionally, the price charged is limited by the order value; hence it will never exceed the cost deemed acceptable by the ordering party. If required, selection criteria beside distance to the loading plant and price can be implemented into these functions for future implementations.

In the model, data is easily shared between the truck agents as this function is part of a cooperative scenario, assuming that trucks are benevolent towards each other (Castelfranchi, 1995). However, the model does support a strict separation of information and can be configured to share only minimal data to address concerns of privacy.

The truck agent further contains a speed variable which is re-determined before each delivery. The variable indicates the average speed the truck will drive on its delivery run. It is used to simulate the impact of traffic on the model's performance. The GIS space configuration and the simulation tool offer interfaces to integrate traffic data and automatic route planning into the simulation run. However early simulation runs during prototype phase have shown, that this adversely affects the execution speed of the model, significantly increasing runtime of simulations with larger numbers. This could

be addressed with more powerful hardware and faster internet connections when implementing the agent model as control instance. For the purpose of this simulation experiment, the distribution below was used to approximate average truck speed for each delivery run

$$vt = \text{beta}(20, 4, 30, 65)$$

Another important variable controls the operational status of the trucks. As with any technical equipment, trucks require planned and unplanned maintenance and may, therefore, become unavailable for transport services. This is modelled via a breakdown variable which indicates the operational status of the truck represented by this agent. To account for unplanned events such as breakdowns, the variable is set via a breakdown event that is executed daily and uses a random function to determine the operational status. The probability value can be passed from the simulation control screen as parameter. If the breakdown variable is set to non-operational, the truck will return to the truck depot after completing its current delivery. Only once it arrives at the depot, the breakdown variable can be reset, considering the truck depot functions as a repair shop.

The *update utility event* is another important function that is implemented as an event in each truck agent. This event is triggered periodically as soon as a truck is waiting at the truck depot for new orders. The purpose of this function is to decrease the markup factor over time. Trucks incur cost for waiting time, such as personnel or financial cost. This is expressed in the model by the waiting cost variable mentioned above. At the same time, the trucks' income depends on having orders assigned for delivery. The function, therefore, assumes that with increasing waiting times truck agents would be willing to accept a less favourable offer instead of waiting for an order that returns their target price. As the markup factor expresses the trucks' expected gain, it is assumed that the truck would, after a waiting period, reduce its expected return. The lower limit is constituted by a markup factor of 1 which effectively signifies that the truck agent is aiming to recover its cost only, accepting zero profit. The reduction itself is based on the cost of waiting. This process is described in greater detail as part of the delivery process in the following section.

4.3. Process Flow

The focus of this section is on elaborating the process flow within the model. When looking at the end-to-end process that is reflected in this model, it becomes evident that it can be separated in two process areas. The first one being the order process, focusing on assigning orders to the transportation unit. The second area is the delivery process and the necessary steps executed by each truck agent. Both areas are linked together at order allocation, which depends heavily on the execution scenario. The scenarios are described in greater detail in section 5.2.

This section will first describe the order process, followed by the truck agent’s state chart diagram illustrating the delivery process.

4.3.1. Order Process

This section serves to provide a complete view of the order process flow, placing the individual agents functions outlined above into context. The Figure 4.2 offers an overview of this process.

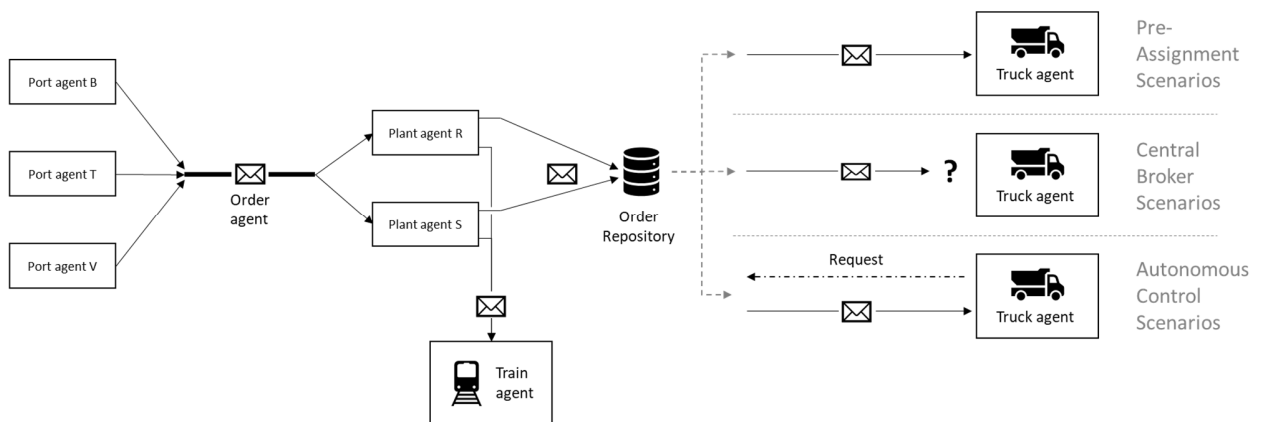


Figure 4.2 - Order process flow

The starting point for this process is the order agents created by the different port agents at random intervals. As laid out above, the orders reflect the demand for transportation in the model. The orders are sent as a message to the plant agent for processing. The messaging between agents is one of the core functionalities of agent frameworks (Bradshaw et al., 1997). The plant agents will determine the length of the transportation route and use this information to calculate the order value, which is the product of the *trip length* and the *order rate* parameter. Both variables are updated in the order agent.

Next, the plant agents will check whether the order can be transported by train, meaning that the plant and port are connected via train, the train is operating, and it has sufficient capacity for this order. If this is the case, the order is sent to the train agent for further processing. Any order sent there is not relevant for truck transportation anymore reflecting the real situation, where train wagons will typically not be unloaded, even though the train may have undergone significant delay.

If train transportation is not available for the order, it is again sent as a message to the truck depot agent, which hosts the central order registry in the model. As mentioned before, the placement of this order registry within the truck depot agent has primarily technical reasons, as it facilitates the integration of the different control methods in one simulation model.

The next step, the order allocation differs significantly depending on the control scenario chosen for the simulation run. In the pre-assignment scenarios, the plant agents take their orders from the order registry on a first in, first out basis and allocate them to trucks assigned to their plant as soon as a truck is marked as free. This order allocation behaviour can be described as a push strategy (Adler & Blue, 2002; Bretzke, 2010), as the truck agents are not involved in the order selection process. On the other hand, pull strategies (Klaus & Kille, 2008) can be found both in central and autonomous control. In the central broker scenario, the truck depot agent acts as broker by selecting the next order from the order registry and offering it to all free truck agents, asking for their respective price (Sandholm, 1993). The truck agents use their *calculateUtility()* function to determine whether to bid for this order or not. If a truck decides to bid for the order, it returns its price to the central broker. The broker then picks the lowest price offered and sends the order as message to the winning truck. If no truck bids on the order, the order is placed back into the order registry and the next order is offered.

In the autonomous control scenarios, each truck agent polls the order registry for an order upon becoming free. It receives the next order from the order registry. The truck agent will then calculate its utility and decide whether to accept the order or wait for a better order. Additionally, in the cooperative scenario, before accepting a suitable order, the truck agent will check whether other trucks are in a better position to fulfil this transportation request using the *closestTruck()*. As described above, the truck acts as

temporary broker, aiming to find a truck which is better located and willing to accept the order. The order is then either allocated to the truck with the shortest distance to the loading plant or if no truck is in a better position, the polling truck itself will start the delivery. The delivery process is described in the following section.

4.3.2. Delivery Process

The second process area is the delivery process carried out by the trucks for each order. This process is represented by a state chart diagram that controls the various steps, from order receipt until delivery for each truck agent. The state chart diagram is shown in Figure 4.3.

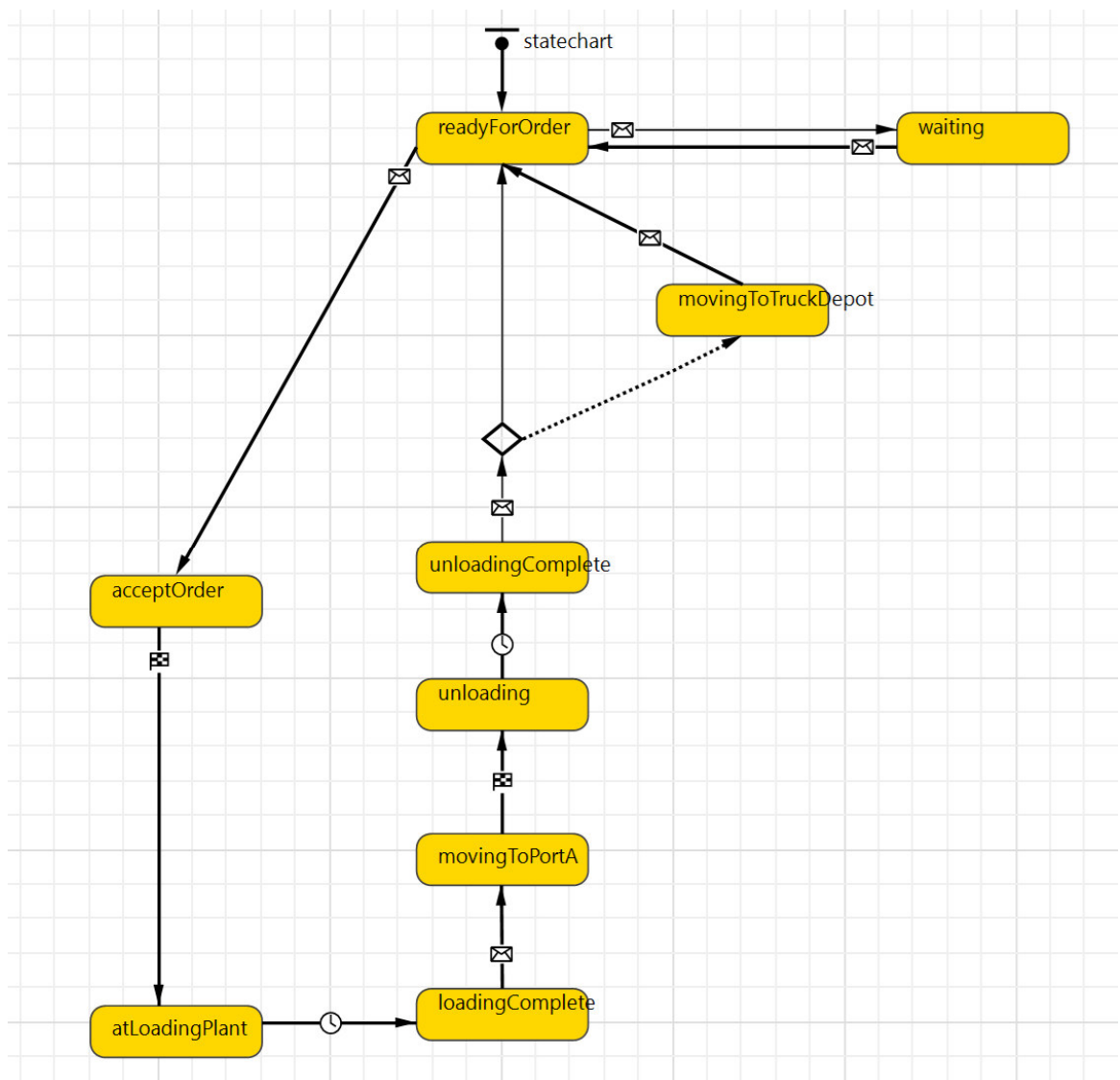


Figure 4.3 – Delivery process flow

State chart diagram as introduced by Booth (1967) consist of states and transitions that lead from one state to the next. Transitions can be conditional, requiring a certain trigger or guard conditions to be fired and moved to the next state. State chart diagrams are quite commonly used in agent modelling because, while being easy to create and understand, they can be executed at runtime and even be used to generate code (Cossentino, Gaud, Hilaire, Galland, & Koukam, 2010). The entry point represents the starting point of any state chart diagram. It is connected to the ‘Ready for order’ state in this case, which at the same time is the end state, that truck agents enter after completing delivery of an order. Whenever a truck is in that state it is available for new orders. As illustrated in the previous section, depending on the control scenario it will either request or be assigned a new order while in that state. The transition leaving this state is triggered by a message of the type order. As described above, this order is sent by the central order registry as a message. The transition has a threshold implemented, that again verifies the utility of an order. This threshold is in effect, for all but the fixed assignment scenario, where the utility function is not active.

This transition terminates in the state ‘Accept order’ which serves several purposes. Primarily it determines a route from the trucks’ current location to the order’s loading plant using the GIS space road network, similar to any GPS route planning service. As mentioned before, the ability to integrate real-time traffic data into this route determination process was deactivated for performance reasons. Instead, the function to determine the average truck speed for this delivery run is executed in this state, updating the speed variable. In addition, on exiting the ‘accept order’ state, several tracker variables that support process control and result documentation are updated. For example, timer and distance tracker variables are initialised to document this delivery run. Finally, an acknowledgement message is returned to the truck depot agent to confirm the order receipt. Having completed all functions in the ‘Accept order’ state, the truck will start moving through GIS space along the previously determined route towards the loading plant.

The following transition is triggered by the arrival of the truck agent at the plant. It serves as a guard to the ‘At loading plant’ state. This state indicates the completion of the first leg of the journey and documents the arrival of the truck at the loading plant.

The state updates the relevant tracker variables and determines the loading time required for this truck. As mentioned, the differences in loading time encountered in reality due to external factors, such as availability of equipment, number of trucks etc are represented by the following distribution:

$$loadingTime = weibull(1, 1.6, 1)$$

Applying the distribution above, about 70% of the loading times observed lie in an interval of 1 to 3 hours, which reflects quite accurately the loading times observed in reality. The loading via wheel loader itself takes up only a small portion of this time span. The trucks spent most of the time waiting for their turn at loading and the weighing station, which has to be passed before and after loading to get an exact measurement of the load weight. The chosen Weibull distribution at the same time helps to introduce a desired level of uncertainty, producing rare cases with significantly longer waiting times that reflect breakdowns of equipment or personnel shortage for example. The loading time is calculated in the 'At loading plant' state and applied as guard to the transition leaving that state. This means that this transition will fire once the previously calculated time has passed, effectively simulating the previously mentioned loading process in the model.

The transition leads to a state named 'Loading complete' which has been introduced to effectively track completion of the loading process. The state is left via a transition that uses the native agent function *moveTo()* to trigger the start of the trucks journey to the destination port. Again, the truck will find its way via the route functionality provided by the GIS space network.

The truck's journey towards the destination port is represented by the state 'Moving to Port' in the state chart diagram. Similar to the trip to the loading plant, the arrival of the truck at the port location triggers the transition that connects the 'moving to Port' state with the state 'unloading'. The time required to perform the unloading is again modelled by a distribution with the following parameters:

$$unloadingTime = weibull(1, 1.4, 1)$$

The results of this distribution have been verified against the observed unloading and waiting times. Unloading occurs slightly faster than loading, as trucks typically just dump material into underground pits from where it is transported via conveyor belt into

the storage areas. In the diagram, the unloading state also serves to update several tracker variables. As it concludes the end of the delivery, time and distance variables are updated at this point. The ‘unloading’ state is left once the unloading time determined by the distribution above has passed.

When reaching the ‘unloading complete’ state, the delivery of an order is understood to be completed. Thus, the truck assumes a ‘free’ status making it available for new orders. The truck agent will now request new orders from the central order registry. Even though the structure of the state chart diagram is identical, the model behaviour differs depending on the control scenario.

Technically in the model, in all cases the *findNextOrder()* function is called. In autonomous control scenarios the function requests an order from the central order registry and evaluates whether to take it as described in the previous section. In central control scenarios the function reports the truck’s state as ‘free’ to the central broker agent which, in turn, considers it for the next order to be tendered or, in the fixed assignment scenario, assigns the next corresponding order to the truck.

Under any scenario, the function returns a Boolean value, depending on whether a suitable order has been provided or not. This is reflected in the state chart diagram as a conditional transition.

If a suitable order has been found, the truck agent will move directly to the ‘Ready for order state’. The new order will be received as a message as part of the next execution cycle of the state chart diagram. As part of this execution cycle, the truck will directly move to the loading plant. The loading plant and any other order related information is passed as attribute of the order agent.

If the *findNextOrder()* function returns with a negative result, the second fork of the conditional transition will be executed instead. It leads to a state called ‘move to depot’ representing the return journey of the truck back to the truck depot. The state is used to trigger that journey, again invoking the *moveTo()* function and providing the truck depot as destination. The state chart diagram will, however, directly transition to the state ‘Ready for order’ thus placing the truck into the right state to receive new orders. While in that state, the truck agent will periodically execute the *findNextOrder()* function to announce itself and request new orders. This is triggered by a periodic event that is

scheduled to be executed in time intervals every 20 minutes of simulation time. Once the truck arrives back at the truck depot and has not yet found a new suitable order, in addition to searching for an order every 20 minutes, it will enter the waiting state at the same time interval. The state 'Waiting' forms a loop with the 'Ready for order' state. The periodic event used to trigger the search for a new order also triggers the transition leading to the 'Waiting' state. This transition has a guard that checks for the truck location being equal to the truck depot location. If this is the case, the waiting state is reached. The primary functionality provided in this state is the update of the truck's markup value. As mentioned before, the underlying assumption is, that after a waiting time, the truck will be willing to accept an economically less rewarding offer. As the expected gain in the model is expressed by the markup that trucks calculate on top of their cost, the markup factor is consequently decreased over waiting time. Technically, this is realised as a function within the state 'Waiting'. Each time the truck enters this state, the function below is executed.

$$mf = mf - (costWaiting * 10)$$

The reduction is realised as a function of the waiting cost. The idea behind this is that waiting cost expresses mostly fixed cost such as cost for capital bound, personnel cost and maintenance cost. The model assumes that the higher the fixed cost, the higher the motivation of the truck to find a new order.

The linkage is based on observations, where a correlation of age of the trucks and their willingness to accept orders at lower prices was evident. Newer trucks had a notably higher tendency to accept offers below their asking price. This could be linked to their higher fixed cost, which was mostly driven by cost of capital.

As a result, each time the truck agent enters the 'Waiting' state the aforementioned function is executed and reduces the markup factor. This is done until either the truck receives an order and the markup factor is restored to its initial, truck specific, start value or the markup factor reaches a value of 1. The lower limit signifies that the truck agents in the model will always aim to recover at least the cost incurred during an order run.

There is no distinction made between short and long-term profit expectations, meaning that truck agents will not accept temporarily a price below their cost threshold to invest in the relationship with their customer. In the current implementation the trucks have no

memory, meaning that each delivery is a new start for them, which is also expressed by resetting the markup factor. While this could be an interesting area for future research it is not considered here.

4.4. Testing the Model

When talking about testing in the context of simulation modelling, the terms verification and validation are commonly used to describe the relevant activities in that area. As mentioned in chapter 3, verification asks the question, whether the model was build right, whereas validation aims to answer the question whether the right model was built (Sargent, 2013). Both verification and validation are vital tasks in order to establish credibility of a model (Birta & Arbez, 2013). Credibility is a relevant property of any model, describing whether results and conclusion reached by simulation will be accepted by sponsors and SME (Law, 2003).

Verification and validation are integral parts of the model creation process. As indicated, this process follows the state of art in software development, using an iterative and agile approach. Agile development aims to break down large development cycles into smaller, iterative units and produce working software early on (Beck et al., 2001; Cohen, Lindvall, & Costa, 2003). This idea is applied to the model creation process at hand, by building a prototype early on and feeding back verification and validation results to incrementally improve this prototype in the direction of the final simulation model. The above described close interaction with client SMEs, such as through the regular simulation review meetings, enabled this feedback to be gathered and integrated into the next version of the model. This way validation and verification became a continuous process, performed alongside each iteration in the model creation process (Robinson, 1997).

The prototype approach further proves to be a great advantage in the area of model verification. Using the graphical capabilities offered by the simulation tool, visual debugging greatly reduces time and effort required, enabling efficient step-by-step analysis of the process (Law, 2003). In addition, for validation of the model, the prototype provides an accessible communication basis for conversations with SMEs and stakeholders. The prototype enables structured walkthroughs and provides

understandable results early on, thus helping to ensure the simulation model is an accurate representation of the SUI (Law, 2003).

While there was constant feedback and an ongoing validation process throughout the model's built phase, the final validation step was carried out as a detailed pilot study. The pilot study is split up in two steps, with the first one focused on identifying limitations and validating assumptions taken (Birta & Arbez, 2013). The second step, however, serves as a final "assessment of accuracy" (Balci, 1990, p. 25), ensuring the model is close enough to the real-world example to fulfil the purpose of the simulation study (Greasley, 2008).

4.5. Ethical Considerations

When discussing the credibility of a simulation model the ethical aspect must be considered as well. Being a powerful tool, simulation brings great responsibility to the researcher regarding usage and application (Kruger, 2003). To address this issue Oren, Elzas, Smit, & Birta (2002) introduced a code of ethics for simulation researchers. While this code of ethics addresses a wide range of behaviours, two aspects seem particularly relevant in the context of this thesis.

The first one demands to "Provide full disclosure of system design assumptions and known limitations and problems to authorised parties." (Oren et al., 2002, p. 1). This has been realised in this thesis by explicitly documenting assumptions and constraints in the relevant sections and validating them through proper testing. Additionally, as mentioned above, subject matter experts and stakeholders were involved throughout the model built and simulation phase, providing input and feedback on limitations and constraints of the simulation model. Closely connected is the second behaviour to be highlight which asks to "Assure thorough and unbiased interpretations and evaluations of the results of modelling and simulation studies." (Oren et al., 2002, p. 2). This is demonstrated for this study by thorough and detailed testing as documented in the thesis as well as by reflecting and validating results with experts and stakeholders, such as the SME interview, to ensure understanding.

One additional aspect regarding ethics is the aforementioned concerns around confidentiality of business data. This has been noted and taken seriously for this research process, evident, for example, in the concealed locations or omission of names. Another area with ethical implications is the aspect of consequences brought by new technologies (Langheinrich & Mattern, 2002) such as the proposed autonomous control approach. Consequences such as the impact of the solution on the workforce and external partners have to be considered during an implementation project. A final ethical consideration is regarding the choice of simulation method and tool. Van Dyke Parunak et al., (1998) mention, that the researcher's responsibility is to select the method and tool offering the best fit for the research problem and area and withstand influence by stakeholder interests, funding or similar. The selection of the simulation method and tool for this thesis was based on purely functional considerations, as documented in the following section.

4.6. The Simulation Tool

There is a wide range of simulation tools available, both for general simulation as well as specifically for agent-based simulation. Agent-based simulation software can be categorised into multi-purpose software and programming languages on the one hand and specially designed agent simulation software on the other (Macal & North, 2014). Multi-purpose software can be as straight forward as using Microsoft Excel and VBA scripts to generate agents, or it can be about relying on more sophisticated modelling and simulation tools such as MATLAB, for example. Software specifically designed for agent-based simulation can be grouped according to functionality and size or along the lines of open source versus commercial simulation tools.

A third approach is to develop software agents and their simulation environment entirely from scratch using object-oriented programming such as Java or Python. Looking at the literature surveyed, it becomes evident that this third approach has been used frequently. Several authors or research groups have created their own simulation tools and agent environments for their research work. Prominent examples are the AGENDA tool (Fischer et al., 1999), TRACONET (Sandholm, 1993) or MATSIM (Bernhardt, 2007). Weiß & Jakob (2006) provide an extensive overview and comparison of agent

simulation tools and platforms available, while Tobias & Hofmann (2004) focus on Java-libraries for agent-based simulation.

While a custom developed simulation tool can potentially be tailored more closely in the direction of the specific research purpose, it is often difficult to extend its functionality beyond the initial scope. This was found true for the PLASMA framework as introduced by Schuldt & Werner (2007), which was used for the first modelling attempts.

Unfortunately, the PLASMA tool, as with many others of the above cited custom developed simulation tools, is poorly documented beyond the publication scope. Further, no continuous support is offered for these tools and experts on the usage and development of these tools are hard to find.

Therefore, it was decided to use a commercial grade simulation tool for this thesis.

Among the available commercial simulation tools, AnyLogic (AnyLogic, 2018) was chosen for several reasons. The most important one is its unique ability to implement and simulate different simulation methods in one environment (Macal & North, 2014). The methods are discrete event, agent based and system dynamics simulation, allowing to model and simulate object, process, continuous world views in the same model (Greasley, 2008). For the thesis at hand, having discrete event simulation and agent-based simulation available in the same simulation model, allows for direct comparison of established and proposed control methods.

AnyLogic has been successfully used in a wide range of professional and academic research projects. For example, in modelling supply chain disturbances (Hoffa & Pawlewski, 2014), container loading (Mustafee & Bischoff, 2011) or vehicle scheduling (Merkuryeva & Bolshakovs, 2010).

Being a Java based tool, AnyLogic, on the one side, provides unlimited flexibility by offering a complete system development kit allowing the option of invoking any Java libraries desired. On the other side it offers an easy-to-use graphical user interface, lowering the entry barrier for new users. This graphical user interface further enables the creation of visual representations of models and simulation, such as the GIS landscape model used in this thesis. Having a visual representation of the model available at runtime greatly facilitates communication with non-technical stakeholders and advances understanding.

Having described the model layout, its design and the implementation in the simulation tool, the following chapter will show how the simulation experiments using this model were set up and executed.

5. The Experiment

5.1. Purpose of the Experiment

To understand the purpose of the experiment at hand, it helps to recall the research structure and the questions as repeated below.

Research Aim	Research Objectives	Literature Gaps	Research Questions	Results
<p>Aim: The aim is to investigate how autonomous control can improve the performance of logistics networks over conventional control methods</p>	<p>Objective 1: Understand the challenges of logistics networks and the need for autonomous control</p> <p>Objective 2: Investigate how autonomous control can be applied to bulk transportation networks</p> <p>Objective 3: Create an agent-based simulation model of a bulk truck transportation network</p> <p>Objective 4: Conduct a simulation experiment to compare the performance of autonomous control over existing control methods</p>	<p>G1: Objective gap</p> <p>G2: Simulation gap</p> <p>G3: Implementation gap</p>	<p>RQ1: Can agent-based modelling be used to apply autonomous control to a bulk truck transportation network?</p> <p>RQ2: Can autonomous control improve the performance of bulk supply networks over existing control approaches?</p>	<p><i>Defined through the findings in chapter 6</i></p>

Figure 5.1 - Research Structure

Looking at **RQ1**, the application of autonomous control to the logistics networks under investigation has been described in the previous chapter. To provide an answer to the remaining question is the primary purpose of this simulation experiment.

The experiment is designed to compare the performance of different control methods when applied to the simulation model. These methods have been assigned to different scenarios which are explained in the following section. The experiment consists of several simulation runs, with the control method being the independent variable (Creswell, 2014). To enable a comparison of performances, several key performance indicators are identified later in this chapter. These KPIs are applied to the model and are recorded for each simulation run.

5.2. Scenarios

5.2.1. Overview

The simulation model at hand is built to support a variety of configurations relating to supply chain control methodology. To structure the comparison of simulation results, five scenarios are defined. Shown in Figure 5.2 are the scenarios and the control method they belong to:

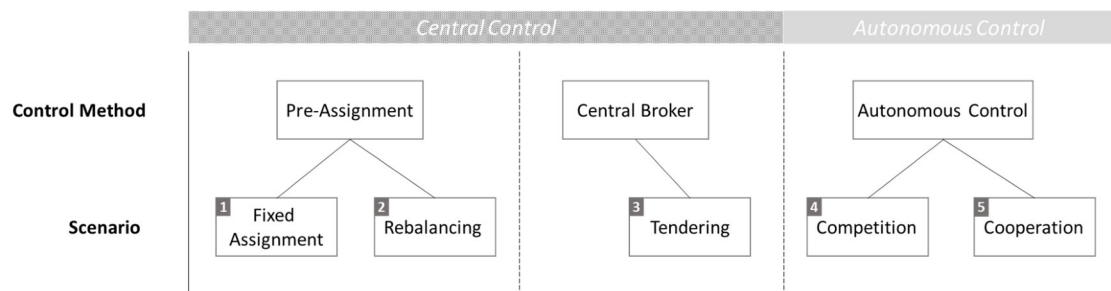


Figure 5.2 - Scenario overview

As indicated by the research questions, the main comparison is between the proposed methods of autonomous control and established central control methods. These central control methods are further subdivided into pre-assignment and central broker. While the pre-assignment method aims to closely reflect the control method applied to the SUI, the central broker method is introduced to offer another option and to control for effectiveness of the proposed autonomous approach.

The following sections are grouped by control method and serve to describe the contained scenarios in greater detail.

5.2.2. Pre-Assignment Scenarios

The pre-assignment scenarios aim to reflect the observed situation in the supply network. The group consists of two scenarios. In both scenarios trucks are assigned to the vehicle pool of a production plant. Orders are assigned to these trucks in the same sequence as they are received from the ports e.g. first in, first out. The trucks are assigned to the plant, signifying that the plants can freely dispatch the trucks as required. On the other hand, this means that all cost incurred by these trucks is to be covered by the plant they are assigned to. In the fixed assignment scenario, the number of trucks assigned to a plant is fixed.

In the market under examination, all trucks have been outsourced to a service provider. However, contracts indicate that trucks need to be preordered on a weekly basis, with fixed cost rates for both driving and idle times. This implies that adjustments to number of trucks and assignment to plants can be done once a week only. These conditions are reflected in scenario called 'Rebalancing'. In this scenario, the trucks again are firstly assigned to one of the plants. Once a week however, the distribution of trucks between the plants is adjusted. In the model two constraints apply to this scenario. In reality, trucks may leave the network or join late, while in the model the total number of trucks remains constant for the whole simulation. This technical constraint has however little effect on the overall results, as confirmed during validation of the model in section 6.1. The reason being, that the number of trucks is barely adjusted at all. As the outsourcing contract is with one company only, there are hardly any additional trucks available to be added to the truck pools. This close dependency on one key supplier is among the concerns leading to this DBA study. The same holds true for the opposite case: under normal circumstances the contracts offer little leeway to significantly reduce the number of trucks. Therefore, shifting trucks between plants is the tool used to optimise the supply network. The basis for the shifting of truck capacity constitutes the second constraint for the rebalancing scenario in this model. A weekly transportation demand forecast is created based on the demand situation of the ports. As this forecasting is a highly manual process, relying primarily on tacit knowledge by the planners, the model relies on a simpler approach to execute the rebalancing each week. The model uses the current order backlog for each plant and divides the trucks proportionally based on the number of orders waiting for transport at each plant. As shown in the model validation section, this approach produced satisfyingly accurate results.

5.2.3. Central Broker Scenario

The third scenario applies a central control approach as well. While order allocation is still executed by a central instance as in the two scenarios above, the main difference is that trucks are not pre-assigned to a particular plant anymore. Instead, a central broker instance which is responsible for assigning orders to transportation units is installed. It is implemented in the model as a function of the truck depot agent. This does not

necessarily reflect any association of this central broker with the logistics service provider itself. It is done in the model for practicality as the order registry has been implemented in the truck depot agent as well. The functionality could also be assumed by a different agent as required. The broker function of the truck depot agent assigns orders to trucks, taking into consideration the price demanded by them and the order value offered, acting as a market maker (Bonabeau, 2002). In the model, the broker agent cannot see the truck agent's price. It rather offers an order to all available trucks and the truck agents will respond with their offer. The central broker then sends the order to the truck with the lowest price offered. In future implementations of the model, more advanced price determination strategies such as sealed bid auctions could be implemented here (Mes, Van Der Heijden, & Van Harten, 2007; Schepperle & Böhm, 2007).

For the scope of this study accepting the lowest price offer is sufficient as the central broker scenario serves to showcase an easy transition from the fixed assignment of trucks towards a market-based allocation approach. In the context of the simulation experiment, the central broker scenario is intended to control the result of autonomous control strategies for the effect of price based allocation.

5.2.4. Autonomous Control Scenarios

The remaining two scenarios both belong to the group of decentral and more precisely, autonomous control. A distinction is made with regard to the trucks' behaviour towards each other. In scenario four the truck agents show competitive behaviour, each individual truck aiming to maximise their respective utility. In the cooperation scenario number five, the trucks behaviour is benevolent (Davidsson et al., 2005; Nwana, 1996), meaning the trucks are willing to forgo individual benefit, hence working towards a more globally optimal solution (Bazzan & Klügl, 2014). In both scenarios trucks will request orders from the central registry and decide, based on their respective utility function, whether to accept the order or to reject it. In the cooperation scenario, trucks will additionally check if there is another truck that is both willing to take the order (meaning its utilisation function is fulfilled) and is better positioned with regards to distance to the plant location. The truck agent will therefore poll all other trucks acting

as a temporary broker for the particular order. The process flow follows the description provided in the previous chapter.

5.3. Performance Indicators

Looking at the literature, several authors offer approaches to categorising and structuring logistics performance indicators. At the same time there seems to be agreement that there is no universally applicable logistical controlling framework (Gleißner & Femerling, 2008). The reason for this being the large variety of logistical activities and different requirements across industries and even companies. An example to illustrate this, is the supply readiness KPI, which aims to express how many deliveries were supplied within the agreed timeframe (Schmidt & Schneider, 2008). By varying the measurement baseline from delivery line items to full deliveries only, Bretzke (2010) demonstrates how difficult it can be to find meaningful and comparable logistics KPI even between companies in the same industry.

Gleißner & Femerling (2008) distinguish structural, productive, economic and qualitative KPI while Hellingrath (2008) differentiates between performance, cost and service KPI. An example for a structural KPI is the number of trucks owned by the company, which, according to Hellingrath's (2008) definition, is a cost KPI. The number of orders delivered per day is listed as productive KPI (Gleißner & Femerling, 2008) or performance KPI (Hellingrath, 2008). Hellingrath (2008) does include absolute and relative KPIs in this category, such as the number of orders delivered in relation to the total order number. Examples for both the category named economic or cost, are delivery or personnel cost. Naturally there is a conflict between the cost KPI and the performance KPI, as lower cost may lead to reduced performance and quality (Schuh, Stich, & Schmidt, 2008), however this conflict is an inherent issue of logistics. The final category named qualitative KPI is a subset of the service category offered by Hellingrath (2008). It contains indicators such as the customer service, flexibility or product quality. While having an impact on the customer satisfaction, these KPI are typically hard to quantify. In addition, quantitative service KPI, such as supply readiness or delivery delays can be summarised in this category.

Considering these categories and the performance indicators provided as examples above, the KPI selected for this simulation model fit well within the defined categories. Below the relevant performance indicators are listed and described with regard to their functionality and meaning. Aside from the theoretical categorisation, the indicators have been aligned with the business under observation to ensure they are meaningful and relevant with regards to applicability to practice as well.

- *Number of orders delivered*

This KPI is the adaption of the supply readiness indicator introduced above, providing the absolute number of orders that have been delivered to the port location. It can be measured on a total level or per port, truck or plant agent for example.

- *Order completion rate*

The order completion rate is a relative service KPI putting the number of orders delivered in relation to the total number of orders placed, again similar to the supply readiness rate indicators found in literature (Hellingrath, 2008). For the model, a rate of >99.5% has been defined to constitute full order delivery, as determined during the prototype run. As the SUI operates in a continuous mode, no cool down period has been foreseen for the model. As a result, at the cut-off date for the simulation, there will inevitably be open or in-transport orders. Because of this fact, an order completion rate of 100% is never reached.

- *Number of trucks*

The number of trucks is understood as a performance indicator in this model as it expresses the number of trucks required to achieve full order delivery, e.g. an order delivery rate of >99.5%. This KPI is used in this way as fewer trucks required, translates to a more efficient use of resources in the network which can be translated into a performance and cost advantage.

- *Price per ton*

This relational cost KPI puts the total price charged by the individual transportation units in relation to the total quantity of material delivered. This indicator expressed the cost incurred by the ordering party in this logistics network, showing cost advantages of one scenario over the other. It is measured at an aggregated level only.

- *Total cost*

This absolute cost KPI captures the cost incurred by each transportation unit. It considers both the fixed and variable cost components. It is captured both on an individual unit and global level.

- *Total earning*

This KPI also is part of the cost category and captures in absolute values the earnings of each truck as well as an aggregated total earning value. Together with the total cost KPI, it serves to provide insight into the profitability of the individual transportation units and facilitates understanding of their economic interest and motivation to participate in the supply network under investigation.

All the above listed KPI are quantifiable indicators but are used to measure both quantitative and qualitative aspects of the transportation performance in the model. For example, the flexibility of the network and the reliability are deducted by comparing order completion rates, hence offering a qualitative performance measurement (Hellingrath, 2008).

There are many other performance indicators that can be captured by the model such as service times of trucks or distances driven. However, they are not relevant to this thesis and will therefore not be explained in detail in this section.

5.4. Experiment Setup

5.4.1. Overview

As mentioned above, a two-phase approach was taken to testing and running this experiment.

The first phase being the pilot study, which serves both as a proof of concept and a validation of the model against the actual system under investigation. The pilot phase verifies the accuracy of the model and the configurations applied, creating and ensuring a valid basis (Law, 2003) for the second phase. At the same time, it is necessary to determine boundaries and limitations of the model to ensure applicability and validity (Birta & Arbez, 2013).

The second phase constitutes the main experiment of this simulation study. It is broken down into a set of simulation runs, serving different individual experiments and comparisons of performance indicators and control methods.

5.4.2. Simulation Modes and Parameters

The model built allows for two different simulation modes, namely individual simulation and parameter variation. The individual simulation mode provides a graphic representation of the model's GIS space and shows the movement of the truck agents in that space. To allow for simulation of different configurations and scenarios, for both modes, several parameters of the model can be controlled via a user interface before each run. The possibility to control the parameters described below from a simulation user perspective without having to change the code of the model offers strong scalability and makes the model more flexible and versatile.

When using parameter variation mode, additionally a subset of these parameters can be provided as value ranges, allowing automated simulation runs with varying parameters such as, for example, the number of trucks.

The control screen layout is shown in Figure 5.3

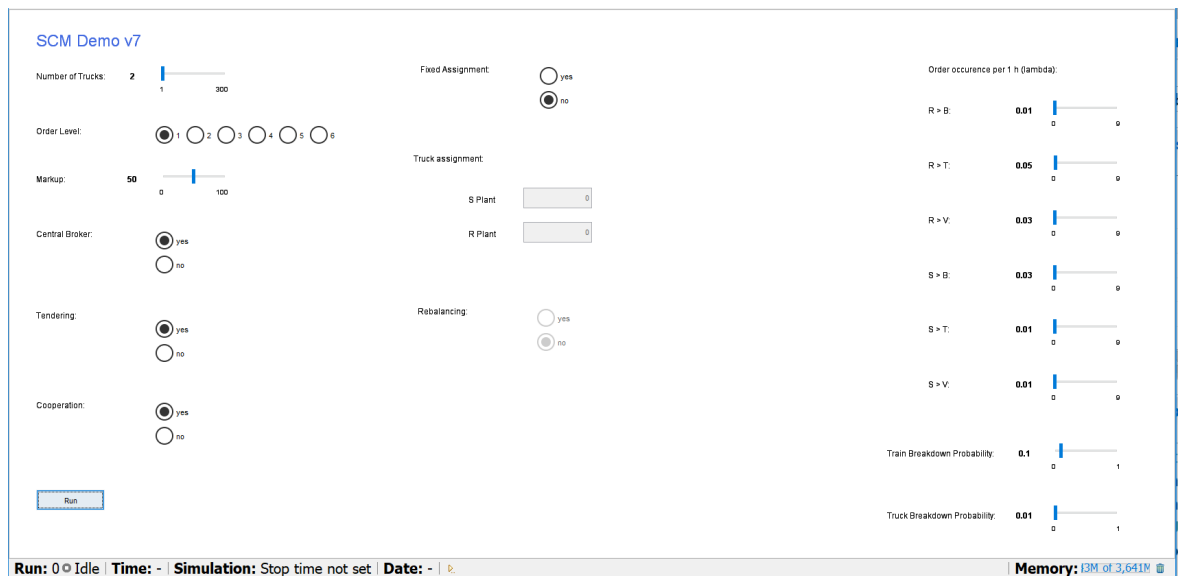


Figure 5.3 - Simulation Control Screen

The parameters available on the screen are listed below with their range. They can be grouped into three main areas, namely model environment, control method and order

occurrence parameters. Parameters controlling the model environment provide the necessary limits for the simulation to execute. They are independent of the control method used. The control method parameters are used to select and configure the scenario which is to be simulated. Not all parameters are available for all scenarios. The third group, order occurrence, allows order occurrence parameters to be set for each port-plant relation. The parameters are pre-set for each order level but may be adjusted individually as required. A more detailed explanation on the functionality of each parameter is provided in Table 5.1.

Parameter	Value range	Parameter variation
Model environment		
Number of trucks	Range 1-300	Range
Order level	Single values, 1-6	Fix
Markup factor	Range, 0-100	Range
Train Breakdown Probability	Range, 0-1	Range
Truck Breakdown Probability	Range, 0-1	Range
Control method		
Central broker	Yes/no	Fix
Tendering	Yes/no	Fix
Cooperation	Yes/no	Fix
Fixed assignment	Yes/no	Fix
Truck assignment	Value entry per plant; total is verified against total number of trucks	Fix
Rebalancing	Yes/no	Fix
Order occurrence		
Lambda per port-plant relation	Range, 0-9	Fix

Table 5.1 – Simulation Parameter Overview

The model environment parameters help to set the environment that the agents encounter during the simulation. The first parameter allows the number of trucks available in the model to be set. It can be set in a range between 1 and 300 truck agents for each simulation run. The number of trucks has, of course, a great impact on the available transport capacity. Varying the number via a parameter allows for a fast way to create situations of over or under capacity, enabling the evaluation of the behaviour and

effectiveness of the different control methods under these circumstances. The truck number can be varied automatically during parameter variation runs. The next parameter from the model environment group sets the order level for the simulation run. This parameter cannot be varied during parameter variation runs, requiring individual simulation runs for different order levels. The order level represents a set of order occurrence parameters for each port-plant relation. It, therefore, relates to the individual lambda parameters found in the order occurrence group. Setting an order level will automatically pre-set the corresponding mean and standard deviation values for each relation. As outlined above, the order placement follows a Poisson distribution in the model. Each port has its individual distribution for placement. The lambda parameters of the order occurrence group represent the rate parameter value for each of those individual distributions. The next parameter from the model environment group is the markup parameter. The markup parameter serves as seed value to calculate the individual markup factor each truck uses as part of its utility function, as explained above. This markup parameter is set for each simulation run via the control screen and can be varied in parameter variation simulation.

The final parameters that help set the model environment are breakdown rates for both trains and trucks. These parameters serve again as input values for distributions used to calculate the probability of a breakdown for the transport vehicles. A separate parameter and, hence a separate calculation of the probability, is done for truck and train agents as explained in the individual agent's section.

The second group of parameters mentioned above is related to the control method used. These parameters depend on the scenario which is to be simulated in the current run. The parameters enable or disable certain functionalities required for the particular control method. Enabling particular parameters excludes others and vice versa. Given in Figure 5.4 is an overview of the settings applied in this research project. Following the figure, the parameter settings for each scenario are discussed in more detail.

Scenario	Parameter					
	Fixed assignment	Rebalancing	Central Broker	Tendering	Cooperation	Truck assignment
Fixed assignment	Y	N				
Rebalancing	Y	Y				
Central Broker			Y	Y	N	
Autonomous Control			N		N	
Autonomous Control + Cooperation			N		Y	

Figure 5.4 - Control Method Parameters

- *Fixed assignment*

For the fixed assignment scenario, the corresponding parameter is active. Additionally, the entry fields for the number of trucks assigned to each plant are available. If no input is provided, the available trucks are split evenly between the plants. At the same time, the parameter for central broker, cooperation and tendering are deactivated.

- *Rebalancing*

In addition to the settings described above for the fixed assignment, the rebalancing scenario requires the rebalance parameter to be active. The distribution of trucks represents the initial distribution. After each week, the trucks are automatically redistributed between the plants based on the current order load (e.g. the more orders a plant has pending, the more trucks it gets assigned).

- *Central Broker*

To execute the simulation for the central broker scenario, the parameter with the same name is activated. At the same time the parameter for fixed assignment and rebalancing are not available as these functions are not applicable for the central broker scenario. The parameters for tendering and cooperation can be adjusted. For the central broker scenario as described here, the tendering parameter is activated. Cooperation, however, is not applied, as the functionality of finding the agent best suited for the order at hand is largely covered by the central broker function itself.

- *Autonomous control*

For the autonomous control scenario to be executed, the central broker parameter needs to be deactivated. This will automatically disable the tendering parameter as well. The parameters for fixed assignment and rebalancing are also disabled as these functions do not apply. The cooperation parameter is deactivated for this scenario. By executing the simulation model with those parameters, order selection and assignment will be executed by the truck agents decentral and autonomously as described in the section on the technical model.

- *Autonomous control with cooperation*

The parameter settings for the autonomous control scenario including cooperation between the truck agents are the same as above except for the cooperation parameter. Activating this parameter provides the functions for truck agents to pass orders to better positioned trucks as described above.

The third group of parameters, called order occurrence, provide the order rate input for each port-plant relation. They are primarily controlled by setting the order level.

However, to support the initial process of finding the relevant order levels and to allow for further investigation, the order rate can be adjusted directly via the simulation control screen.

5.4.3. Pilot Simulation Study

Being an integral part of the DBA approach, the pilot study serves as a proof of concept and helps in validating the chosen research method. Regarding the simulation model built as part of this thesis, the primary purpose of the pilot study was to validate the model against the logistics network under investigation.

To achieve this, the pilot phase is subdivided into two steps. The first step aims to identify and understand limitations and constraints of the model. Relevant parameter settings, order levels, required simulation duration and the number of trucks will be identified. Along with that, the distribution rates applied in the model will be verified.

The second step of the pilot study contains the actual validation experiment, comparing the simulation model against real-world observations and data. Focus during the pilot will be on the pre-assignment scenarios as they reflect the control method and setup

encountered in the system under investigation. Using the “rebalancing” scenario introduced in the previous section, the simulation model is driven under identical input conditions as the real-world system (Balci, 1990). The model behaviour and output data is then compared to the system under investigation, aiming to establish the validity of this simulation model.

5.4.4. Main Simulation Study

The second phase of the simulation experiment contains the simulation runs required to compare the different control methods and document their respective performance. The main simulation study is structured along the relevant key performance indicator. All of the scenarios described above will be simulated. The relevant parameter settings for order level, markup factors and breakdown rates identified in the pilot phase will be applied. Each configuration will be run repetitively, making use of the modelling tool’s randomisation functions. This repetition will produce relevant results, accounting for observed variations.

The aim of this phase is to produce the simulation results required to answer the research questions listed above.

5.5. Running the Experiment

To address the different simulation phases previously described, several simulation runs were carried out. For the pilot study, several individual simulation runs with different parameter were executed as described in the corresponding section in chapter 6.

For the main simulation phase three full scale simulation experiments were executed to provide the data required for analysis. Each of these experiments consisted of four individual simulations, one for each scenario. Within each simulation the parameter variation functionality was used to vary the number of trucks. The number of trucks was increased by 10 in an interval from 150 to 300. To account for variations each step was executed 10 times. 10 repetitions proved to offer a good compromise between accuracy and runtime as validated during the pilot study. As a result, each full-scale simulation experiment consists of a total of 640 individual simulation runs. Table 5.2 provides an overview of the experiments carried out:

	Pilot Simulation Study	Main Simulation Study		
		Simulation Experiment 1	Simulation Experiment 2	Simulation Experiment 3
Number of individual runs:	<i>various</i>	640	2560	640
Simulation Parameters:	<i>varying</i>	12 week duration 150 - 300 trucks 10 truck step 10 iterations / step 4 scenarios		
Markup parameter		50	0, 25, 75, 99	50
Train Breakdown Probability		0.3	0.3	0.7
KPI		- Order completion rates - Cost price comparison	- Impact of markup factor	- Impact of train failure

Table 5.2 - Experiment overview

The first experiment was executed with a markup factor of 50, providing data for order completion rate as well as cost and price comparisons. To support the discussion of the impact of the markup factor, the second full scale run included the markup factor as an additional variation parameter. This means that the 640 individual runs were executed four more times to cover the required markup factors of 0, 25, 75 and 99. The third and final full-scale experiment used the same variation parameters as the first one. It was however executed with an increased train breakdown probability rate to support the discussion on the impact of train failure on the network performance.

Counting individual simulation runs, the main simulation experiment required a total of 3,840 individual simulation runs, plus the runs required for validation and verification during the pilot study.

5.6. Data Obtained

Given the large number of simulation runs necessary to obtain relevant data for analysis and discussion, an automatic form of data capturing was required. Therefore, an output procedure was developed which produces a spreadsheet of results for each individual simulation run, listing a wide range of performance indicators and documented parameter settings. Additionally, the most relevant KPI, such as number of orders placed, orders delivered, order values, cost and price were automatically added to a central spreadsheet file serving as database for each run.

Usage of a dedicated database was considered but not deemed necessary at that stage, as most data processing was done locally by the researcher himself.

Below is an example of the individual result sheet generated is provided to illustrate the content. As mentioned, a wide range of performance indicators are recorded. Not all values are used in the study but were requested by the business sponsors or added for technical reasons.

Simulation Parameters																			
Number of Trucks:	290																		
Markup Boundary:	50																		
Order Level:	6																		
Central Broker:	no																		
Tendering:	no																		
Cooperation:	no																		
Fixed Assingment:	no																		
Rebalancing:	no																		
Trucks R Plant:	n/a																		
Trucks S Plant:	n/a																		
Simulation Results																			
	Total	B Port	T Port	V Port															
Total Orders placed:	36398	15578	11810	9010															
Total Orders Plant R:	24655	9212	9366	6077															
Total Orders Plant S:	11743	6366	2444	2933															
Orders Delivered Total:	31069	10395	11749	8925															
Orders Delivered %:	85.359																		
Orders Delivered Plant R:	23240	5903	9318	6019															
Orders Delivered R Plant %:	86.149																		
Orders Delivered Plant S:	9829	4492	2431	2906															
Orders Delivered S Plant %:	83.701																		
Orders Delivered Train Total:	5133																		
Orders Delivered Train R:	3259																		
Orders Delivered Train S:	1874																		
Outages Train R (days):	55																		
Outages Train S (days):	59																		
Orders Delivered incl. train %:	99.462																		
Orders Delivered R Plant incl. train %:	99.367																		
Orders Delivered S Plant incl. train %:	99.659																		
Total Order Value placed:	444585775.4																		
Total Order Value placed Plant R:	334240213.7																		
Total Order Value placed Plant S:	110345561.7																		
Sum Order Value Delivered:	391944743.5																		
Sum Order Value Delivered Plant R:	290536515.7																		
Sum Order Value Delivered Plant S:	101408227.8																		
Sum Order Value Delivered Train R:	4098967.63																		
Sum Order Value Delivered Train S:	8261855.637																		
Price Total:	143292059.7																		
Price Sum Plant R:	105498128.1																		
Price Sum Plant S:	3840831.6																		
Price for Order Value Ratio:	0.367																		
Price charged per Ton delivered:	231.63																		
Price offered (Value) per Ton delivered:	630.76																		
Order Value Mean:	12214.566																		
Order Value Mean Plant R:	13556.691																		
Order Value Mean Plant S:	9396.71																		
Delivered Order Value Mean:	12815.3																		
Delivered Order Value Mean Plant R:	13678.744																		
Delivered Order Value Mean Plant S:	10317.248																		
Delivered Order Rate Mean Plant R:	0.702																		
Delivered Order Rate Mean Plant S:	0.7																		
Truck Data																			
Truck ID:	12247	12248	12249	12250	12251	12252	12253	12254	12255	12256	12257	12258	12259	12260	12261	12262	12263	12264	12265
Cost waiting parameter:	0.09	0.08	0.08	0.08	0.05	0.05	0.05	0.04	0.03	0.06	0.06	0.03	0.06	0.05	0.03	0.1	0.07	0.08	0.07
Cost driving parameter:	0.38	0.47	0.46	0.41	0.34	0.23	0.43	0.39	0.23	0.46	0.32	0.29	0.45	0.4	0.36	0.34	0.38	0.44	0.46
Markup Constant:	58.068	44.563	41.23	58.72	47.385	56.008	56.128	40.849	43.767	57.728	55.483	54.874	41.474	46.909	50.493	54.555	54.236	58.745	41.609
Markup Average:	55.653	41.911	39.508	56.102	46.037	54.818	54.54	39.388	42.891	55.764	53.707	39.756	44.996	49.54	51.014	51.853	56.434	39.727	
Cost waiting:	378.21	480.32	274.55	446.92	193.67	141.81	211.38	243.1	114.06	309.71	278.64	173.94	294.44	342.12	111.66	681.53	415.11	382.19	328.13
Cost driving:	15825.59	18539.68	19628.8	17456.59	13997.03	10404.94	18102.6	15714.92	9906.89	20021.23	13687	12321.13	19047.21	17321.88	16823.34	13371.55	15333.73	18872.74	20735.31
Total price earned:	899932.59	796836.79	796972.34	997071.51	661637.65	583789.99	1011413.87	638806.45	434965.19	1139823.62	751464.87	672623.19	777272.25	800091.27	851641.65	697105.58	815411.06	1092957.91	853361.52
Total order value transported:	2481598.75	2075222.05	1895316.03	2427730.81	2039697.93	1912460.76	2360532.39	1769816.53	1940747.03	2462446.8	2183873.87	1862678.48	2230028.52	2089409.88	2329665.53	1774678.63	1832587.78	2284700.35	2164736.7
Average Winning Price:	6817.67	6177.03	5994.94	7979.85	5056.09	4324.37	8156.56	5057.03	3242.2	9029.52	5860.46	5454.35	5844.15	6159.85	6702.68	5403.92	6230.24	8346.79	6616.46
Last Winning Price:	7812.95	6810.73	6350.13	8389	5765.63	4564.21	8412.23	5551.12	5974.19	15954.93	10395.5	9170.71	10985.55	6848.58	6301.79	5995.08	6980.41	8817.95	6778.77
Average Accepted Order Rate:	0.986	0.844	0.801	0.969	0.799	0.699	0.905	0.729	0.722	1.011	0.828	0.739	0.87	0.833	0.834	0.671	0.772	0.876	0.818
Total KM driven (complete orders only):	58464.128	56837.889	58448.234	58382.874	57843.701	60196.48	57952.008	56573.156	58869.727	58725.413	57008.378	58178.468	58677.406	58302.816	60605.734	57587.611	58089.484	58601.593	58930.07
Average speed Km/h:	59.13	59.38	58.99	59.32	58.96	59.39	59.11	59	59.35	59.05	59.05	58.93	59.09	59.03	59.05	59.29	59.29	59.14	59.17
Total Time waiting (min):	4020	6000	3520	5660	3960	2820	4100	6700	3480	4780	4700	5080	4580	6700	3420	6860	5820	4560	4880
Total Time driving (min):	116180	114080	117160	114780	116600	116900	115980	113980	117000	115300	116100	115360	115020	113980	117020	113340	114860	116360	115920

Figure 5.5 - Sample Individual simulation result sheet

6. Findings and Discussion

6.1. Pilot Simulation Study

The pilot study is a central element of this thesis as it served the verification and validation of the model. It was conducted once all relevant logistical objects and transportation routes were coded into the model. The pilot study can be grouped into two main steps, with each of the steps being documented in a separate section below.

The first section focuses on identifying limitations and constraints of the model as well as to validate assumptions taken (Birta & Arbez, 2013).

The second section described the model validation against the system under investigation.

6.1.1. Limitations and Constraints of the Model

This section documents limitations and boundaries of the simulation model along with identifying required settings and ranges for the main simulation experiment. It starts with the simulation time, before looking at order levels and the number of trucks required. On closing a detailed examination of limitations identified in the tendering scenario is provided.

6.1.1.1. Model Time Duration

When considering time in a simulation model it is important to distinguish three different notions of time (Fujimoto, 2000). The first one being physical time, or model time as it is sometimes referred to (Perumalla, 2006). Physical time describes the time in the simulation model, such as the start date of each simulation model. In the simulation experiment at hand, each simulation run starts at physical time April 4th, 2016. This date was chosen based on availability of comparison data from the SUI. The simulation runs for a total of 12 weeks from that start date. This time span is denoted as simulation time. Simulation time can be understood as “an abstraction used by the simulation to model physical time” (Fujimoto, 2000, p. 27). Simulation time and physical time have a linear relationship, meaning that intervals of simulation times correspond to durations in physical time. The third concept of time in a simulation is called “wall clock” time. This

is the time that elapses in reality while the simulation is being carried out (Perumalla, 2006). Typically, simulation time elapses faster than wall clock time, allowing the simulation to compress time. Only in special cases simulation and wall clock time are synced, for example in simulators, such as a flight simulator (Birta & Arbez, 2013). Generally, the ability to compress simulation time is one of the intended benefits of simulations. In the simulation at hand, the 12 weeks of simulation time can be executed in the range of minutes to a few hours, depending on model load and computing power available. This allows several simulation runs to be executed in limited time and enables such a comparison experiment as described here.

Both start date, as well as duration, were chosen with regard to availability of real data from the SUI. The 12 week time span further proved during initial validations to offer sufficient time to account for variations in demand while at the same time being long enough for short-term effects (traffic obstructions, down times of either truck or train) to have no disproportional effect on the model performance. Longer periods of simulation time showed little to no effect on the results observed. The simulation is cut off after completion of 12 weeks or, more accurately 2016 hours. No cool down period is considered, as no such period was observed in reality. Stopping the simulation abruptly on that given date naturally leads to a small number of orders still being transported or otherwise in process. However, the same is observable from the real system data available and has little impact on the overall results as numbers of in process orders are comparatively small.

6.1.1.2. Order Levels

One of the central parameter settings influencing the model's performance is the order rates for each of the port-plant relations. As the average number of orders placed by each port to each plant were available on a weekly and monthly basis from observation of the real-world supply network, the approach was to approximate these rates using the previously described distributions.

Particularly during the build phase of the model, it was necessary to execute the model with lower load levels as well. Therefore, different order levels were determined and configured. The approach was to take proportional rates from the before established full

load setup. Meaning that order level 6 sets all individual order rates to account for the full order load observed, whereas order level 4 accounts for 25% of the order load. The predefined order levels and the resulting order rate parameter are shown in Table 6.2. It further provides the average number of orders observed in the real-world supply network for each plant-port relation. The baseline for the number of orders is one calendar week.

Order Level	Load Level		S -> B	S -> T	S -> V	R -> B	R -> T	R -> V	Total	Max Train Capa
6	100%	No. of Orders	540	210	250	750	750	500	3000	180
		Rate parameter	3.24	1.24	1.47	4.6	4.6	3		
5	50%	No. of Orders	270	105	125	375	375	250	1500	90
		Rate parameter	1.54	0.6	0.7	2.2	2.2	1.47		
4	25%	No. of Orders	135	53	63	187	187	125	750	46
		Rate parameter	0.8	0.35	0.37	1.1	1.1	0.7		
3	10%	No. of Orders	54	21	25	75	75	50	300	20
		Rate parameter	0.35	0.13	0.15	0.4	0.4	0.3		
2	5%	No. of Orders	26	11	13	37	37	26	150	10
		Rate parameter	0.16	0.06	0.07	0.2	0.2	0.16		
1	1%	No. of Orders	5	3	3	7	7	5	30	2
		Rate parameter	0.03	0.01	0.01	0.04	0.04	0.03		

Table 6.1 - Order levels and rate parameters

The usage of these pre-set order levels provides a convenient way to change order rates with one central setting and to set up lower load levels when required. It also serves to validate specific effects observed in over/under-load situations as demonstrated later. To allow for additional variations, the individual order rates can still be adjusted via the before described parameters from the central control screen.

To verify the accuracy of the order rate parameters introduced above, the order levels generated by the model were compared with the data observed. The rates were obtained through 50 runs of the model in fixed assignment mode for the selected standard simulation duration of 3 months. The mean value measured is with 36557.39 orders slightly above the observed mean. The distribution of the generated order rates follows a normal distribution which was verified by applying an Anderson-Darling test (Anderson & Darling, 1954; Razali, Wah, & others, 2011). The measured standard deviation is 231.972 with $p=0.769$. Displayed in Figure 6.1 is the resulting probability distribution for the number of orders generated during each run.

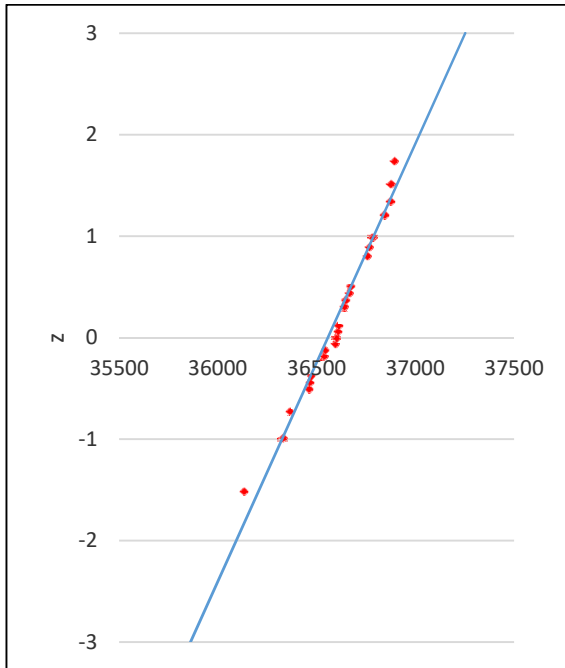


Figure 6.1 - Order rate validation

6.1.1.3. Full Order Delivery

When identifying boundaries of the simulation model at hand, another important fact is to understand the total transport capacity. Full order delivery is reached, when all orders placed during a simulation run are delivered. This value is put into relation with the number of trucks required. To determine this number a simulation experiment is set up. As the aim is to both identify boundaries in the model and validate it against the real-world example, the order level chosen for this experiment is order level 6, the 100% load configuration. Following that line of thought, the simulation will first consider only the pre-assignment scenarios. Model execution time was set to the standard 12 week duration as described above. The result of this simulation is exhibited in Figure 6.2.

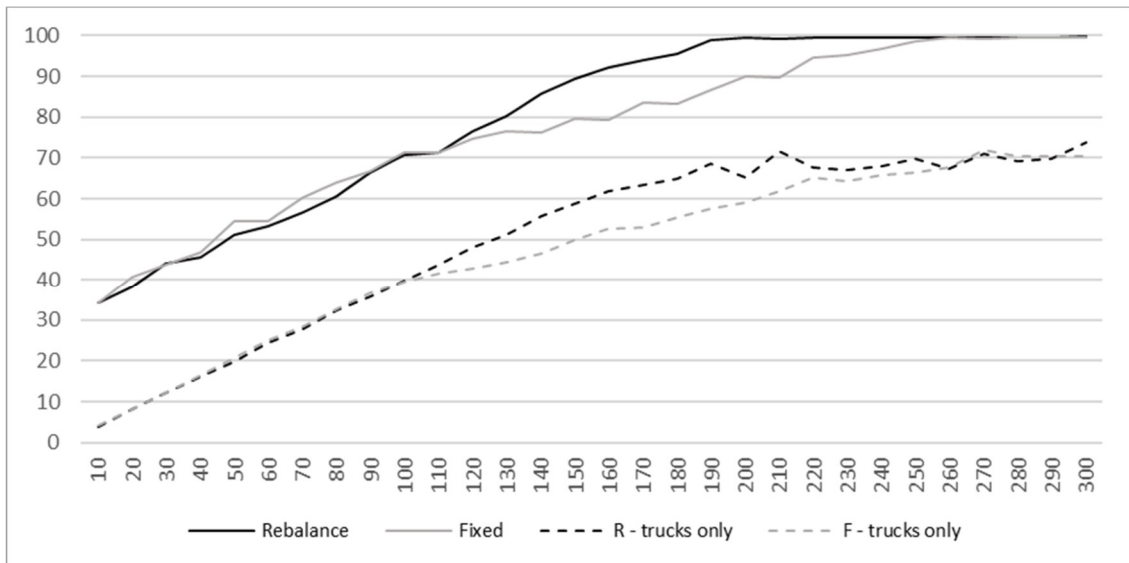


Figure 6.2 - Order completion percentage - Order Level 6

The results shown above were obtained using the parameter variation functionality of the model. The parameter varied is the number of trucks, starting at a lower limit of 10 trucks and increasing the number by an increment of 10 trucks for each simulation run until the upper limit of 300 trucks has been reached. This experiment was carried out once for the rebalancing and once for the fixed assignment scenario. The result measured is the order completion rate, comparing the number of orders delivered to the number of orders placed in each simulation run. The completion percentage is shown on the y-axis of the diagram while the number of trucks is indicated on the x-axis. In addition to the full order completion rate, the dashed lines provide the order completion rate without the orders delivered by train.

The central observation is, that 100% order completion is never achieved. As mentioned before, this is due to the fact that the experiment stops exactly after the 12 week time period is over with a number of orders still in delivery. For the scope of this research project order completion rates above 99.5% are, therefore, defined as full delivery to capacity. When looking at the diagram above, it becomes evident that for the rebalancing scenario this rate is reached for roughly 200 trucks whereas for the fixed assignment the trucks required number closer to 260 units.

The irregularities in the graphs above are due to the variation introduced by distributions such as the train availability and breakdown rates for instance. To account for these variations several simulation runs would be necessary at the same truck level. While this

will be done for the model validation run and the main simulation experiment, it was not deemed necessary during this phase of the pilot, as the focus was on identifying relevant ranges and limits.

6.1.1.4. Number of Trucks

In the previous section the number of trucks required to achieve full order delivery in pre-assignment scenarios was identified and validated against observed values. To better understand the number of trucks required and to identify the relevant range for the main simulation phase, the same experiment as before is carried out for all control methods. The experiment uses a fixed seed value across the scenarios, to create comparable results. Figure 6.3 shows the results of this simulation run.

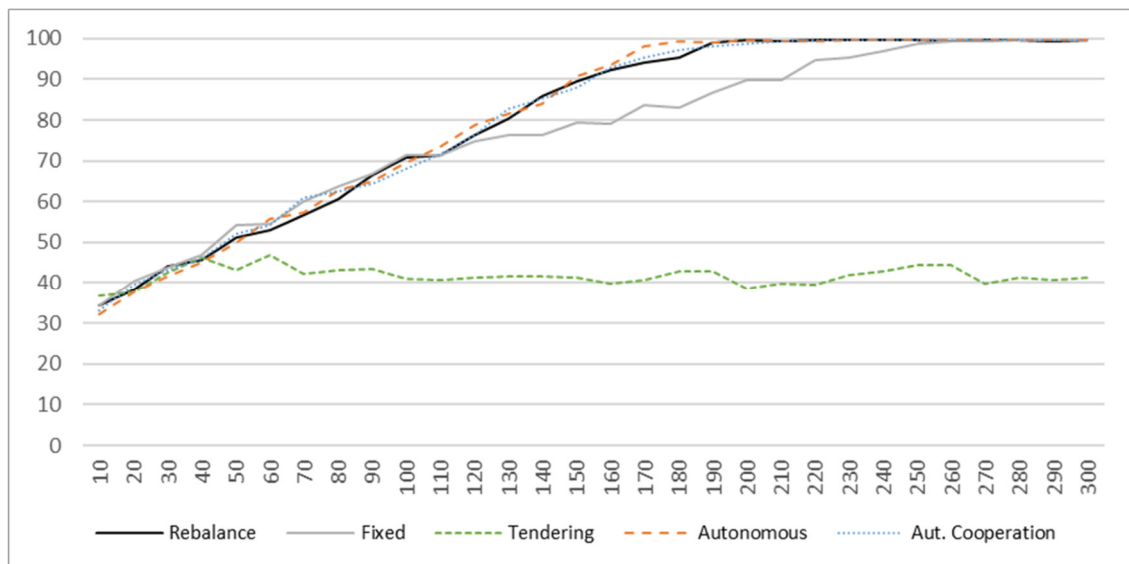


Figure 6.3 - Number of trucks

The diagram again shows the order completion rate on the vertical axis while the number of trucks is denoted on the horizontal axis. As before, the number of trucks is increased by a step of 10 for each simulation run. The number of trucks required to achieve an order completion rate above 99.5% for the fixed and rebalancing scenario are 260 and 200 units respectively.

Interesting is the performance of the autonomous control scenarios. The cooperation scenario appears to require with 210 units a slightly higher number of trucks than the rebalancing scenario. The competition scenario on the other side seems to achieve full order completion with an even lower number of trucks, crossing the 99.5% mark with

about 180 units. These values need to be validated in repeated simulation runs, of course, but they help to determine a range of interest regarding the number of trucks, setting it between 150 and 300 units. This helps to significantly reduce the number of simulation runs for the following experiments, allowing a saving in computing time to be made and a better resolution of results within that range.

Looking at the graph for the tendering scenario, it seems to be able to deliver only a maximum of 45% of the orders placed, irrespective of the number of trucks. As this behaviour contrasts the other scenarios, it is examined in detail in the next section.

6.1.1.5. Limitations Tendering Scenario

To better understand the low order completion rate displayed by the tendering scenario, another simulation is carried out. It uses the same input parameters as above, however, it has a step of 1 for the parameter variation of the number of trucks, offering a better resolution of the issue. Also, the maximum number of trucks is set to 100 as the effect seems to stabilise at larger truck numbers. The results are displayed in Figure 6.4.

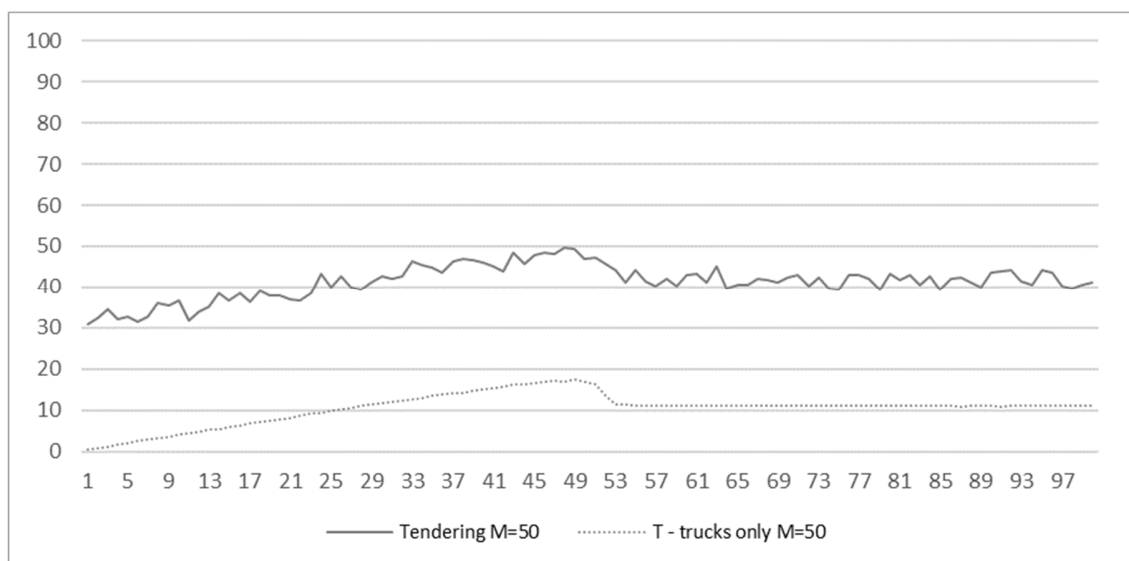


Figure 6.4 - OL6 Tendering; 1 truck step

When considering only the truck performance, the figure above shows that the order completion rate only increases up to around 50 trucks. Beyond that, the value decreases and stabilises at a lower level.

There are two potential explanations for this behaviour, both connected to the complexity of the tendering algorithm in finding the most cost-efficient solution. On the

one hand, the cause for the limitation could be due to the available computing power. On the other hand, it could be that the implementation of the tendering algorithm limits the performance of the model. To further narrow the cause for the observed behaviour another simulation with a lower number of orders will be conducted.

The order level parameter is used to set order level 3 which correspond to 10% of the original order load. This will both reduce the number of orders and, as a consequence, the number of truck agents required to achieve full order delivery. By significantly reducing the number of orders and trucks it should become evident whether computing power or inefficiencies in the algorithm are causal for the observed behaviour.

In Figure 6.5 the result of a simulation run at order level 3 are portrayed. The number of trucks was again varied in steps of 1 up to a level of 30 trucks. The simulation was carried out twice to account for different markup factors.

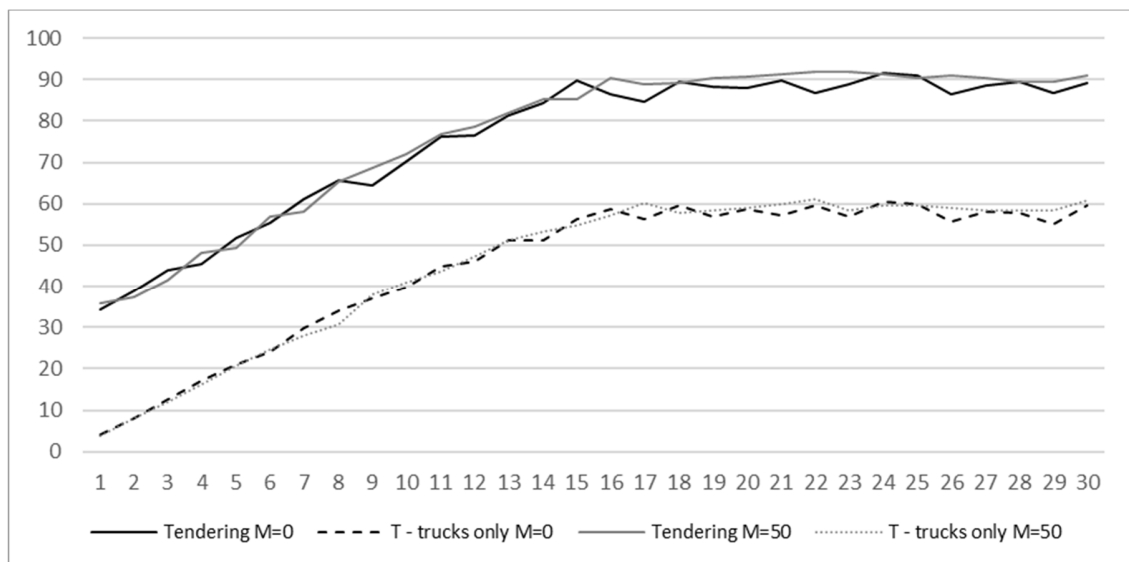


Figure 6.5 - OL3 Tendering, M=0 & M=50

From the above diagram it also becomes evident that with significantly reduced order load completion rates are falling short of full order delivery. Including train capacity, the model is not able to deliver significantly more than 90 % of the orders placed (observed maximum at 91.63% for M=0 and 91.99% for M=50). This observation leads to the conclusion, that the tendering algorithm, as implemented, has limitation regarding effectiveness when tasked with large numbers of orders and truck agents. As the focus of this study is on the evaluation of autonomous control methods, more detailed examination as to how to improve performance of the tendering algorithm will be left

for future research. The tendering scenario will not be investigated in greater detail in the main simulation study.

6.1.2. Model Validation

This section describes the validation of the simulation model against the real-world system under investigation. It is based on the scenario called ‘rebalancing’. The reason for this being that this scenario setup reflects most closely the observed control approach. As laid out before, the planning of the supply network serving as an example for this simulation model, is carried out on a weekly basis. Trucks are assigned to a particular plant and deliver orders in the sequence in which they are received. Each week, based on the current demand situation, trucks are redistributed between the plants. To account for variations introduced by the various distributions used in the model, the experiment is carried out repeatedly with the same setting. A total of 100 replications was chosen for this particular experiment, as this provided a good compromise between result variation and runtime. The number of trucks was fixed to the 200 trucks required for full order delivery as determined above. Model execution time was again the standard 12 week duration. The results of this experiment are visualised in the following figures.

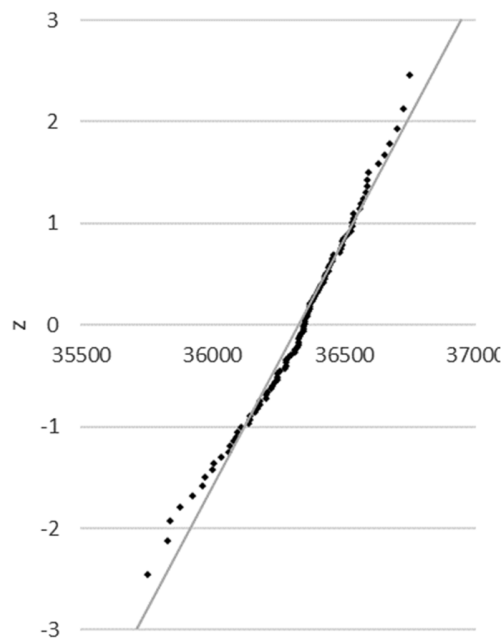


Figure 6.6 - Orders completed absolute – distribution

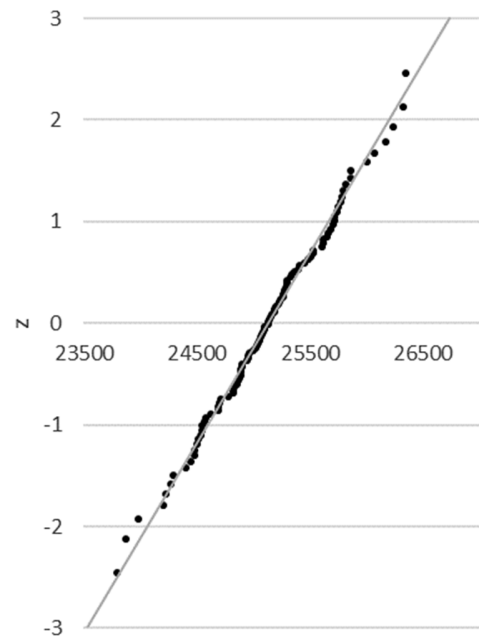


Figure 6.7 - Orders completed trucks - distribution

The first diagram above shows the distribution of the total number of orders completed for each simulation run. The average number of orders delivered was 36326.45 with a standard deviation of 204.61. As Figure 6.6 shows, the obtained values follow a normal distribution according to the Anderson-Darling test. The order completion rate was on average 99.33% with standard deviation of 0.35. Isolating the number of truck transports without the transportation capacity of the train, the second diagram shows that the mean number of orders delivered by trucks was 25131.27. Again, values follow a normal distribution, deviating by 535.55 orders.

To compare these results to the situation observed, the quantity structure described in section 4.1.3 will serve as baseline. The values observed are on a weekly basis. To allow comparison with the simulation results, they need to be multiplied with the standard duration of 12 weeks for the simulation run. The simulation results are compared to the observed values in Table 6.2:

	Observed values		Simulation results		
	Transports	Tonnage	∅ Orders delivered 12 weeks	∅ Transports 1 week	∅ Tonnage 1 week
Total	-	50,000 - 70,000	36,326.45	-	60,551.40
Train	9.4 - 11.1	17,000 - 20,000	11,195.18	10.37	18,666
Truck	1,900 - 2,200	38,000 - 44,000	25,131.27	2,094.27	41,885.40

Table 6.2 - Comparison observed values vs. simulation results

When considering the table above it becomes evident that the mean values of the simulation experiment conducted fit accurately within the observed value ranges of the real-world example. When considering deviations, the measured simulation results for the tonnage transported stay well within range of the observed values, and within no more than 3 standard deviations as Figure 6.8 shows.

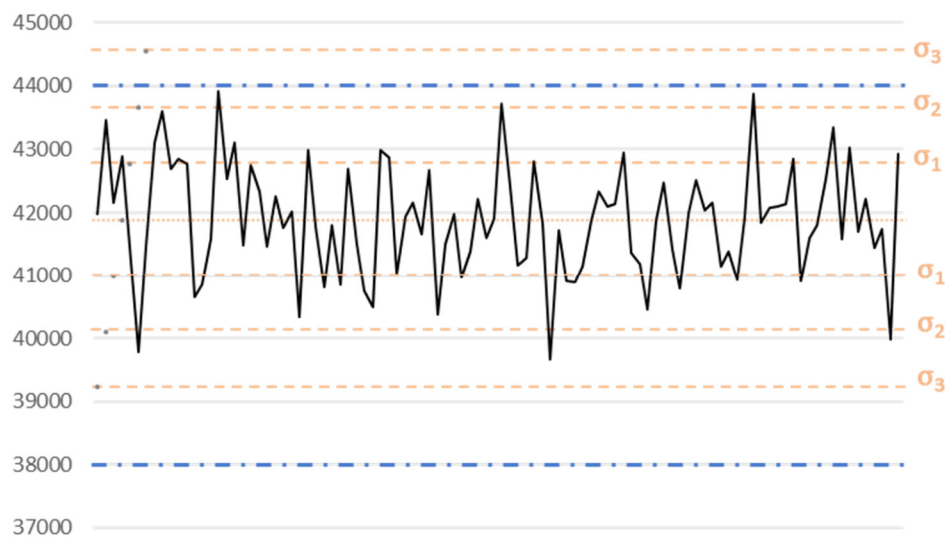


Figure 6.8 - Tonnage transported by truck - simulation result validation

When looking at the train, the aberration for the tonnage transported still stay within the 3 standard deviation range. They do however for a small number of instances violate the range observed from the system under investigation as apparent in Figure 6.9.

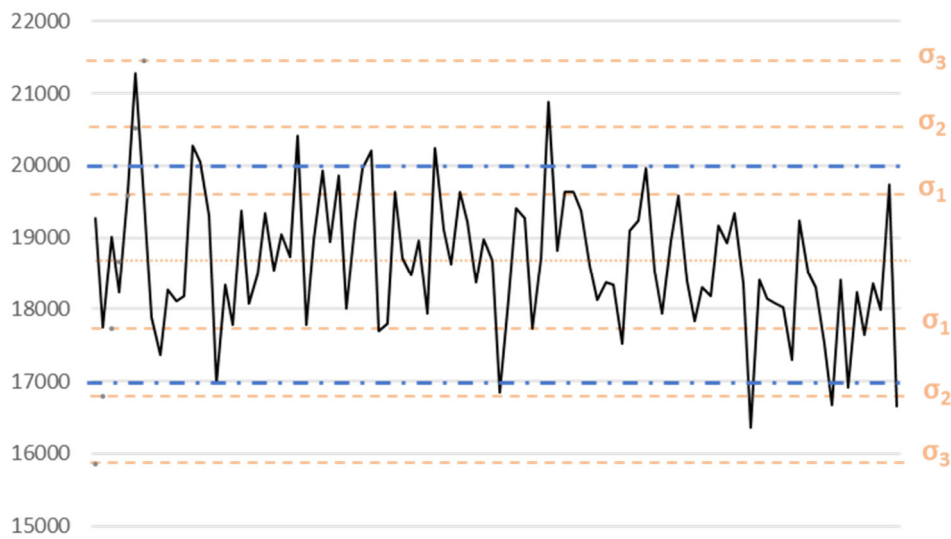


Figure 6.9 - Tonnage transported by train - simulation result validation

In summary, both comparisons above suggesting a high match of the simulation model with regards to the average simulation results as well as standard deviations. Following the idea that if these values corresponded to a significant extent (Banks et al., 2005) the model can be understood as an accurate representation of the SUI for the purpose at hand (Birta & Arbez, 2013). Passing the mathematical inspection, the simulation results were additionally verified with business stakeholders to ensure validity with regard to application in practice.

6.1.3. Summary Pilot Study

The pilot simulation study was of great significance to the model creation process, as it served as validation point for the model (Birta & Arbez, 2013). However, it also provided valuable insight and learning into limitations and boundaries of the model. By identifying relevant ranges and parameter values, such as the model duration and the number of trucks required or by defining the limit for full order delivery, it helped to prepare the main simulation study. It also enabled to focus on experiments relevant to answer the research questions, by identifying and excluding the tendering scenario.

6.2. Main Simulation Experiments

This section discusses the findings from the main simulation study. The section is constructed along the executed experiments with each experiment focusing on a key

performance indicator. The first indicators examined are the order completion rates compared across different scenarios. This is followed by a cost to price comparison. The final section investigates the impact of environmental factors on order completion rates.

6.2.1. Order Completion Rates - Scenarios Comparison

To answer the research question, whether methods of autonomous control can improve the performance of the logistics network under investigation, the first simulation experiment compares order completion rates across the different scenarios. The number of trucks required serves as a performance indicator. The fewer trucks required to achieve an order completion rate of 99.5%, the better for the logistical network. This assumes that a lower number of trucks signifies a more efficient use of resources. More efficient use of transportation resources is typically associated with a cost advantage, due to scale effects and fixed cost degression (Gudehus, 2012b). The economic aspects, such as cost, incurred and prices charged under the various scenarios will be investigated later. For now, a lower number of trucks required to complete delivery of all orders placed is considered an advantage of one control method over the other.

In the experiment, the truck number is varied within the above determined range of 150 to 300 trucks with steps of 10 trucks. To allow for grounded comparison each simulation run is replicated 10 times, reflecting the observed variation. The chosen order level is level 6, simulating the full observed order load. The markup factor is set to 50. The impact of this factor is analysed in a later experiment. The figures on the next page show an overview of the obtained results.

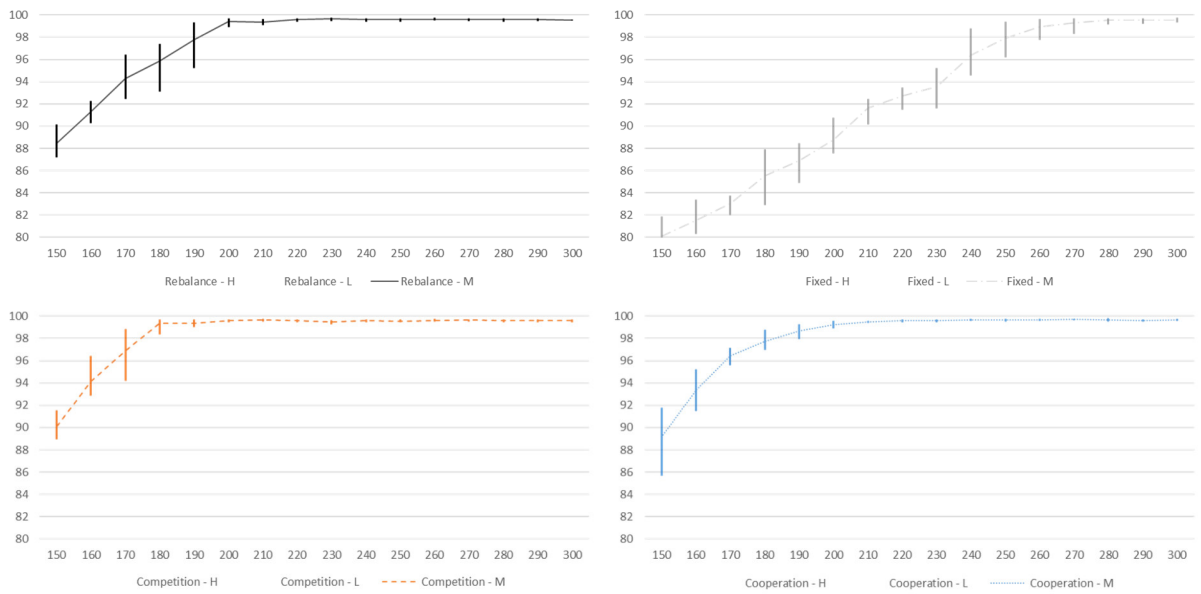


Figure 6.10 - Overview Scenarios

Each of the diagrams above shows the results for a particular scenario. The line connects the mean values obtained in the 10 replication runs for each truck number. The vertical lines displayed show the range between minimal and maximal values obtained for each number of trucks.

In the first two charts in Figure 6.10, the clear difference between the rebalancing and the fixed scenario becomes visible with regard to number of trucks required. The rebalancing scenario manages to reach an order completion rate of 99.5% between 200 and 220 trucks. In the fixed assignment scenario, the number of transportation units required to achieve the same performance varies between 260 and 280 trucks.

To facilitate the comparison of the different scenarios, the figure below offers an overlay of the 4 scenarios. To retain readability, only the graphs of the mean values are compared in this diagram.

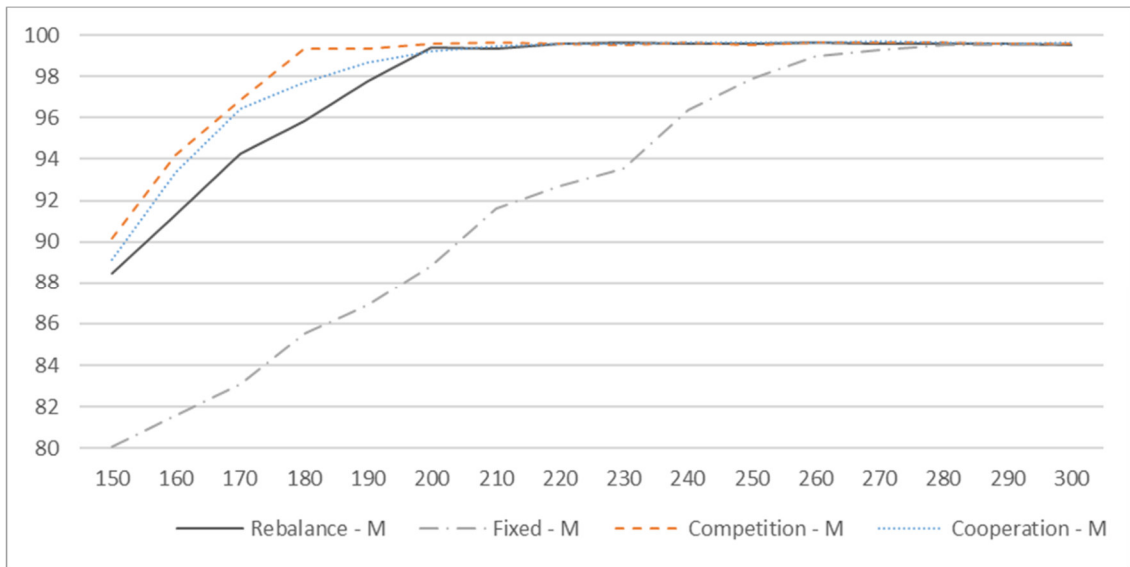


Figure 6.11 - Order Completion Rates - Scenario Comparison - Mean values

The clear difference between rebalancing and fix assignment scenario has already been discussed before. More importantly, the diagram above shows that both autonomous control scenarios require fewer transportation units than the rebalancing scenario to achieve full order delivery. As this difference is at the core of the investigation in this research project, it is analysed in greater detail below.

The diagram above only compares the mean values obtained. The figures in the following sections will also contain the value ranges resulting from each individual simulation run. To ensure readability only two scenarios will be compared at a time as the range indicators tend to overlap.

6.2.1.1. Comparison: Competition and Rebalancing Scenario

Shown in Figure 6.12 is a direct comparison of the rebalancing and the competition scenario. The simulation parameters are unchanged as the results are from the same simulation run.

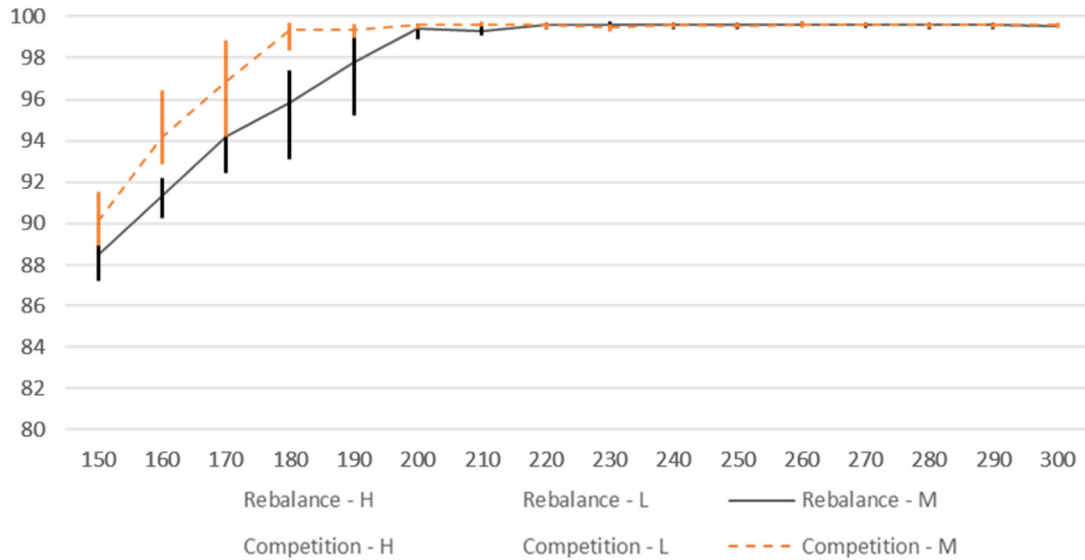


Figure 6.12 - Comparison Competition vs. Rebalancing Scenario

The figure above clearly shows that in the competitive autonomous control scenario a smaller number of trucks is required to achieve full order delivery when compared to the rebalancing scenario. Considering the mean values captured, the competition scenario requires on average between 190 and 200 truck units to achieve full order delivery whereas the rebalancing scenario reaches that point only when applying at least 220 trucks. When looking at the maximum results obtained in the 10 individual runs, in the competition scenario, 180 trucks were sufficient to achieve an order completion rate of 99.697%. The rebalancing scenario required even in the best case 200 truck agents to deliver a total of 99.659% of the orders placed. When looking at the lower limit, results range close to the limit of 99.5% missing it by less than one standard deviation even for high truck numbers. This exemplifies again, why this lower boundary was chosen as limit to define order completion. Comparing the scenarios, the competition scenario reaches the area of 1 standard deviation of the full order completion limit with 210 truck units whereas the rebalancing scenario requires a total of 260 trucks.

6.2.1.2. Comparison: Cooperation and Rebalancing Scenario

Compared in Figure 6.13 are the rebalancing scenario and the cooperation scenario. As described before, in the cooperation scenario, truck agents show benevolent behaviour towards one another by forwarding orders to better positioned trucks.

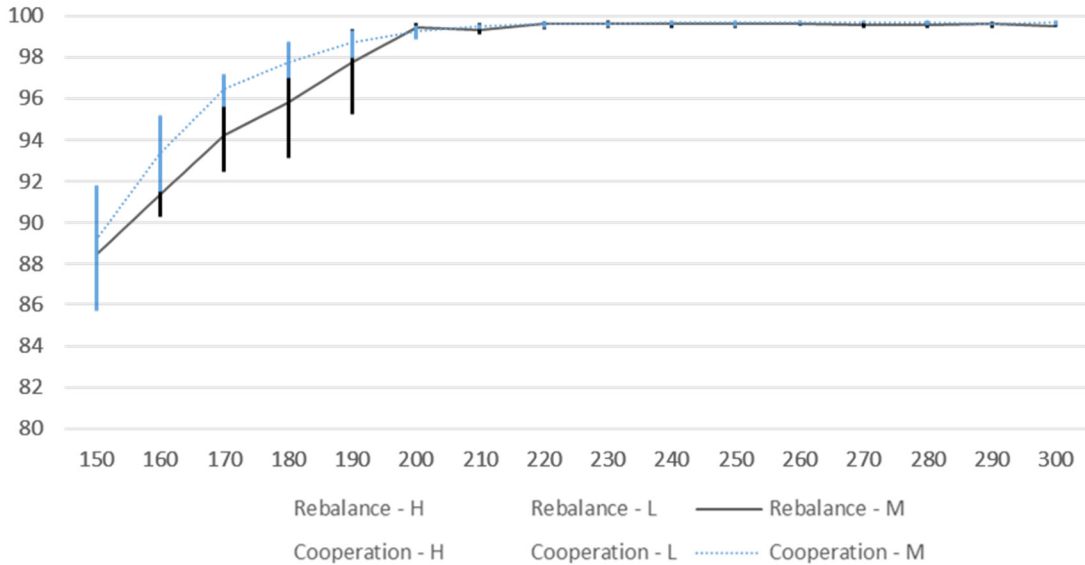


Figure 6.13 - Comparison Cooperation vs. Rebalancing Scenario

From this comparison it becomes evident that again the autonomous control method achieves higher order completion rates, than the rebalancing scenario particularly for lower number of trucks. When, however, identifying the number of trucks required to cross the threshold of 99.5% for full order completion, both scenarios require on average 220 transportation units. Similarly, comparing the best-case values out of the 10 replication runs, both scenarios cross the threshold with about 200 trucks each. However, a better performance for a smaller number of trucks, may hint at a more efficient use of resources for the cooperation scenario. This will be analysed in greater detail in the section cost-price comparison.

6.2.1.3. Comparison: Competition and Cooperation Scenario

As mentioned above, there are two scenarios based on autonomous control methods. In the competition scenario trucks would compete for orders to maximise their own utility function, whereas in the cooperation scenario, trucks aim to reach a more globally

optimal solution by passing on orders. Therefore, the initial expectation was, that the cooperative scenario would produce a better overall result, requiring fewer trucks. The diagram below compares those two scenarios to verify that expectation.

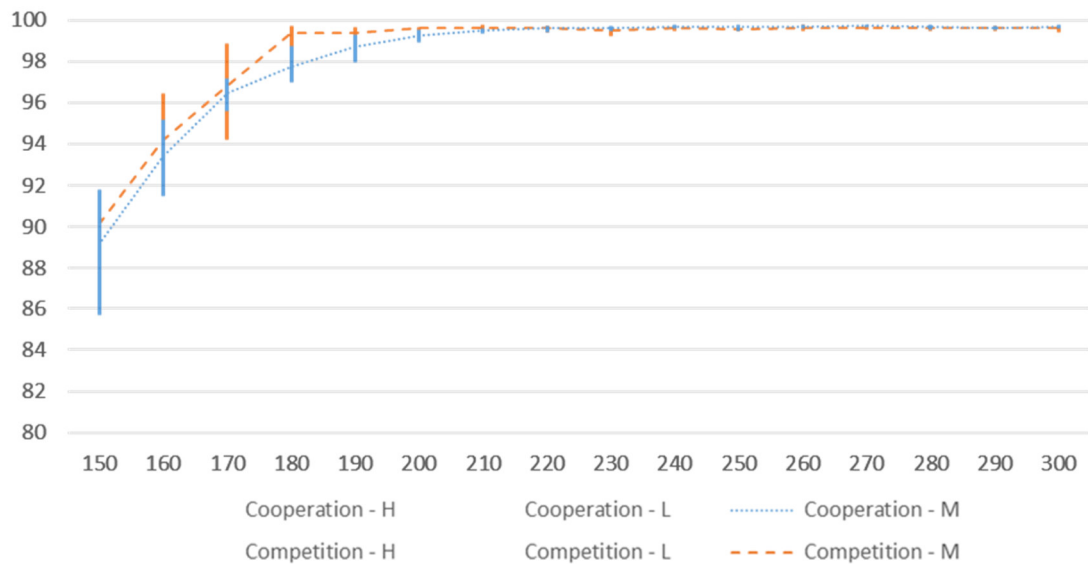


Figure 6.14 - Comparison Cooperation vs. Competition Scenario

Interestingly when looking at the mean values, the diagram shows that for all truck numbers, the competition scenario outperforms the cooperation scenario, achieving a higher order completion rate with the same number of transportation units. That is in line with what was observed when comparing the cooperative scenario to the rebalancing scenario. There the number of transportation units required to achieve full order completion was about equal, even though the gradient of the completion rate graph was slightly higher, hinting at a higher efficiency of the cooperative scenario.

As a result of the above comparison, the competition scenario seems to outperform the cooperative scenario. This observation is somewhat surprising as the collaborative element was introduced with the intent to even better allocate orders to trucks and further reduce transportation costs. It will, therefore, be analysed in greater detail in the following section.

Overall, the above experiment clearly shows that, under the given settings, an autonomous controlled scenario performs better with regards to resources usage, than the rebalancing scenario, representing the currently used real-world best practice.

In the following section, the focus will be on evaluating the impact of the scenarios on cost and price structure, aiming to gain a deeper understanding and validate the previously observed effects.

6.2.2. Cost and Price Scenario Comparison

The previous simulations comparing order completion rates showed a measurable and significant advantage for the autonomous control scenarios with regard to the number of trucks required. Compared in this section is the financial impact of the different control methods. The comparison will consider two main areas, first looking at the price per ton required under each control method before looking in greater detail at the economic situation of the individual transportation units, evaluating their cost and earning situation in the different scenarios.

6.2.2.1. Price per Ton Comparison

A performance indicator capturing the price per ton delivered was created and implemented in the simulation model. The indicator accumulates the final price charged by the individual transportation units and divides this value by the total quantity of material delivered as described by the formula below.

$$pricePerTon (ppt) = \frac{totalPrice}{Deliveries * Quantity}$$

Only completed deliveries are taken into consideration. All financial indicators are measured in US Dollars (USD).

The simulation results shown were obtained in the same simulation experiment as the order completion rates above, to ensure comparability. The diagram on the next page shows the price per ton performance indicator for all four scenarios.

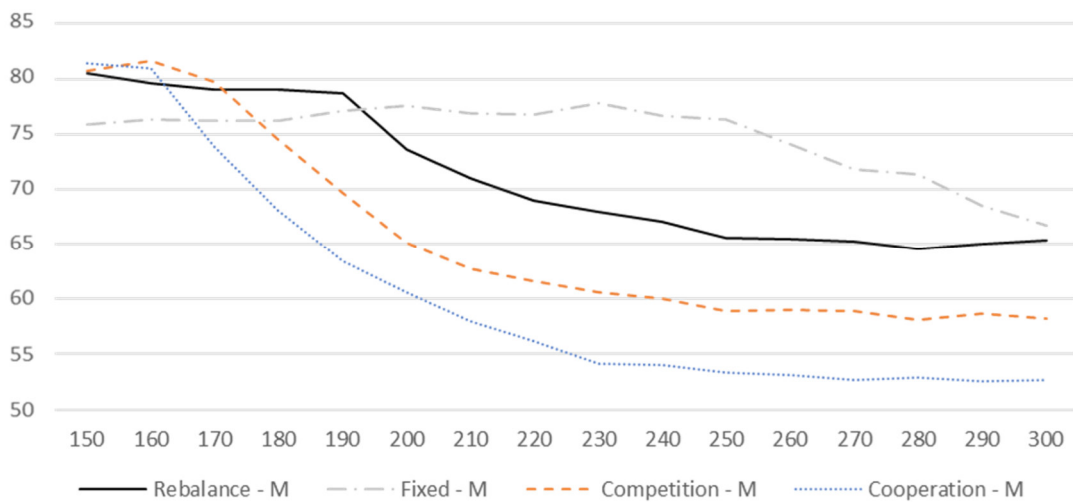


Figure 6.15 - Price per ton delivered (mean)

The diagram above indicates the number of trucks on the horizontal axis, while denoting the price per ton on the vertical axis. Looking at the graph, two observations can be made. The first is that for all control scenarios the cost per ton decreases with an increasing truck number. This result is to be expected as it demonstrates the well-known concept of economies of scales. While it is typically described in a production environment it applies as well to transportation scenarios (Koshal, 1972). With the increasing number of trucks, the fixed costs incurred are divided between a higher number of trucks and a larger transport quantity, decreasing the cost impact on each individual ton transported.

The second observation drawn from the diagram above is that there is a clear difference in price per ton for each of the different scenarios. The comparison helps to further emphasise the case for autonomous control, as these scenarios offer a significantly lower price per ton delivered than the scenarios relying on central control. To verify this observation, the prices of the rebalancing and the competition scenario will be compared. Building on the insights obtained in the preceding section and to account for the previously described fixed cost degression, the price per ton will be compared for the corresponding number of trucks where full delivery was reached. As identified above, the mean value crossed the defined threshold of 99.5% of orders delivered at 220 trucks for the rebalancing scenario, whereas in the competition scenario only 200 trucks were required. The respective price per ton was \$69.02 for the rebalancing scenario versus

\$65.12 in the competition scenario. Again, the mean value out of the 10 individual simulation runs was taken for this comparison. This comparison of absolute values shows that the autonomous control scenario offers a price advantage of 5.65% per ton at full order delivery.

Considering the remaining scenarios, similar to what was observed for the order completion rates, the fixed assignment scenario does not perform well in comparison to the other scenarios. It requires a mean price per ton of \$71.31 when reaching full order delivery at 280 transportation units, asking for the highest price in this comparison. The graph for the price per ton in the cooperative scenario indicates that for any number of trucks greater than 170, decentral control with cooperation seems to offer the lowest price per ton. This is noteworthy, as with regards to order completion rates shown in the previous section, the cooperation scenario seemed to fall short in performance when compared to the competition scenario. It reached full order delivery only for 220 trucks, similar to the rebalancing scenario but requiring 20 trucks more than the competition scenario. When looking at the price per ton however, the mean price asked for is \$56.17 at 220 trucks. Comparing this to both the prices for the competition and the rebalancing scenario, the price is significantly lower. The cooperation scenario offers a price advantage of 13.74% over the competition and 18.62% over the rebalancing scenario. Even when comparing the price per ton at equal number of trucks, a price advantage remains for the cooperative scenario. At 200 trucks, the cooperative scenario requires only \$60.60 as mean price per ton, still offering a 6.94% reduction to the above cited \$65.12 for the competition scenario.

Looking at the findings, the cooperative approach to autonomous controls appears to be the most promising control method, as the slightly higher truck number is balanced by the cost savings.

Whether these savings can be realised in real-world application remains however subject to concern and will be analysed in more detail in the following section.

6.2.2.2. Cost to Earnings Comparison

The lower price per ton in the autonomous control scenarios translates to lower cost for the company contracting the transportation services. However, at the same time, the

lower price per ton signifies a reduction in income for the transportation service providers. This is particularly relevant in the cooperation scenario, as the success of this control method relies on the cooperation of the truck agents and their willingness to share information. As described before, the truck agents will poll other agents, to determine whether they are better located to carry out a given order and pass orders to better positioned trucks. As shown above, this behaviour leads to a globally more optimal solution by making more efficient use of the resources available in the supply network. However, it may mean that individual transportation units have fewer orders to deliver, so reducing their income. While this solution may be preferable from a global, cost optimisation point of view it does not constitute a pareto optimal solution (Petrie, Webster, & Cutkosky, 1995).

As this fact may impact the successful implementation of this control method, it is worthwhile taking a closer look at the effect of the different scenarios on the economical profitability of the individual transportation units. As no real-world implementation experience is available, the results from the simulation runs executed before will be used. To understand the economic profitability of each truck agent, its cost incurred, and earnings realised will be compared. This profit that each transportation unit can make out of its participation in this supply network serves as indicator of the willingness or likelihood of a transportation unit to participate and adhere to a certain control method. The values will be plotted and analysed for each of the simulation control scenarios. The following diagrams provide a significantly different point of view than the previous charts. In this chart one individual simulation run out of the 10 repetitions is presented. To keep variation as small as possible, the simulation run with the smallest deviation from the mean order completion rate was chosen. Each data point in the diagram reflects the intersection between the total cost incurred on the horizontal axis and the total earnings on the vertical axis of an individual truck agent.

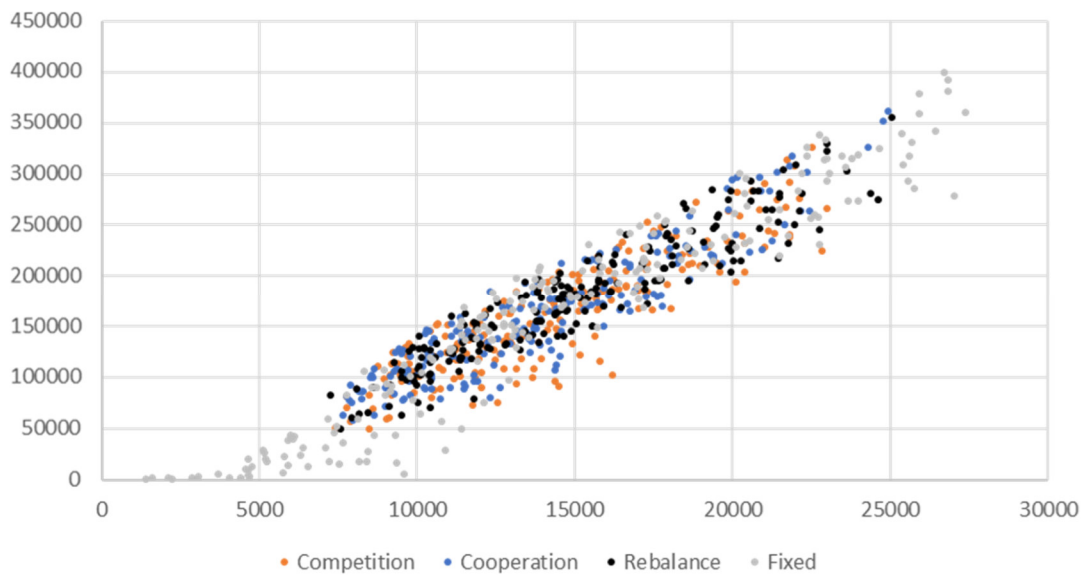


Figure 6.16 - Cost/Earning Comparison @ 200 trucks

The first diagram shows the previously described comparison for all 4 scenarios at a number of 200 trucks. The high number of data points does not allow an easy distinction of individual values, but the plotting allows for a good overview of the distribution of the values. The first observation is that trucks which are able to realise higher earnings also incur higher cost, leading to the sloping form of the graph. That behaviour was to be expected, as the total cost indicator includes both fixed and variable cost. As more deliveries are carried out, variable cost increases proportionally for each truck.

In the fixed assignment scenario, there is a significant number of trucks that can be found on the lower left spectrum of the diagram. These truck agents receive no or only a very small number of orders, providing them with little opportunity to generate earnings out of their participation in this supply network. On the other extreme, on the upper right-hand side of the diagram, several truck agents seem to be able to make large earnings by capturing a larger share of the overall order value offered. Considering the raw data, even under fixed assignment all trucks are able to recover their cost. However, the distribution shows a significant spread. The top 10% of trucks generate more than 51 times the earnings of the lowest 10%. For all the remaining scenarios, this factor is between 3.5 and 3.7, varying slightly between simulation runs.

It is fair to say that under fixed assignment, the profitability is distributed quite unequally among the individual transportation units. Even though, the fixed assignment

scenario is not suitable for implementation, it serves as a benchmark to understand the profitability of the remaining scenarios.

Under all control scenarios with exception of the fixed scenario, most truck agents are able to realise a significant profit margin out of their participation in this supply network.

The markup factor, which will be analysed in greater detail in the following section, has, of course, significant impact on the profitability. However, as all agents operate under the same environmental parameters, the comparison between the different scenarios can be executed on that basis.

6.2.2.3. Cost to Earnings Comparison – Autonomous Control

Having analysed the overall distribution of cost and earnings, the next diagrams focus on comparing the profitability of both autonomous control. The comparison will be done in two steps, with the first diagram offering a comparison at equal number of truck whereas the second one will compare the two scenarios at order completion rate > 99.5%.

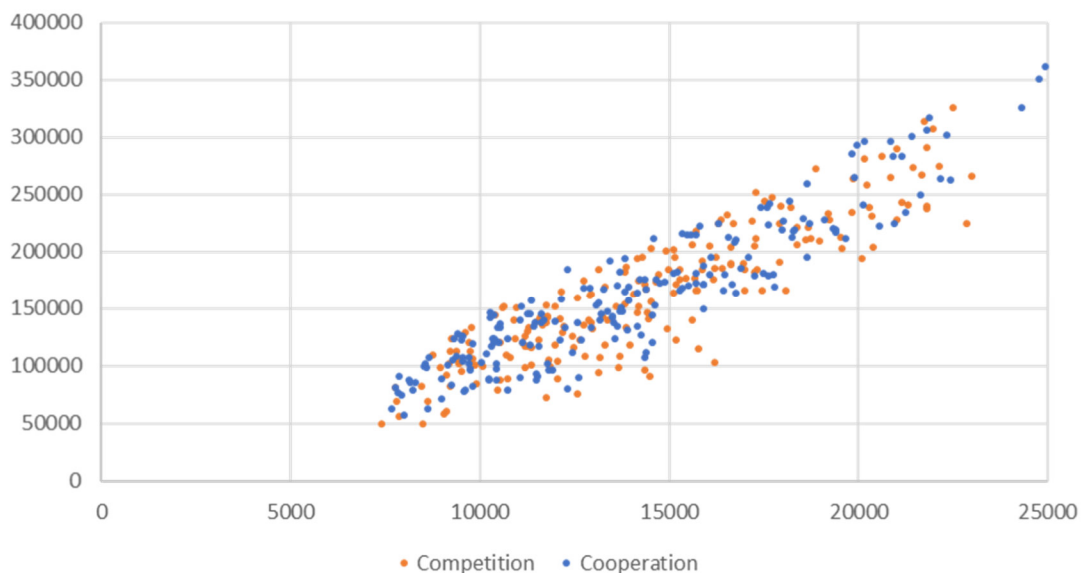


Figure 6.17 - Cost/Earning Comparison @ 200 trucks - Detailed View

The diagram above uses the same data as the previous one, however, now only data points are shown for the competition and the cooperation scenario. In the previous section, the cooperation scenario seemed to offer a cost advantage over the competition

scenario, demanding a significantly lower price per ton transported. This raised the concern that the lower price may lead to an unequal distribution of income among the truck agents, making them less likely to cooperate with each other. At equal number of trucks, the mean profit for the cooperative scenario is with \$157,915 about 1.22% lower than the mean profit of \$159,873 made by the truck agents on average in the competition scenario. However, by looking at the previous diagram one can conclude that this distribution does not constitute a reason for any individual agent not to participate in a cooperative control model.

Accounting for the different number of trucks required to achieve a delivery completion rate > 99.5%, Figure 6.18 compares the individual truck agent's profit for 220 trucks in the cooperation scenario against 200 in the competition scenario.

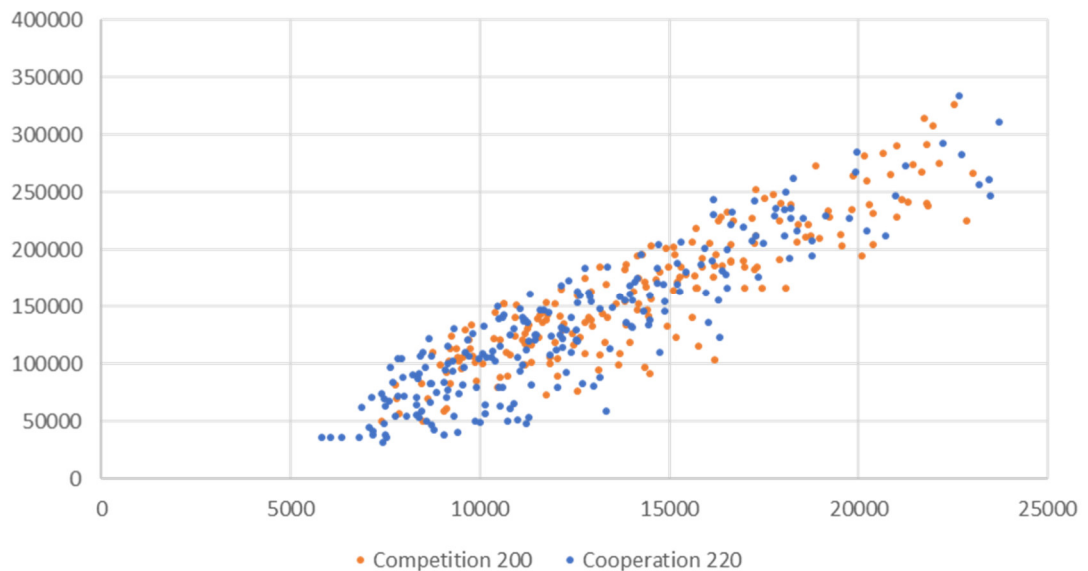


Figure 6.18 - Cost/Earning Comparison > 99.5% Orders Delivered - Detailed View

It appears as a larger number of trucks in the cooperative scenario is located on the lower left side of the diagram than before. In absolute numbers, the mean profit per truck drops to \$129,851, which constitutes a difference of 18.78% compared to the mean profit of \$159,873 under competition. This large difference can be explained partially by the larger number of trucks dividing up the earnings. However, comparing the total earnings across the whole truck population, a decrease by 10.52% from competition to cooperative scenario can be observed. This means, that a significant part of the potential savings, due to the lower price per ton, is financed by the truck agents. This quite large

reduction in income may lead to acceptance issues when introducing such a control method. On the positive side however, the trucks seem to operate more effectively in the cooperative scenario, reducing the overall total cost by 4.63%, even though 20 trucks more are in use, contributing to a larger fixed cost base.

To summarise the section on cost and prices, it is fair to say that autonomous control scenarios offer better economical results than the central control mechanisms. Whether the additional savings promised by the cooperative approach can be realised will have to be verified during actual implementation. To account for this uncertainty, a two-step approach may offer best results, first introducing decentral control, thus establishing the technology and building trust within the system while adding the cooperative component at a later stage to make additional savings. The technological base used for this model supports such a modular approach.

The final section will discuss the impact of variations in selected environmental factors, establishing the adaptability of the model to changing circumstances.

6.2.3. Impact of Environmental Parameters

To control execution of each simulation run, a wide range of parameters can be modified. So far, the focus has been on parameters related to the control methods. This section will evaluate the impact of environmental factors on the model, looking at two distinct parameters and their effect on logistical performance.

Continuing the investigation on the financial aspects of the model, the first section will explore the impact of the so called markup parameter on the model's performance. The second section will then examine the effect of fluctuation of the transport capacity, as created by the unreliable railroad service, and analyse the model's behaviour.

6.2.3.1. Impact of the Markup Parameter

As described before, the markup factor was introduced in the model to reflect the intention of each of the individual transportation units to generate an economic benefit out of their transport activities. The factor thus represents the trucks' expectation of profitability.

Each truck has an individual markup factor which is derived via a normal distribution from a common seed value, the markup parameter.

The markup factor changes during simulation execution, as external factors may reduce a truck agent's expectations of profit. For example, a long waiting times for orders, may make the truck agent willing to accept orders that offer lower earnings.

The markup parameter is set initially via the simulation control screen. It can be understood as an environmental parameter, as it controls the overall level of profit for the whole supply network. It is an artificial factor, not representing a certain monetary value.

This section analyses its impact on the order completion rates and financial results of the simulation model.

To cover the available range, simulation experiments with a markup parameter of 0, 25, 50, 75 and 99 were carried out. All experiments use again steps of 10 trucks in the range from 150 to 300 trucks, executing 10 replications for each step. The comparison of the experiment is shown in Figure 6.19.

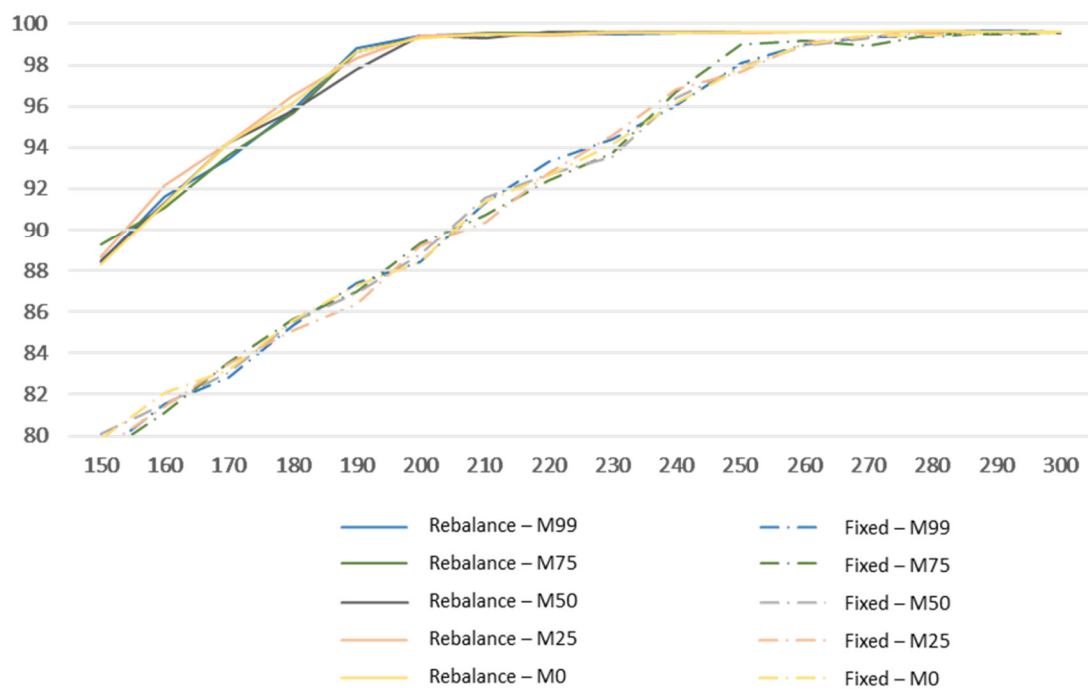


Figure 6.19 - Comparison Markup Parameter - Order Completion - Pre-Assignment Scenarios

The figure above compares the order completion rates obtained for the different markup parameters for both the rebalancing and the fixed scenario. The deviations of the

individual graphs are minimal, resulting only from the variations introduced by the distribution functions. This was expected and serves to prove the previously mentioned fact that in pre-assignment scenarios, the truck agents accept any order assigned without considering the economic benefit.

The following figures illustrate the situation under autonomous control.

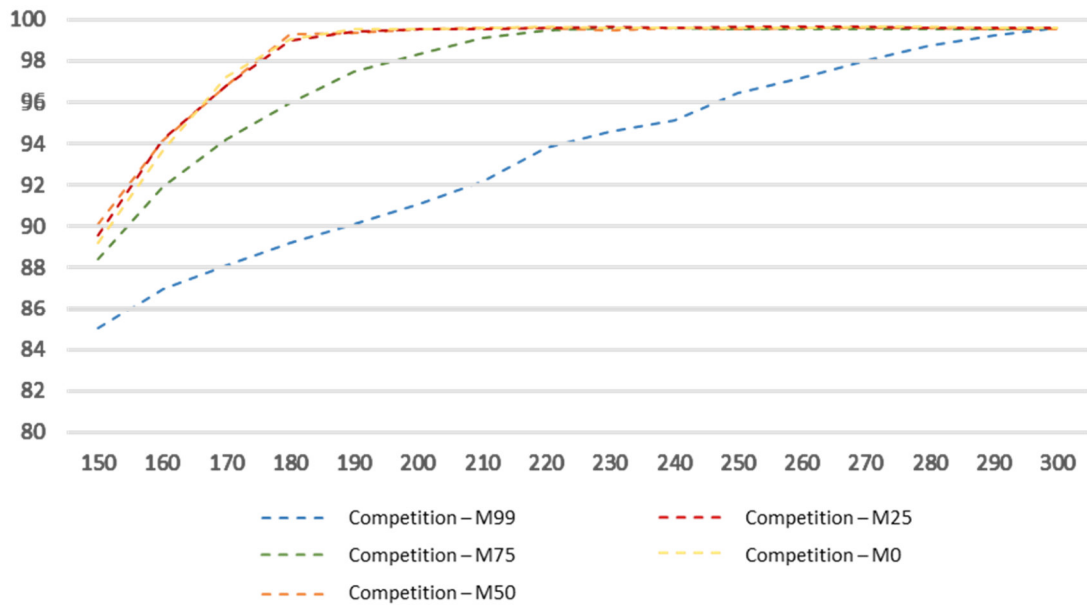


Figure 6.20 - Comparison Markup Parameter - Order Completion - Competition Scenario

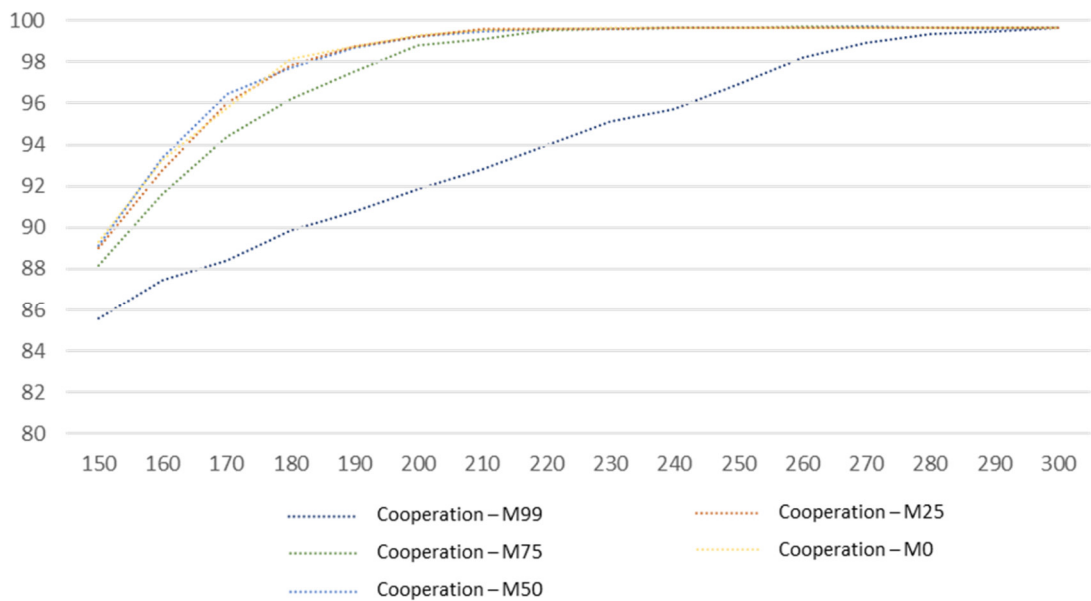


Figure 6.21 - Comparison Markup Parameter - Order Completion - Cooperation Scenario

The diagrams above show the impact of the markup parameter for the competition and the cooperation scenario respectively. For both scenarios, the impact is similar in proportions between the different result graphs. For markup factors 75 and 99 the order completion rate is reduced significantly in both scenarios. This means that the profit expectations of the trucks exceed the value offered for a significant number of orders. Full order delivery is achieved later e.g. for larger number of trucks in these simulation runs. The reason for this being that waiting times for individual trucks increase as their utility functions choose to wait for orders offering a higher price more frequently. Full order completion rate is eventually achieved, as with a growing truck population the probability of having trucks with an initially lower individual markup factor increases. Additionally, as there are more trucks, truck agents spent more time waiting; hence the above described *waiting()* function takes effect, reducing their profit expectation. For markup parameter 50 and below, the simulation results again overlap to a large extent, showing that the impact of the markup parameters below this threshold is limited. This observation offers an initial explanation as to why the previous simulation experiments were carried out with a markup parameter of 50. To fully understand the impact of this parameter, the financial aspects will now be analysed.

The data visualised in the diagrams on the next page was obtained in the simulation experiments previously described. As intended, the result range varies significantly for the individual markup parameters, not allowing for an overlap of the individual simulation results in a single diagram. Hence Figure 6.22 shows each of the results as an individual diagram. The simulation results for price per ton at markup parameter 50 have been presented in the previous section.

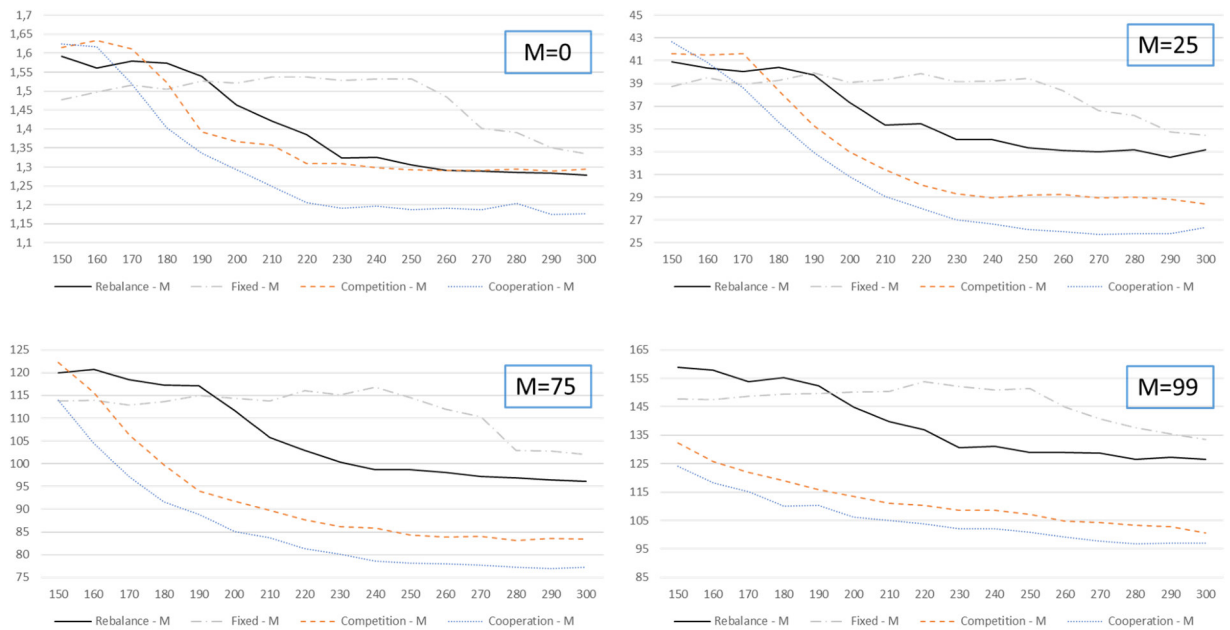


Figure 6.22 - Price per Ton Overview Markup Parameters

By comparing the range of the vertical axis in the diagrams above, it becomes evident that the different markup parameters have an impact on the price per ton. With the price ranging from about 1.6 at markup 0 to 158 for a markup parameter of 99 the effect is clearly visible. The two values mentioned also show that the markup parameter works as a factor on the price per ton. This becomes even more evident when comparing the shape of the respective graphs for each scenario and their relation among each other. For each individual markup parameter, the cooperation scenario performs better than the competition while both outperform the rebalancing scenario. For all three scenarios, the shape of the graphs looks similar, showing a long tail as the initially steep negative gradient approaches 0.

Exceptions can be observed for extreme values of the markup parameter. At a markup parameter of 99 the graphs for the autonomous control scenarios do not follow the observed pattern of reaching a plateau with a gradient close to 0 for a higher number of trucks. Instead they continue to decline steadily until the maximum number of 300 trucks is reached, indicating that the minimal price per ton would be reached for an even higher number of trucks. However, reaching this point is not desirable from an overall optimisation point of view, as it would be achieved only with a large overcapacity of trucks, making participation in the supply chain unattractive for individual truck agents.

On the other side of the spectrum, for a markup parameter of 0, the behaviour of the graph for the cooperation scenario is noteworthy. While the competition and rebalancing scenario reach a similar minimal level, the cooperation scenario manages to offer a lower price per ton for instances with a number of trucks larger than 170. That means that even when looking at a pure cost comparison, assuming that trucks are not aiming for any profit, the cooperative scenario can achieve a lower price per ton. This reduced cost level shows, that resources are used more efficiently in this scenario, further helping to manifest the observed advantage autonomous control can provide for the logistics network at hand over the currently used control method.

The markup parameter of 50, selected for the previous simulation experiments, offers balanced results, providing sufficient earnings potential for the individual truck agents as motivation to participate in the supply network while keeping overall cost at a reasonable level, even offering savings beyond the status quo. Having explained this choice and demonstrated the impact of this environmental factor, the next section will consider the impact of the train failure rate on the simulation model.

6.2.3.2. Impact of Train Failure Rate

A key concern to the logistics network under investigation is the low quality of service of rail transportation. Train transport is crucial to the operation as it offers large capacities at a significantly lower price than the truck transportation. However, the service is unreliable with trains being cancelled on short notice or not departing as planned. It is, therefore, important for this research project to show, whether autonomous control approaches could address this high variability in transportation capacity more effectively or at least do not further aggravate the situation. The model has been designed to address that requirement, modelling both truck and train transportation accordingly. As explained in the section on individual agent design, the train agent uses a random distribution to determine daily the operational status of the train, to model the fluctuation in availability of service. The probability value for this distribution can be adjusted via an environmental parameter named 'Train Breakdown Probability' on the simulation control screen.

To evaluate the impact of the train availability on the performance of the logistics network, a separate simulation experiment was executed.

The experiment runs the model with a significantly higher probability of 0.7 for train failure. In a first step, the results are compared to the previous simulation run, which was carried out with the observed average train failure probability of 0.3.

To allow for comparison, all remaining parameters remained unchanged. That means, again at order level 6, the number of trucks is varied within the range of 150 to 300 trucks with a step of 10 trucks. Each simulation run is replicated 10 times. The markup factor is set to 50.

Figure 6.23 shows the result for the simulation experiment with elevated train failure probability. For better comparison, Figure 6.24 directly below repeats the results obtained from the previous simulation experiment, using the same plot resolution.

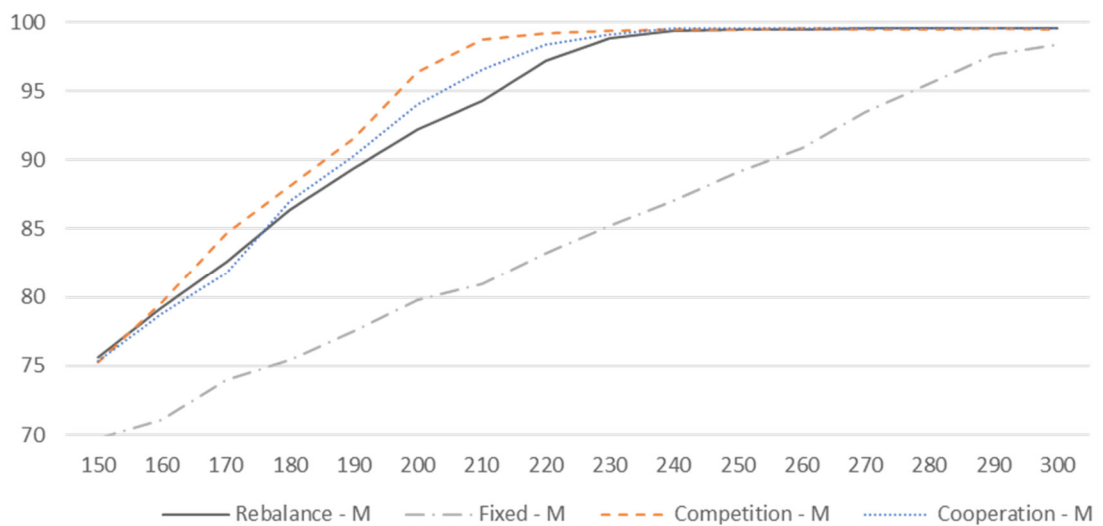


Figure 6.23 - Order Completion Rates - Scenario Comparison at 0.7 Train Breakdown Probability

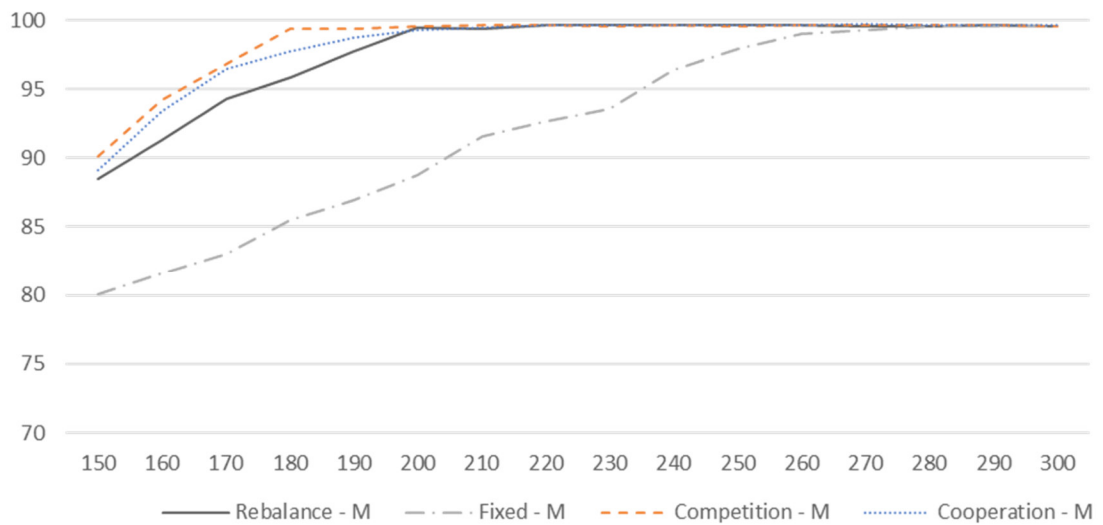


Figure 6.24 - Order Completion Rates - Scenario Comparison at 0.3 Train Breakdown Probability

From the comparison of the two figures it becomes evident that the increased failure rate of the train did affect the overall transport capacity of the logistics network. This reduction was expected, as the train capacity makes up a significant share of the overall transport capacity. Comparing the corresponding graphs, the shift to the right can be observed for all control scenarios. Looking at absolute numbers, previously the rebalancing scenario was able to achieve order delivery > 99.5% with 220 trucks on average, whereas with the higher train failure rate 270 trucks are required. Similar behaviour can be observed for the autonomous control scenarios, with the cooperation scenario now requiring 240 trucks instead of 220.

Considering the minimal requirement stated above, to not aggravate the situation caused by fluctuations in train availability, it can be concluded, that all autonomous control methods perform better than the pre-assignment scenarios, even with an increased train breakdown probability.

To answer the question, whether the autonomous control methods can improve the performance of the supply network with increased train breakdown probability, a separate analysis of the simulation data was realised. To see whether the autonomous truck agents can respond more flexibly to changes in the transport demand situation and compensate these accordingly it is necessary to compare the individual transportation rates for trucks and train. Therefore, it is necessary to look at the individual simulation runs, including the necessary repetitions. The diagram on the following page provides an

overview of the results obtained out of the competition scenario's simulation run with increased train breakdown rate.

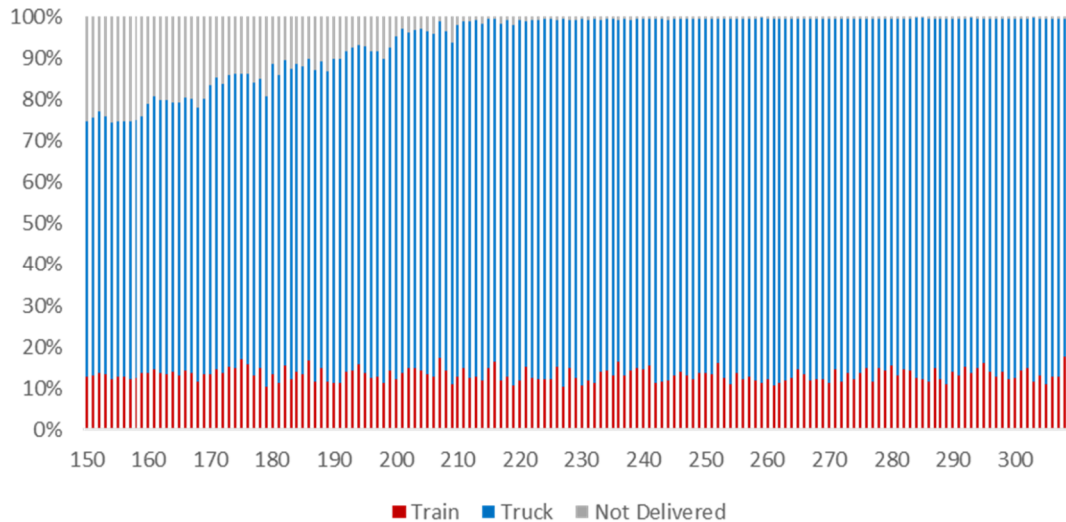


Figure 6.25 - Competition Scenario Individual Results

The diagram lists the train and truck order completion rates for each individual simulation run. The red marked, lower part of each column represents the train's contribution to order delivery. The truck units' total delivery rate is stacked on top of this, represented by the blue marked part of the column. As seen before in the diagrams on order completion rates, for lower truck numbers full order delivery is not reached, represented by the grey, top area of the columns. The train completion rate columns clearly show the fluctuation of the train capacity between the individual runs, proving that the train breakdown probability does affect the available transport capacity. The order completion rate varies between 10.23% and 17.48% with a mean value of 13.28% and standard deviation of 1.249.

Based on these individual simulation results, a comparison of the contribution of the different means of transports and between the different control methods was created. As the competition scenario performed slightly better than the cooperation scenario, it was selected to represent the autonomous control scenarios. It is compared to the rebalancing scenario, representing the status quo of the supply network.

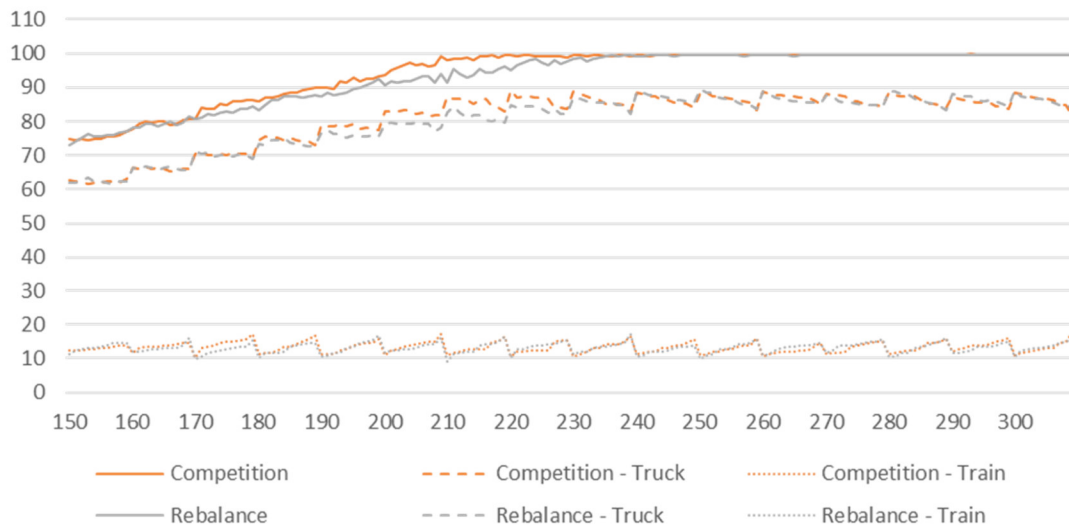


Figure 6.26 – Comparison of Order Completion Rates per Means of Transport across Scenarios

Given in Figure 6.26 is a comparison of the order completion rate for trains and trucks, as well as the combined total rate of orders delivered. Each of these rates is provided for both the competition as well as for the rebalancing scenario. Looking at the dotted lines, representing the train order completion rates, the saw-shaped pattern of the graph strikes the eye. This pattern is the result of grouping the individual simulation replication runs by number of trucks and sorting them within their group in an ascending manner. This sorting is necessary to allow comparison between the different graphs, as each simulation run produces unique results and order rates. Therefore, comparisons within one group, e.g. the same number of trucks, can be considered valid. Comparing across groups would lead to distortions as higher truck delivery rates may result from higher number of trucks available and not from changing train transportation capacity. Considering these restrictions, the comparison shows that even though train transportation rates fluctuate similarly across the scenarios, there is an area in the graph where in the competition scenario the truck agents seem to achieve higher order completion rates than under the rebalancing scenario.

To facilitate this examination, a more detailed view is given in Figure 6.27.

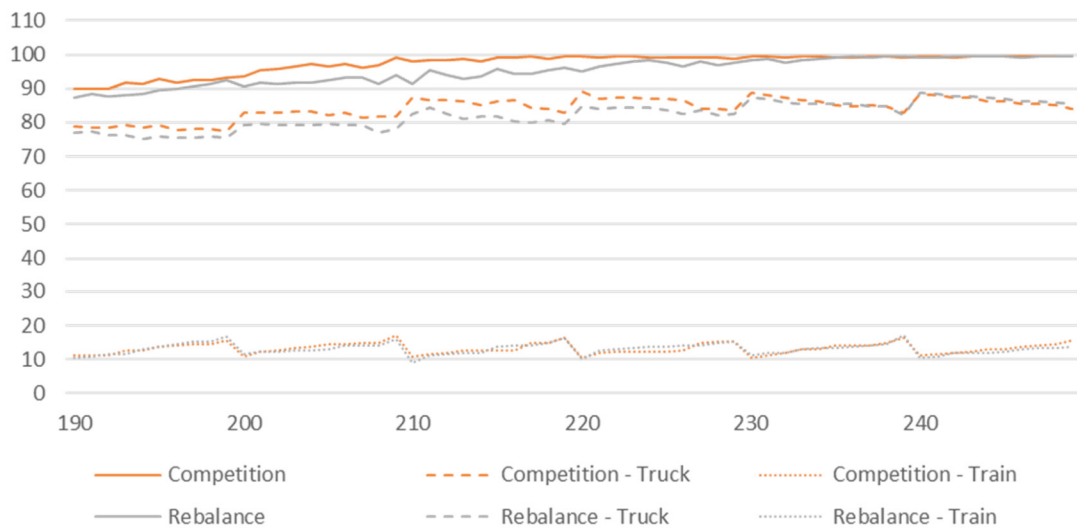


Figure 6.27 - Detailed View Comparison of Order Completion Rates per Means of Transport across Scenarios

The diagram above displays the same data as before, however, it focuses on the above identified area. The reason for this focus can be explained by considering the previous figures on order completion rates. Below the chosen 190 truck agents, full order completion was not achieved, as transportation capacity in the supply network is not sufficient. In other words, the trucks have no free capacity to take over orders to compensate for failing trains. The area above 240 trucks is not of great interest for the comparison at hand as the number of trucks is greater than required, hence providing over-capacity. While offering trucks to take on missing train capacity, this additional capacity is bought at the expense of a decrease in efficiency, as this spare truck capacity would be only used in case of train failure.

Hence these areas can be eliminated when trying to find out whether autonomously controlled truck agents can better use the existing resources in case of train failure. From Figure 6.27 it becomes evident, that while the graphs for train order completion only vary to a small extent, there is a significant difference between the order completion rates for truck agents when comparing the competition and the rebalancing scenario. It is clearly visible that truck agents in the competition scenario manage to deliver a higher number of orders in most simulation runs, smoothing variations caused by fluctuating train availability.

Considering these results, one can conclude, that autonomous control methods address the issue of high fluctuations in transport capacity more efficiently than the currently used control method.

7. Conclusion

7.1. Reflection of Findings

This section will provide an overview of the main findings from the simulation experiments and reflect on them by putting them into perspective with the research questions, as repeated in the figure below.

Research Aim	Research Objectives	Literature Gaps	Research Questions	Results
<p>Aim: The aim is to investigate how autonomous control can improve the performance of logistics networks over conventional control methods</p>	<p>Objective 1: Understand the challenges of logistics networks and the need for autonomous control</p> <p>Objective 2: Investigate how autonomous control can be applied to bulk transportation networks</p> <p>Objective 3: Create an agent-based simulation model of a bulk truck transportation network</p> <p>Objective 4: Conduct a simulation experiment to compare the performance of autonomous control over existing control methods</p>	<p>G1: Objective gap</p> <p>G2: Simulation gap</p> <p>G3: Implementation gap</p>	<p>RQ1: Can agent-based modelling be used to apply autonomous control to a bulk truck transportation network?</p> <p>RQ2: Can autonomous control improve the performance of bulk supply networks over existing control approaches?</p>	<p>R1: Agent-based application of autonomous control on level of individual transportation unit for bulk industry</p> <p>R2: Full scale comparative simulation model and experiment based on real data</p> <p>R3: Performance improvement of autonomous control over central control methods</p> <ul style="list-style-type: none"> • Clear reduction in truck number required • Potential saving in price per ton <p>R4: Adjustable and re-useable simulation platform</p>

Figure 7.1 - Research Structure

Figure 7.1 contains the results obtained which will be set out in this section.

RQ1 was primarily addressed in chapter 4 on the model and agent design along with input from the pilot study validation, which is explained in section 6.1. In these sections it was clearly demonstrated how the supply chain at hand was being reflected with the right level of detail in this simulation model. These details were validated with subject matter experts from the client side through several rounds of presentations and feedback, establishing credibility of the model. Carried out with the same control method as currently used in the world, the pilot study served as the validation point, ensuring the model was close enough to the real-world example to fulfil the purpose of the simulation study (Greasley, 2008). The model was built as a multi-agent simulation model, applying the concepts of autonomous control by representing all relevant logistical entities of the network and, most importantly, the individual transportation units, by software agents. The model created represents result **R1** and at the same time answers **RQ1**.

This model was used to conduct the simulation experiment, producing the performance measurements discussed below. The experiment was setup as a comparative simulation with different scenarios, allowing for comparison of the results from the different control methods. This full-scale comparative simulation of an actual supply chain constitutes the result **R2**.

The achieved performance improvements are certainly the central results achieved in the simulation above. The first finding is regarding the number of trucks required to achieve an order completion rate of 99.5% or greater. This performance indicator was used to measure the performance of the different control methods in terms of effectiveness and resource usage. As described in section 6.2.1, both autonomous control scenarios required a lower number of trucks to complete the delivery of this target percentage of orders. The competition scenario achieved the threshold with 180 trucks on average whereas the rebalancing scenario required 200. That constitutes a reduction of the number of trucks required by 9.1% to achieve the same transportation capacity. That saving value was determined by the difference between the mean values of the individual simulation runs. Looking at extreme values, the savings rate is even slightly higher at 10% for both comparisons of maximum and minimum delivery rates. Thus, the competition control scenario outperforms the established rebalancing method in this simulation.

As indicated before, the difference is not as clear when comparing the rebalancing with the cooperative scenario. Looking at exact truck numbers for both mean and maximum values no difference is notable, each scenario requiring the same 220 and 200 trucks respectively to achieve full order delivery. For the minimum case, an advantage for the cooperative scenario can be reported, as 7.69% fewer trucks are required. This, together with the above observed better performance at lower truck numbers, still constitutes a small advantage for the cooperative scenario.

These findings clearly indicate that autonomous control can improve operational efficiency of this logistics network when compared to the currently used control methods, contributing to the third result listed above.

Looking for further proof that autonomous control can improve performance in logistics networks, a financial indicator was considered next. As explained in the findings, the

price per ton of product delivered was chosen to facilitate a comparison between the different scenarios and simulation runs.

The result again shows a significant advantage for the autonomous control scenarios as the average price per ton asked is lower at comparable order completion rates. At full order delivery, the competition scenario required a mean price of \$65.12, which equals a 5.65% price reduction over the \$69.02 required in the rebalancing scenario. Analysing the cooperative scenario, the price advantage becomes even more significant. For full order delivery at 220 trucks the cooperative scenario required an average price per ton of \$56.17. This is a price advantage of 13.74% over the competition and 18.61% over the rebalancing scenario, also clearly manifesting the performance of the autonomous control scenarios with regards to financial performance.

As mentioned above, logistical performance in this thesis is not only evaluated in a quantitative dimension, but also considers qualitative aspects, such as the reliability of the supply network and its participants. In this context, two aspects were examined: the cost to earnings comparison and the response of the supply chain to fluctuations in transport capacity.

The cost to earning comparison is of interest, as the lower price per ton shown above, may translate to lower earnings for the individual truck agents. This reduction in income may, however, impact the willingness of trucks to participate in the supply network and pose a potential barrier to the introduction of a new control method.

The main finding from this examination was ambiguous, as a comparison between the competition and the cooperation scenarios showed that the mean profit per truck drops by 18.78%. This translates to a 10.52% decrease in earnings across the whole truck population, confirming the concern that the cooperative scenario does indeed adversely affect the earnings situation of the truck agents. However, on the positive side, the experiment showed that the trucks seem to operate more effectively in the cooperative scenario reducing the overall total cost by 4.63%, even though 20 trucks more were in use.

So even though the result is inconclusive for the cooperation scenario, as the truck agents' income may reduce under the autonomous control method, it does positively impact the operational efficiency. To evaluate the impact of this decrease in earnings

regarding the acceptance of this control method, further studies involving the trucking companies would be required and are not part of this thesis.

The second aspect of qualitative performance under evaluation was the ability of the logistical network to respond to frequent changes in transportation capacity. This is a critical ability for this supply chain, as the train service is described as unreliable. An additional simulation experiment with increased train failure rate was carried out. The experiment was able to show, that the truck agents in the competition scenario manage to deliver a higher number of orders in most simulations, smoothing variations caused by fluctuating train availability. In direct comparison to the rebalancing scenario, the autonomous control scenarios did manage to deliver a higher number of orders, as trucks were taking on orders that the train could not deliver due to failure. Considering these results, one can conclude, that autonomous control methods address the issue of high fluctuations in transport capacity more efficiently than the currently used central control method.

The findings listed above show that concepts of autonomous control can improve the performance of the supply network at hand, thus answering **RQ2**. Looking at the results, they show a clear performance improvement over existing control methods, measuring the number of trucks required and price charged, constituting result **R3**. As laid out, the financial aspects have to be validated in a later implementation project. Beyond the quantitative improvements, the simulation was able to show, that autonomous control improves the robustness of the supply network and its ability to respond to change.

While not directly addressing the research questions, result **R4**, the creation of an adjustable and reusable simulation platform, has been achieved through the simulation model created and offers a relevant contribution to practise.

Having answered all research questions, the following section will put the results into the perspective of the gaps identified in the literature and describe their contribution to existing knowledge.

7.2. Contribution to Literature

This section aims to highlight the contribution to existing knowledge this simulation study provides. It is structured around the previously identified gaps in the literature on

agent-based modelling and simulation in logistics, namely the research objective gap, the simulation gap and the implementation gap.

This study clearly shows how autonomous control can improve the performance and robustness of a bulk supply network when compared to conventional control methods. It demonstrates this by executing a comparative simulation experiment using an agent-based model of an actual bulk supply network. This model sets out how autonomous control can be applied on the level of the individual transportation unit in a bulk supply chain using software agents, thereby addressing the objective gap.

The research objective gap stated that in the literature review effected for this thesis, no study could be identified that, at the same time, addressed the problem at hand in the right industry context using the right level of description. The model built for this thesis represents the outbound logistical network of a representative client example from the bulk shipping industry. The problem described and modelled is centred on allocating bulk orders to transportation units using mechanisms of autonomous control. To implement these mechanisms, each transportation unit is represented by a software agent in the model. This level of detail was selected to present and validate the effects of decentralising control to the individual truck, showing the benefit of autonomous control. As a result, this thesis contributes an agent-based application of autonomous control on the level of individual transportation units in bulk shipping industries, effectively addressing the research objective gap.

As noted before, a comparative simulation experiment was conducted, using an agent-based model of an actual bulk supply network, addressing the second gap identified. The simulation gap described, that very few studies had been identified in the literature which offered comparative simulation, allowing the performance of autonomous control methods to be validated in contrast to other control approaches. Creating a comparison between the existing and the newly proposed, autonomous control approaches is one of the key contributions of this thesis. The side by side simulation and result comparison allowed to clearly show and measure the performance increase provided by autonomous control. As such studies still are rare, on academic side, this thesis helps to reduce the gap on comparative agent-based simulation.

As a means to do so, a comparative simulation experiment will be conducted, using an agent-based model of an actual bulk supply network. This will provide a showcase indicating how autonomous control can be applied on the level of the individual transportation unit in a bulk supply chain using software agents. Such a showcase can help narrow the gap regarding the implementation of software in supply chain planning and operation.

The third research gap identified was related to the implementation maturity of agent-based solutions in logistics. The study offers a full-scale simulation using an agent-based model of an actual bulk supply network. Even though this thesis is not able to present a full productive implementation of agent technology in the field of logistics, it still can be considered successful. As Robinson & Bhatia (1995) point out, implementation often depends on factors beyond the control of the modeler and should, therefore, not be included in the definition of success for a simulation study. Looking at the maturity index (Davidsson et al., 2005) as described above, this thesis reaches the level 2.2.2 providing a simulation study using real-world data and offering a full-scale simulation experiment. Reflecting the figures provided above, in the survey study conducted by Davidsson et al., (2005) only 10.7% of all paper surveyed reached this or a higher level. Thus, this thesis contributes to this selected group of full-scale simulation studies, offering valuable insights by applying the theoretical concepts to an actual supply network. This is also relevant from the practical side, as this study provides a relevant showcase for the application of IT systems in supply chain management, helping to close the observed implementation gap in this area (Bell et al., 2014).

The next section will continue this discussion by evaluating the contribution to practice of this study.

7.3. Relevance for Practice

When evaluating the relevance of this DBA work for practise, both the general applicability as well as the specific relevance for the system under investigation have to be considered. This section, therefore, first looks at the relevance of the study and its results to the client example at hand before discussing its contribution to the wider practice.

While the success of a simulation study may not depend on the actual implementation, it is vital that the results and recommendations are accepted by the client (Robinson & Bhatia, 1995). To achieve this, it is important to not only communicate the results but also to ensure and verify understanding thereof (Robinson & Pidd, 1998).

The results of this simulation study, namely, strong evidence that autonomous control can improve the performance of the SUI were, therefore, presented to a group of key stakeholders and subject matter experts on the client side. While interaction with SME on the client side was close and frequent throughout the model creation and validation, this final step served to provide credibility to the results as well (Law, 2003).

To ensure the understanding of the results and document their relevance, a final interview was conducted with a selected key stakeholder. The head of supply chain operations for Europe, Middle East and Asia was chosen, as he is both responsible for the supply network analysed and has worked previously for several years as local supply chain operations manager for this network, thus offering both a strategic as well as an operational perspective on the challenges faced.

A semi-structured interview approach was chosen, with the questions of the interview grouped into four main areas, covering the motivation to participate in this research, validating the study's approach before taking a closer look at the relevance of the results and finally, discussing the path and barriers towards implementation.

While the main purpose of the interview was to validate whether the study, as such, and the obtained simulation results are relevant from a practical point of view, it helped to confirm that the study addresses an actual business problem. The main challenges faced by the supply network studied are the need for "constant re-planning" (JF2018) of truck assignment caused primarily by short term demand changes and unreliable train services. The motivation to participate in the study was therefore to "improve the allocation of vehicles" (JF2018). In the interview it became evident, that from the company's point of view this improvement can be split up into two areas. On the one side the aim is to improve planning and execution of the transportation tasks while on the other side reducing the effort required for the allocation activities. Therefore, the proposed solution of shifting control to autonomous units is considered a highly interesting approach to address both focus areas. Additionally, the interview showed that

this approach is in line with an ongoing strategic initiative, which aims at “cutting out the middle man” (JF2018), effectively reducing dependency on the single logistics service provider by placing transportation orders directly with the truck operators. The points mentioned outline the motivation to participate in the study at hand and again confirm the observations and assumptions from the previous sections.

Looking at the approach chosen, the interview aimed to verify whether the creation of a multi-agent simulation was perceived as a suitable method from a practical point of view as well. Considering the feedback, it can be clearly confirmed, that simulation was the right method to choose under the given circumstances. The subject matter expert confirmed that “it was extremely beneficial to see a simulation model of our supply chain in action.” (JF2018). Particularly, the ability to experiment and see “what happens if” (JF2018) was highlighted as a benefit from a practical application point of view. The comparative approach was further mentioned to help in understanding the difference between the current setup and the proposed solution and understanding the relationship of variables (JF2018). Ultimately, it was confirmed that having an executable simulation available “helped to better understand what is meant by autonomous control and also what the impact would be” (JF2018).

These remarks clearly show that using a simulation model to conduct this study was a suitable and adequate choice from a practical view point.

The next questions aimed to determine whether the results obtained are relevant contributions to practice as well. The results were presented in the form of a presentation prior to the interview, so the questions aimed to gather feedback on selected values. Primarily, the presented reduction of 10% in required truck capacity for equal delivery quantity was validated. It was stated by the expert that “10% fewer trucks is a significant reduction for our supply chain” (JF2018), showing that the results are within a relevant range for practical application. The argumentation provided is, that an increase in efficiency leads to better fixed cost distribution and thus a cost reduction. Similar to this, the second figure presented was the maximum 18% saving potential per ton which in the word of the expert “...is of course a huge number and as such of great interest” (JF2018). At the same time, concerns were raised, with regards to the ability to realise these savings in practice. The concerns are rooted in previous experiences with cost

reductions, where too low prices led to undesired side effects, such as trucks refusing service or organising strikes. As the expert phrased it, “there is a certain degree of co-dependency here” (JF2018), referring to the relationship to the truck operators, which results from the limited transportation market due to the remote geographic location. These concerns have, however, been addressed by the study, as the arguments stated were raised in the early conception phases of both the study and the accompanying business project. The simulation analysed the distribution of cost to earnings and the impact on individual trucks, showing that while cost savings can be realised the concerns around the effect on the trucks cannot be entirely dismissed and has to be analysed in actual implementation. In that context an interesting remark was made during the interview, stating that “...the savings do not necessarily have to come out of the pocket of the trucks” (JF2018), meaning that, as indicated before, the autonomous control methods may help to cut out the logistics service provider, acting as middle man and thus enable a reduction of cost without affecting the earning situation of the truck operators.

This discussion around the impact on the truck operators leads to the final aspect of validation of business relevance, namely the question if the proposed solution can be implemented. With regard to the reduction in number of trucks and the improved compensation of fluctuations caused by train services, this was clearly confirmed by the expert in the interview. Doubts were again expressed towards the extent of the cost savings for the reasons mentioned above. Given the positive estimate to the feasibility of implementing such a solution, the next question was why the solution is currently not being implemented. The expert listed commercial and financial constraints as the main reasons which inhibited an actual implementation project. To gain an understanding of potential implementation barriers, the expert was asked, which risks and limitations he perceives for a later deployment of the solution. Two focus areas emerged, namely, technology and acceptance of the solution by the end users. While both of these areas need to be addressed during an actual IT implementation project, the question was raised as to whether the simulation study did help to reduce these concerns. The following statement by the expert helps to underline the positive feedback received on this question “Before it was all quite abstract ideas and concepts but seeing the results first

hand in the model, really allowed me to better grasp and understand the concept” (JF2018).

Finally, being asked whether this study increased the likelihood for implementation of autonomous control in his supply network, the SME answered he felt “Absolutely more inclined” (JF2018) towards implementation of such a solution.

This statement again helps to establish the relevance of the simulation study conducted in this thesis for the business at hand.

Looking at the contribution to practice beyond the specific client example under study, the aspect of implementation is also highly relevant. As mentioned earlier, there is a significant gap with regard to software implementation in supply chain management.

The gap is reflected in the literature (Bell et al., 2014; Fawcett et al., 2011) and has been observed first hand by the author across several enterprises. From a practical point of view, the study at hand therefore offers a valuable showcase of how software can support decision-making and thus planning and control of supply networks. The study demonstrates how software agents can shift control to individual transportation units without large investments in software and high risk to operations. The executable agent-based simulation model further serves as a communication tool (Greasley, 2008), greatly helping understanding of the proposed solution approach and making autonomous control more tangible. The executable simulation model can be understood as the second significant contribution to practice offered by this thesis.

The model has been shared, along with the study’s results, within the expert community of the author’s organisation. In the meantime, the model has been used as a demonstrator in several proof of concept situations with different clients across industries.

The final aspect that this study contributes to practice, is the reusable modelling platform created. It can be easily adapted to different client and industry scenarios with limited effort and training required. The simulation model has already been transposed to an intralogistics scenario, with the agents representing forklifts that supply material to a production line. This shows how versatile software agents and agent-based modelling can be applied to a wide range of areas and how practice benefits from its versatility. The aspect of generalisation will be further highlighted in the context of strength and limitations of this study in the following section.

7.4. Strength and Limitations of this Study

While the quantitative research approach chosen for this study led to the intended measurable results, it certainly lacks the depth of insight into underlying motivations and reasons that qualitative approaches offer. The expert interview conducted compensated this limitation to a small extent, as did the insights gathered by the close interaction with SME and key stakeholder from the enterprise investigated. This limitation however is common to any quantitative work and accepted.

The method chosen for this thesis, a simulation experiment using a model of the supply network under investigation, shows both strength and weaknesses. As set out in the previous section, the advantage of having an executable model of this supply chain is that it provided great benefits to facilitating understanding the network and communication and dissemination of findings. On the other hand, any model is always an abstraction of the real world (Law, 2003), naturally introducing constraints and showing limitations. The largest limitation was undoubtedly the focus on a single supply network. While this was the stated purpose of this study and necessary to conduct the study at this level of detail, it naturally limits general applicability of the study's results. While this cannot be argued from a scientific point of view, there are two aspects to be mentioned in this context. Firstly, the literature overview provided shows a multitude of successful applications of agent-based simulation across various industries and enterprises, highlighting the general applicability of software agent-based solutions. Secondly, based on the author's own experience as an industry consultant, the effects witnessed in this supply network and the results obtained show the potential to be applied to other supply chains. This claim can further be supported by the interest in the study's results shown by the supply chain expert community in the author's organisation and the application of the concepts to other client and industry scenarios in the meantime.

The underlying idea of decentralised decision-making and control (Windt & Hülsmann, 2007) and the following reduction of complexity is a powerful concept for any supply network. Looking back at the theoretical context provided in chapter 1, the concept is not limited to logistics and supply chains. Transportation networks that face similar challenges as the network under investigation can be found across the mobility domain.

Commuter choice simulation (Zellner, Massey, Shiftan, Levine, & Arquero, 2016) or public transport simulation (Fourie, Erath, Ordóñez Medina, Chakirov, & Axhausen, 2016) are just two examples where a high number of individual and independent units coincide with a highly dynamic environment, thus requiring frequent re-planning. In this context, software agents and agent-based modelling can offer a viable approach to addressing this complexity and offer valuable insights, as this study has shown.

Looking closer at software agents, they still offer great potential and can serve as a step towards more advanced technologies in the priority matrix (Gartner, 2018).

Agents do not only help to decompose complex structures and problems (Jennings, 2001), they enable supply chains to benefit from insights based on big data (Louis & Giannakis, 2016).

Software agents further serve as a digital representation of physical objects, such as the trucks in this study. Agents can thus form the basis for “self-aware” machines or sensors (Lee, Lapira, Bagheri, & Kao, 2013) effectively creating what is now often called a ‘digital twin’ (Rosen & Boschert, 2017). This self-awareness is enabled by equipping agents with the ability to learn (Foerster et al., 2017). To provide two examples, Fu & Fu (2015) apply self-aware and adaptive agents to improve cost collaborative management for supply chains whereas Wang, Wong & Wang (2013) rely on agents to create an ontology based negotiation scheme for supply networks. Thus, combining agents with machine learning (Jordan & Mitchell, 2015) is a promising way to benefit from artificial intelligence in logistics.

Continuing to look at strength and limitation, the ethical dimension of the research method shall be considered as well. As Kruger (2003) points out, simulation can be a powerful tool, that also brings great responsibility, regarding its usage and application. Such an aspect can be found here with regards to the impact of the simulation results on the actors in the supply chain. Looking for affected parties, the truck drivers come to mind, as there is a power imbalance between the individual, small businesses owning mostly only one truck and the larger cooperation requiring the services. This potential imbalance can be considered a limiting factor when comparing simulation results to observed results, as the ethical consequences of technologies should be considered (Weber & Weber, 2010).

Considering the model itself, the limitations found largely coincide with the constraints mentioned in chapter 4. The most notable limitations are the assumption of a closed market and the focus on a single product. In the model no participants leave the market and no new transportation providers enter it. While this is a necessary constraint of the model, it does not accurately reflect the real world. Another limitation is the use of a single product which is being transported across the supply network. Those two aspects may limit the model's applicability to a certain degree and should be considered when moving towards deployment of the solution.

Considering the study as a whole, the largest limitation identified, is the missing implementation experience, as the solution proposed has not yet been deployed to the supply network under investigation. While this confines, strictly speaking, the simulation results to the theoretical realm, and thus poses a limitation, the author would like to point out that this simulation experiment is beyond a scientific testbed. As mentioned before, the simulation results have been used in practice, while the model itself has been transposed to addressing different problems from another industry. Further, if it is pointed out that the number of agent-based simulation models publicised that have reached the same level of maturity is quite small, this observation helps to put that limitation in context.

7.5. Recommendations for Future Research

While this thesis shows how autonomous control can be applied to and improve the performance of the logistical network under investigation, there remain various areas which offer options for further research. A total of three focus areas have been identified and are outlined below.

The first area is naturally centred around moving towards actual implementation of the autonomous control approach. An actual implementation would offer additional insights both from academic and practical points of view, helping to verify assumptions made and confirm the results obtained by simulation. Implementation is not only interesting for the supply chain under study but may be adapted to a wide range of supply networks. A qualitative investigation of any implementation project applying autonomous control to logistics would help to verify known implementation barriers and identify new risks,

advancing knowledge in this area. For example, the previously mentioned uncertainty regarding the acceptance of the collaborative control method, due to a reduction in earnings for the individual trucks, could be addressed with a qualitative approach. The second area for further investigation can be summarised as extensions of the model and/or the simulation scope beyond the topics covered in this thesis. This could, for example, include different market participants or evaluations for different key performance indicators. Moreover, different methods for implementing autonomous control in logistics, such as pheromone-based control or queue length estimation (Scholz-Reiter, Görges, & Jagalski, 2011) and the comparison between them, holds much potential for further investigation. These extensions can be summarised as functional extensions. The most promising functional extension is perhaps the integration of artificial intelligence into the agent model. Looking at the current discussions in this area, it appears almost as a logical next step, to further empower the software agents by equipping them with the ability to learn (Russell & Norvig, 2003). By implementing machine learning capabilities, agents could, for example, adapt their prices based on experience (Chan, Son, & Macal, 2010) or change their cooperation behaviour based on strategies developed at runtime. The simulation model would allow for such an extension as it was built on an extendable framework using Java programming language. Suitable machine learning packages such as DeepLearning4J (DeepLearning4J, 2018) are available to provide the required function modules and data structures. The agents coding would need to be extended and additional computing resources may be required. Adding machine learning functionality to the simulation model warrants additional scientific investigation and holds much potential for application to practice.

The third area that offers room for further scientific investigation can be described as a transposition of concepts within the logistics domain and beyond. This is interesting from the practical side because, as mentioned before this has already been carried out. To address a client scenario from a different industry, the model has been modified to represent an intralogistics scenario. The individual agents in this case represent individual forklifts which are assigned to complete delivery tasks within a production

plant. Again, the modular approach of the model built for this thesis allows for easy transition to the new application area.

The listed areas cover only a small range of the opportunities available for further research in the context of autonomous control within the logistics domain. As shown in this thesis, the area still holds much potential both from academic and application sides and will continue to grow with the increased interest in artificial intelligence and machine learning.

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Appendix

Appendix I: Interview Questions

List of questions:

Background & motivation

- Can you please give a short description of your position in the company and relation to this project/study?
- Could you list some particular challenges for the supply network at hand?
- What was your motivation to support this scientific investigation?
- What outcome did you expect / what benefits do you hope to see of this study?

Fit of design of the study

- Do you feel that simulation is the right method to address the research problem?
- Was the comparative approach helpful? Why is that?
- Drawback / negative aspects you associate with simulation and/or the study approach?
- Do the simulation results help to better validate potential impact of the switching the control approach?

Results in detail

- Is the observed reduction in trucks required relevant for you? (10%)?
- Are the assumed financial saving in a relevant range? (Price reduction 13-18%)
- Do you believe to benefit from the improved response of the supply chain to uncertainty? (Train failure)
- Do you believe these results could be realised in reality?
- Where do you see limitations or risks?

Path to implementation

- Having seen the results in simulation would you believe that autonomous control would bring benefits to your supply chain operation?
- What are your primary concerns why you are not moving forward with implementing such a control solution?
- Where do you see the greatest barriers when introducing such a decentral control solution?
- Could the simulation/the study effectively address any of these barriers/concerns?