Master thesis industrial Engineering and Management

Self-organizing logistics in container hinterland planning

A case study at Combi Terminal Twente

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CTT INTERMODAAL TRANSPORT

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Management summary

This research examines the impact of self-organizing logistics (SOL) using multiple scenarios for the last-mile logistics process to support the human truck planner. A case study has chosen at CTT-Hengelo.

Currently, the assignment of containers to trucks is executed manually by human planners in a centralized decision-making environment. However, many assignments are logical and do not require human evaluation. Due to various limitations in this decision-making process, the planning is often sub-optimal and unable to adapt to unexpected changes. Furthermore, due to an increasing trend in volumes, the logistics sector is facing challenges on how to remain competitive.

This study focuses on the combination of centralized and decentralized decision-making in scheduling activities. A multi-agent system is designed, where containers and trucks as are represented as agents. Using sensors and local communication protocols, real-time information can be retrieved by these agents and can be shared with neighbouring agents. This local, decentralized approach enables agents to schedule transports cooperatively, with less, little or no human involvement and may provide more flexibility to respond to unexpected situations more quickly.

The local-based scheduling triggers bilateral communication to activate an auction bidding mechanism. Available Trucks make bids on neighbouring available containers based on four time-dependent characteristics, and the container communicates whether the truck has won the auction and should be directed to the container. Both types of agents evaluate continuously whether new better bids are placed from new arriving agents in the neighbourhood, which can overrule a current assignment. Moreover, each container has a (time-dependent) urgency level (e.g., related to the latest allowed arrival time). This urgency level should coordinate the timely pick-up and delivery of all containers in the system and regulates the nervousness of reallocating containers to other agents.

The multi-agent system tests different scenarios in which the assignment decision is delegated more and more from the human planner to a SOL-system. Nine key performance indicators measure the impact or efficiency of each setup. Human planners focus on the complex decisions and a SOL-system focusses on the more logical decision. This research assumes that a complex decision is a decision in which multiple comparable alternatives are present in the decision-making process. To which extent the decisions are complex or desired to be delegated is studied in the scenarios using scenario-specific variables or thresholds.

Scenario 1	*Human planners* make **all** assignments based on the highest bidding agent, without allowing overruling.
Scenario 2	If **multiple agents** compete for the same agent, the human planners make the assignment. If **only one agent** competes for an agent, the *SOL-system* makes the assignment.
Scenario 3	*SOL-system* makes the assignment if the highest bidder scores much better than the runner up (***Difference Threshold)*** and the highest bidder scores above the ***Bid Threshold***, otherwise, the *human planners* make the assignment.
Scenario 4	*SOL-system* makes the assignment if the highest bidder scores much better than the runner-up (***Difference Threshold***), otherwise, the *human planners* make the assignment.
Scenario 5	*SOL-system* makes the assignment if the highest bidder scores above the ***Bid Threshold***, otherwise, the *human planners* make the assignment.
Scenario 6	*SOL-system* makes **all** assignments based on the highest bidding agent.
Scenario 7	*SOL-system* makes the assignment considering the **least extra driving time** needed, without allowing overruling. This corresponds to cheapest insertion algorithm.

The difference threshold compares the highest bid placed by a truck with the second-highest bid in one auction round. This threshold is only triggered when multiple trucks compete for the same container or when multiple containers compete for the same truck. The bid threshold compares the absolute value of the highest placed bid with the highest possible bid.

This research extensively evaluates and analyses the outcomes of the designed scenarios. Furthermore, sensitivity experiments evaluate the impact of important input variables. This research should be used as an indication of the possibilities and applications using different levels of self-organizing logistics in last-mile transportation. The most important results and findings are summarized below.

- Introducing an SOL-system and more frequent assignment decision-making results not directly in a decrease in human decisions. Figure 1 shows the decision-making overview per scenario.

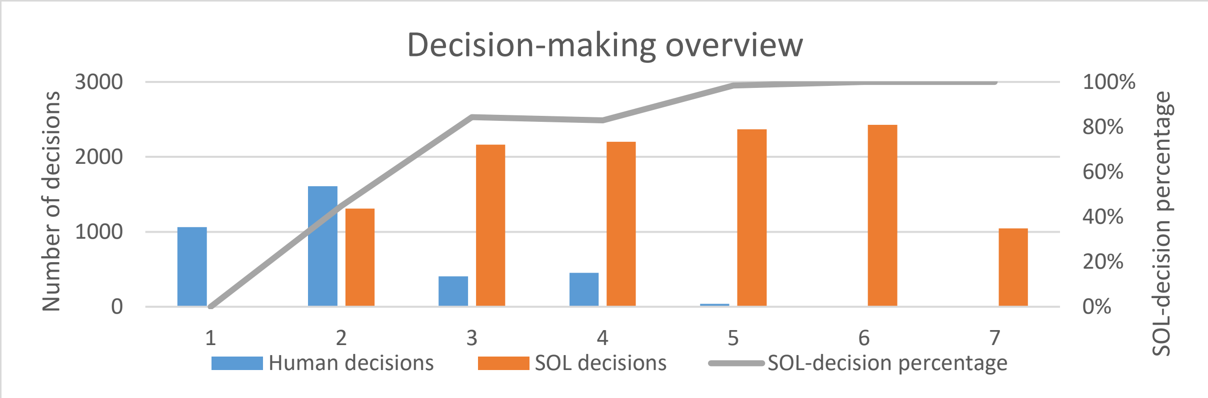

Figure 1: Decision-making overview per scenario

- Especially the truck-related performances indicate remarkable results. The driving time, driving time in overtime and driving distance improve compared to the initial scenario (scenario 1). This is a logical outcome because one of the main improvement perspectives is allowing overruling in which the time-related performances tend to reduce the time needed to transport containers.
- The costs of truck drivers are the main factor within the transportation costs. Therefore, the total driving time has the greatest impact on the average daily costs. Scenario 1 and cheapest heuristic scenario have the highest transportation costs. Scenario 5 has the lowest transportation costs.
- The number of overrules increases when lowering the truck capacity, lowering the interarrival rate, increasing the average placed bids and decreasing thresholds in accepting bids.
- Choosing greater search radii results in more found agents and more options in the evaluation. The results show that more options in the assignment process does not imply linear decreasing turnaround times.
- Choosing the difference threshold is crucial for the results. On the contrary, the bid threshold has only a small impact on the performances. This can also be seen in the delegation of decisions in scenario 4 and scenario 5 in Figure 1.
- Changes in input variables do not show linear changes in resulting performance indicators. This is due to the complexity of the system. Many chosen and unchosen factors, simplifications and assumptions influence the specific performance indicators, which makes concluding on the impact more difficult.

- Changing the demand versus truck capacity ratio indicates correlations in the spreading of the containers. With a lower interarrival time or lower truck capacity, the number of containers at CTT seems not or later to be transported to the client's locations. The number of containers at client locations seems less vulnerable to changing this ratio.

The outcomes of the simulation study show promising results, especially considering the amount of driving distance and driving time, which could improve sustainability performances of transportation logistics. However, a lot of interesting aspects can be analysed in further research. To continue this research a list of recommendations is created for further research.

- Consider and examine the relevance and accuracy and relationships between the chosen input variables and output variables, before starting with a SOL-system. This research indicates some remarkable relationships between the chosen input variables and output variables.
- Especially, in the starting phase of such a system, the decisions should be considered with much human control to ensure the important performances of the system. Tests should focus on more common situations with commonly occurring clients, to check the made assumptions and simplifications. Another option is to create a digital twin or intelligence amplification to have two decision-makers. In this way, the decisions of both decision-makers can be compared. For the future, the most promising scenario is scenario 5. This scenario shows good results in the main performances. Furthermore, it is a simple heuristic in which the human planners collaborate with the SOL-system. Furthermore, it requires only the setup of the auction mechanism and the height of the placed bid by the truck to compare alternatives.
- Mirror this research more to reality to provide more accurate quantitative results. Evaluate more precise the defined assumptions or approximations or use real data to improve the simulation model. Eventually, or an end goal could be to design a decisions support system, which supports the human planner in its decision-making processes in assigning trucks with containers. In such a system, the human planner should be able to have control but should be supported in its assignment activities.
- Evaluate and, if possible, optimise the specific chosen experimental factors and scenarios. Evaluate, the correlations between variables to see the impact or predict the impact on the performance indicators using small adaptions in the designed simulation. Discuss this with the related companies to consider the confidential information or competitive advantage of the concerned companies.
- Investigate further implementations of the different concepts of Physical internet, Internet of Things, and Industry 4.0.
- Consider and evaluate the scanning, auction and assigning mechanism in more detail. Consider different weight for the auction variables, determination of the search radius, penalties on overruling assignments. Furthermore, the defined mechanisms can be replaced by or combined with other mechanisms with different procedures.

Preface

This thesis has been written to finish the master Industrial Engineering and Management at the University of Twente. Started in September 2014 with the bachelor Industrial Engineering and Management at the University of Twente, the educative journey has come to an end.

First, I would like to thank Berry Gerrits, my company supervisor, for the opportunity of graduating at Distribute. Each day, the atmosphere was inviting and stimulating to write my thesis. Numerous discussions helped me to discover or gain more insights into smart approaches. Furthermore, I would like to thank my other colleagues at Distribute! I had a great time working with all of you! Special thanks to Robert Andringa! You helped me a lot with my simulation coding or when I lost the overview.

Second, I would like to thank Martijn Mes, my university supervisor, for the guidance during this research. You supported me and give a lot of useful feedback, which helped me to be critical and it gives me a good direction or multiple insight to finish this thesis. Furthermore, I would like to thank Martijn Koot, my second university supervisor, for the enthusiasm, critical feedback, and improvement suggestions. It helped me to connect the dots.

Third, I would like to thank CTT Hengelo, for providing me with information during this research. You were always willing to help and helped me in understanding the problem situation and problem context within the last-mile transportation.

Fourth, I would like to thank the involved parties within the SOL-port consortium. During consortium meetings, I gained insight and critical reviews to improve my research.

Finally, I would like to thank all people that were involved during my study! My study mates, friends, family, board members, and all that helped me during my educational journey or supporting me to have a good student time in Enschede.

Diederik de Bruin
Enschede, 9 January 2021

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Pre-defined definitions list

"**Self-organizing logistics (SOL)** is a hybrid form of logistics that contains both decentralized and centralized control elements and utilizes automated processes based on real-time system information" (Mes & Gerrits, 2019)

"**Self-organization** is a dynamical process by which a system spontaneously forms nontrivial macroscopic structures and/or behaviours over time." (Sayama, 2015)

"**Autonomous system** is a dynamical equation whose rules don't explicitly include time or any other external variables." (Sayama, 2015)

"**Complex systems** are networks made of a number of components that interact with each other, typically in a nonlinear fashion. Complex systems may arise and evolve through self-organization, such that they are neither completely regular nor completely random, permitting the development of emergent behaviour at macroscopic scales." (Sayama, 2015)

"Discrete event simulation (DES) concerns the modelling of a system as it evolves over time by a representation in which the state variables change instantaneously at separate points in time." (Law, 2015)

"**Continuous simulation** concerns the modelling over time of a system by a representation in which the state variables change continuously with respect to time." (Law, 2015)

"Combined discrete-continuous simulation concerns the modelling in which the system is neither completely discrete nor completely continuous and use aspects of both systems." (Law, 2015)

"An **agent** is an autonomous "entity" that can sense its environment, including other agents, and use this information in making decisions. Agents have attributes and behaviours in specific situations." (Law, 2015)

"A **multi-agent system** is a system which contains a number of agents, which communicate with one another. The agents are able to act in an environment; different agents have different 'spheres of influence, in the sense that they will have control over – or at least be able influence – different parts of the environment." (Wooldridge, 2009)

"**Decentralized decision-making** is the decision hierarchy in which agents make local decisions to optimize their local performance."

"**Hinterland container transportation** is the transport of containers to a region that are not directly supplied from the seaports."

"Real time information is communicated, shown, presented, at the same time as events actually happen."

"IoT sensors are sensors that connects of information technology systems, sub-systems, processes, objects, and networks that communicate and cooperate with each other and with humans." (Maslaric et al., 2016)

"Decision support is the concept in which human intelligence is supported by the technological intelligence to achieve more capabilities."

"The **intelligence amplification"** is a symbiotic relationship between a human and an intelligent agent. This partnership is organized to emphasize the strength of both entities, with the human taking the central role of the objective setter and supervisor, and the machine focusing on executing the repetitive tasks." (Dobrokvic, et al., 2016)

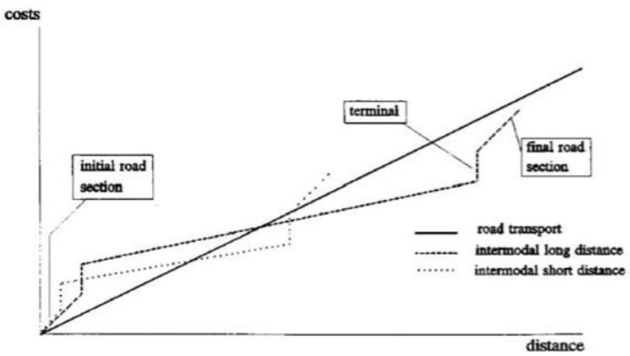
1. Introduction

This chapter introduces the research. First, the research motivation is explained. Section 1.2 handles the research design. Section 1.3 explains the main and sub research questions.

1.1 Research motivation

The hinterland logistic sector faces increasing sustainable restrictions, end-to-end efficiency objectives, market variability, market uncertainty and disruption in the supply chain (Mes & Gerrits, 2019). In the current area of technology, computers can manage all data to come up with a more efficient configuration. The data shared are often not completely trustworthy and the most efficient channel to base schedules on (Feng et al., 2014). This results in continuous rescheduling to ensure the determined or pre-arranged deadlines to deliver a container at a client. This planning activity is very time-consuming and error-prone.

Figure 2 shows the current cost structure and the work intensity of intermodal transport of containers (Bouchery et al., 2015). As can be seen, the first and last distance to be transported is the least efficient phase of the total process of containers. According to Bouchery et al. (2015), transportation systems are evolving. The barge and rail connection between deep seaports and their hinterland is currently evaluated to be used as much as possible because this is in general more efficient and sustainable. Also, the role of the inland terminal is evaluated. For example, bundling strategies and integration with inland terminals could increase the overall performance of the system but this is still a difficult topic. Inland terminals should focus on the final planning phase in which the container is delivered to the client, which has the highest working transport intensity (Bouchery et al., 2015). However, not all destinations can be reached by only barge and rail transportation. Therefore, truck transportation is still needed. To improve the performances of truck transportation, self-organizing logistics is investigated in a consortium project called SOL-port.



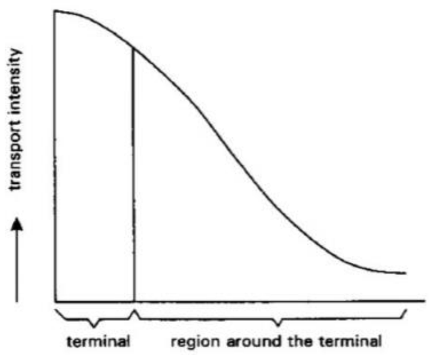


Figure 2: Cost structure of intermodal transport & Transport intensity.

This research investigates and identifies the potential of using a self-organizing system for the planning of container last-mile transportation. Within SOL-port the following thermology for self-organizing logistics is used, formulated by Mes (2019): *"A hybrid form of logistics that contains both decentralized and centralized control elements and utilizes automated processes based on real-time system information".* Related keywords are multi-agent systems, decentralized control, distribution control, adaptive logistics, agile logistics, internet of thing, automated decision making, and physical internet (Mes & Gerrits, 2019). Figure 3 shows an overview of the partners within the SOL-port consortium. CTT-Hengelo is chosen as a case study for this research. Combi Terminal Twente (CTT) is an inland terminal in The Netherlands, with its storage and transhipment terminals in Rotterdam and Almelo. It transports freight in the Netherlands, Germany, Scandinavia, Eastern Europe, and Southern Europe (CTT, 2019).

Figure 3:Related companies in SOL-port.

Figure 4: Hinterland transportation CTT.

Using a self-organizing logistics system, it is assumed that a more decentral decision-making hierarchy is created based on local information. However, the effects of applying such a system and hierarchy in last-mile transportation of CTT are unknown. This research can be used to understand the state of the art of SOL techniques, and to gain insight into the possibilities of working with and implementing a SOL-system, which is the practical motivation of this research.

This research investigates a possible step towards a self-organizing logistics system in the hinterland last-mile logistics using simple decision paths based on the experience of the human planner of CTT-Hengelo and Bolk Transport. A self-organizing system is evaluated to be implemented within the current logistics in the real world. Without full self-organizing decision making, the analyses of the human planners remain necessary.

1.2 Research design

This section describes the research design, the problem cluster, core problem, problem-solving approach, the objective of the research, knowledge to be acquired, limitations and restrictions, data collection, and analysis method. Section 1.3 covers the research questions based on the research design.

1.2.1 Understanding the problem situation

This section identifies the core problem and motivated using a problem cluster. Without a good and clear identification of the problems and core problem, the research could not be effective to fulfil the desires of the problem holder. The cluster is made in collaboration with the CTT Hengelo, consortium partners and supervisors. The core problem is marked yellow in Figure 5.

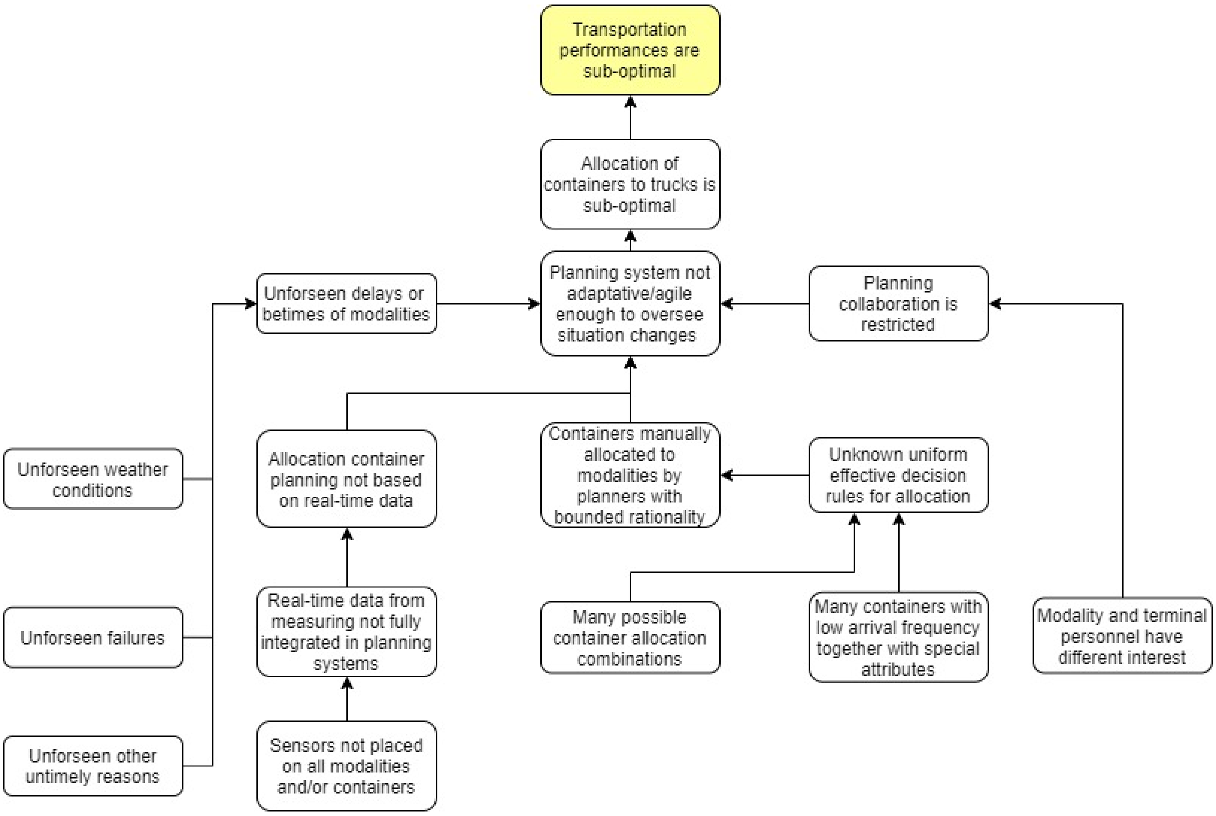


Figure 5: Problem cluster.

Figure 5 shows the core problem with causal relationships. It is unclear for CTT how the decision making in last-mile container transportation can be made more efficient. In the current situation, the containers are manually assigned, using a list of attributes, like the latest departure time or whether a specific truck with a driver is available. Some of these attributes change over time since multiple stakeholders in the transportation process can change these data to inform other parties that the process is delayed. Previous decisions are adapted using the latest information and human experience. Next, the interaction between modality operators and terminal operators is not optimal because of the different interests. For example, terminal personnel want all trustworthy information as quickly as possible to allocate all incoming and outgoing containers. On the other hand, one of the goals of the modality operator is to deliver containers according to the agreed terms. The planning is also influenced by unforeseen untimely reasons, which cannot be anticipated in advance.

To seek for improvements, it is assumed that a self-organizing system lowers the interaction of human planners. Without continuous human evaluations on specific assignments, it is assumed that the transportation performances will improve. This delegation of decisions from the human planner to a system is evaluated using the complexity of the specific assignment. A pre-programmed system can make easy decisions faster and human planners can focus in this way on the more complex situations. An easy decision could be when only one truck can be assigned to a container. Concluding, efficiency in this research holds two aspects:

1. Fewer human interactions in assigning containers.
2. Better tuning of the container assignment activities to fulfil the desired transportation performances.

1.2.2 Determining the modelling and general project objectives

The objective is to indicate the possibilities using a SOL-system with real-time information gathered by sensors, to support the last-mile assigning process.

In this research, a simulation model is used to experiment with different setups or scenarios for the decision-making process and acquire the necessary data. This simulation study should provide insight into the planning actions, complex processes, estimate important performances under a certain projected set of operating conditions, compare different scenarios and allow to study the system with a long-time frame in a short computational time. Using the findings, possible implementation is investigated in which the role of autonomy in the last-mile transportation decision-making processes is increased. This simulation model covers the manual planning actions and (stochastic) processes using the assumed available acquired data from sensors.

In the simulation study, multiple scenarios are designed using different decision delegation-levels to acquire insights to which extent a self-organizing system can be valuable for CTT-Hengelo. In the different scenarios with different delegation levels, assignment decisions or activities are supported or taken over by the SOL-system. The expected first step is to create more insight into the attributes of the assignment on which human planners can base the assignment decisions. The role of a human planner and SOL-system change within these scenarios. Increasing the role of the system results in that the role of the human planner becomes more and more to verify planning decisions generated by a decision support system and focus more on decision-making within complex situations. A 100% SOL-system does not use any human interaction, but this is not expected to be achievable in the short run. Whether it is desirable in the long run is not clear yet. The hypothesis is that the most promising situation for CTT is a specific hybrid collaboration between manual planning and a SOL-system using decentral and central decision making. It is assumed that a complex decision is a decision in which multiple comparable alternatives are present in the decision-making of the assignment process.

1.2.3 Determining the model content scope and level of detail

This section evaluates the limitations and restrictions. An IEM master graduation assignment covers twenty weeks. Therefore, a clear focus or scope should be defined. Section 4.1 discussed the model scope in more detail. The focus and scope of this research are summarized below:

- Inbound and outbound last-mile hinterland container transportation of CTT.
- Data gathering for planning activities starts when a barge leaves the Port of Rotterdam with CTT as the destination. After the container enters CTT, the first activities are initialized.
- The data gathering or scope ends when a container is returned at CTT.
- Simulation study on multiple scenarios using different levels of self-organization.
- Advisory role on how to implement the findings for consortium partners.

Concluding the scope and focus of the simulation study is at the assignment between containers and trucks, starting from the moment the container enters CTT and the scope ended when the container is returned at CTT. This is visualized in Figure 6. The focus of this research is on container transportation and container allocating on trucks. The export flow is from CTT to client and the import flow is from the client to CTT.

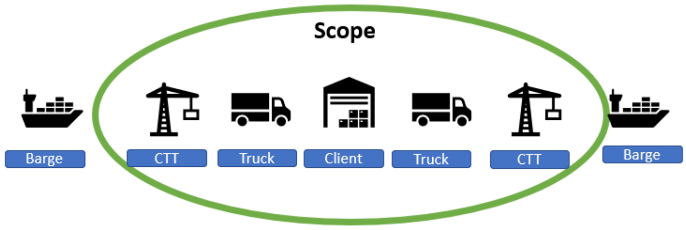


Figure 6: Scope of simulation study.

1.2.4 Validity, reliability, and verification of research

This research uses assumptions and simplifications. These assumptions and scenarios should be validated closely with related parties to increase the validity of this research. Together with the stakeholders, assumptions should be made on how to deal with different situations. The simulation model uses the current available information and simulated sensor data in the last-mile process. Therefore, all assumptions and simplifications should closely be discussed, and findings should critically be reviewed to give recommendations. Several feasibility and verifications checks should be built in the simulation model while seeking the desired situation. Section 5.8 includes further information about the validation, reliability, and verification.

1.3 Research questions

To accomplish the mentioned research objectives, the main and sub-research questions are formulated. Each research question provides a small description.

1.3.1 Main research question

Firstly, the main research question is formulated. This question is formulated, keeping in mind how to solve the core problem, which was mentioned in Section 1.2.1.

> *What is the impact of different levels of self-organizing logistics to improve the last-mile transportation performances of Combi Terminal Twente?*

Knowing the impact and applicability of specific levels of self-organizing logistics is the main goal of this research. The best gradation of self-organizing logistics is investigated combined with the possibility to implement the system to improve or make the planning processes (partly) self-organizing.

1.3.2 Research sub-questions

To answer the main research question, multiple sub-questions are defined. In these sub-questions, the focus is at respectively: current situation, literature review, simulation study, the impact of implementation and recommendations.

1. *"What is the current and expected situation within the hinterland container transportation logistics?"*
   a. *What is the current situation and what are the current important decision-making processes?*
   b. *What are the current performances and what is expected to change within the hinterland container transportation at CTT?*

c. *How can data gathering from sensors be used within the hinterland container transportation planning of CTT?*

In this sub-question, the current situation, performances, and important decision-making processes are examined. Finally, the possibilities with data gathering from sensors are evaluated.

2. *"What is the state-of-art of developments in SOL-systems and how can it be applied to the hinterland container transportation logistics at CTT?"*
    a. *What is a self-organizing logistic system, what is required for such a system and how does such a system use autonomous agents?*
    b. *What are the definitions, applications and future expected developments of Physical Internet, Internet of Things, and Industry 4.0?*
    c. *How are self-organizing strategies used in the container supply chains?*
    d. *How can last-mile logistics and container allocation be applied in vehicle routing problems?*
    e. *What are the different decision control hierarchies and what is their role in self-organizing systems?*

In this sub-question, a literature review is executed on the mentioned topics. Background knowledge is gathered to apply it to the case of CTT. This knowledge is gathered using scientific literature, books, and trustworthy internet sources. The findings are discussed with supervisors in this research to validate and to have a verification of the desired research design.

3. *"How to build and align a simulation model on the current situation and how to apply different levels of self-organization within this model?"*
    a. *How to build a valid model for the self-organizing logistic system?*
    b. *How to build the model for this research with the desired outcomes?*

In this sub-question, first, the way a valid model can be built is discussed. In this chapter, the problem situation and objectives are discussed and the assumptions, simplifications, level of detail, model inputs, model outputs and experimental factors are identified. Next, the designed scenarios are discussed extensively. Furthermore, the role of the human planner is discussed, and possible sensitivity analyses are examined to have more insight into the effect of the initially chosen variables.

4. *"What are the performance changes within the container allocation planning using a specific level of self-organizing logistics? "*
    a. *What are the simulated transportation performances per scenario?*
    b. *What are the simulated performances for the chosen variables in the sensitivity analysis?*

In this sub-question, the conclusions of the simulation study are evaluated extensively. The impact on the performances in each scenario is evaluated to indicate the impact of using a specific level of autonomy.

This research is finalized with conclusions, limitations and recommendations for research.

2. Current situation and case description

This section answers the following question: *"What is the current and expected situation within the hinterland container transportation logistics?"*

At CTT, the container logistics consists mainly of barge planning and truck planning. The focus of this research is on the assignment of trucks with containers. However, the process of barge planning should be understood to know the possible impact when making changes in the decision-making processes in assigning containers to trucks. Furthermore, the data gathering methods of CTT are briefly described to see the possibilities of using sensor data. Finally, the current measured performances of CTT are discussed.

2.1 What is the current situation and what are the current important decision-making processes?

This section focusses on the hinterland container transportation in the Netherlands. After that, the focus is on CTT.

2.1.1 Current situation at container hinterland transportation in the Netherlands

The Netherlands has an important position within the international container transportation logistics. The Port of Rotterdam is the largest logistic port in Europe and is internationally connected with multiple inland ports. According to the Dutch CBS (2019), in the past decades, there is an increasing trend in inbound and outbound cargo throughput of the Netherlands. The outbound is even doubled in the past two decades. In the past two decades, the percentage of the transported containers compared to the total cargo throughput is risen from 14 per cent to 21 per cent. Especially the inland terminals have a high year-on-year per cent change in import and export transhipments (CBS, 2019).

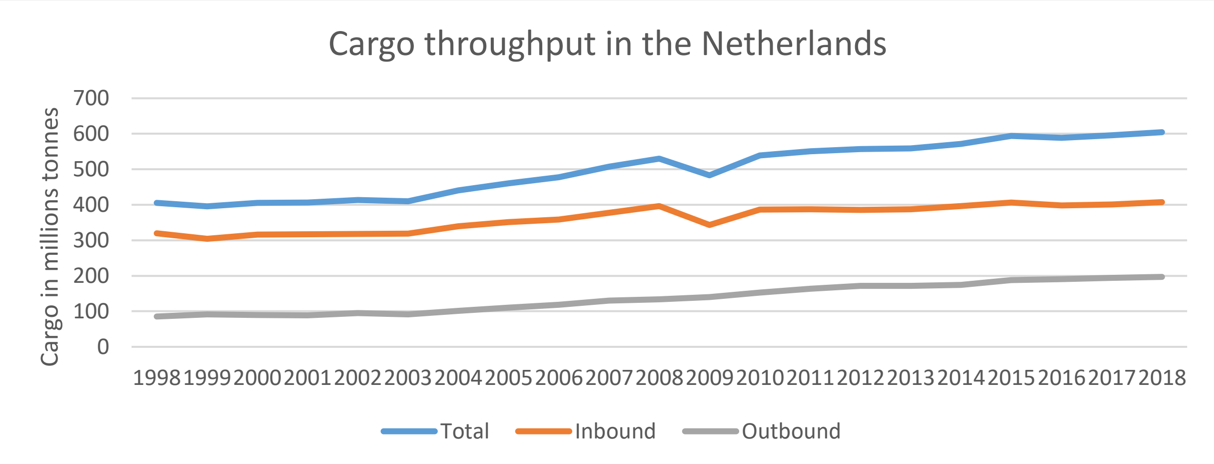


Figure 7: Cargo throughput in Dutch seaports (CBS, 2019).

The Port of Rotterdam is the main gateway to the inland terminals like CTT. Table 1 shows the cargo statistics in TEU of the Port of Rotterdam in 2019.

Table 1: Containers and TEU handled by Port of Rotterdam in 2019 (Port-of-Rotterdam, 2020).

Type	Incoming	Outgoing	Total
Total number of containers	4,567,227	4,213,958	8,781,185
Total number of TEU	7,710,843	7,099,961	14,810,804

2.1.2 Inefficiencies in current container transportation

The current hinterland transport planning systems are often unnecessary delayed because the systems are not adaptive when unexpected situations occur. Many variables should be considered, resulting in complex decisions.

Many large sea vessels arrive and depart, often at different terminal operators at the hub seaport. These sea vessels transport containers that should be delivered or picked up at different terminals. These data are important to base the planning decisions on. Therefore, the hinterland transportation system should continuously be tuned to these arrivals and departures. The logistic planners at inland terminals face this uncertainty and much more restrictions by planning with large planning margins, to ensure the reliability and compliance of the overall container transportation system.

Feng et al. (2014), summarises the main problems within the hinterland container transportation:

- Limited information sharing. Parties are reluctant to share their data with others, which makes it more complex to make an efficient schedule.
- Old-fashioned communication technologies. Mailing and calling do not contribute to efficient planning.
- No autonomy. Related parties do not want to let other parties control their planning systems.

Feng et al. (2014) state that the problems can be solved by a multi-agent-based web application, in terms of the intelligent transport planning system. Agents communicate to enable an automated schedule generation (Feng et al., 2014).

2.1.3 Current container transportation process at CTT

As mentioned in the scope of this research, the focus is on the last-mile transportation of containers. Figure 8 presents the process. The whole process starts when an order information arrives in the planning system of CTT When a container arrives at CTT, it is stored at CTT and waits for the next transportation. When the container is assigned, it waits for the modality to be transported. These steps are the same for the client location. The process ends when the container returns to the Port of Rotterdam.

Figure 8: Container transportation processes CTT (Krul, 2015).

The containers are assigned to a specific modality (barge or truck), considering the modality-specific constraints. Trucks can handle 1 to 2 TEUs per transportation. Inland barges have a maximum capacity in weight and the number of TEUs. The maximum capacity differs per barge. CTT uses 6 barges and 45 trucks of Bolk Transport on a regular basis. Furthermore, some containers are picked up by the client's trucks and do not need to be considered by the human planners of CTT.

2.1.4 Transportation processes

In this research, multiple collaborative processes assign containers to trucks and barges. These assignments are based on the present information at a certain point in time. This section discusses the barge transportation process and the truck transportation process.

Barge transportation CTT

If the container at CTT is assigned to a barge, multiple processes are put into operation. The order-specific data are updated in an online system. This gives visibility for all stakeholders that have access to the system. If barge transport is required and the capacity constraints are not reached, the container is transported by barge. If the container is urgent and needs transport and no barge is available or the maximum barge capacity is exceeded, the decision can be made to use truck transport. Figure 9 shows an extended planning process of CTT.

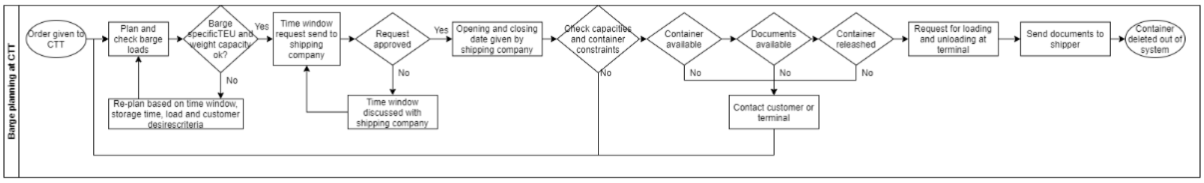


Figure 9: Extended planning process CTT.

Almost every day a barge arrives at CTT from the Port of Rotterdam. The latest information is shared in an online database. Using online tracking programs, the expected arrival time can be estimated by human planners. An arriving barge unloads the containers and places them in the storage area of CTT. Human planners consider approximately 3 to 4 minutes per container for this process.

In the last-mile transport, CTT faces an agreed deadline in delivering the container at the client and returning a container from a client to a seaport. After having an appropriate barge planning considering the given constraints, CTT requests a time-window at one of the terminals in the seaport. When the confirmation is received the process continues. However, this confirmation takes sometimes a long time due to the many planning activities at the seaport. To anticipate on this duration the transportation process of CTT must be started in advance. After having the confirmation, the checks are executed. If all checks are satisfactory, the loading on barges can be started and the documentation is sent to the shipper of the barge. The shipper determines the layout of containers on his ship to have balanced weight and having all dimensions right. Crane operators distribute the containers from the terminal to the barge. It is desired that the barges with the relevant containers are fully unloaded at the hub port before the sea vessel arrives to limit the delays for these sea vessels.

Truck transportation CTT

CTT collaborates with Bolk Transport in the transportation of containers by truck to clients or distribution centres. Bolk Transport has 155 operating trucks, including LZV trucks and trucks that may transport dangerous goods. All trucks can handle specific types of containers. Out of the 155 operating trucks, CTT uses 45 trailers and 10 charters regularly. Besides the truck capacities, the drivers have also specific restrictions. For example, the maximum driving time on one day. According to European law, the maximum driving hours is 9 hours per day with a rest of 45 minutes after each trip of 4.5 hours, which can be done at unloading or loading containers. Furthermore, truck drivers should be presented at the designated location to drive a truck.

Human planners decide whether a truck executes an individual trip or a merged trip. In the individual trip, it transports a container or containers to a client and returns them to the depot (CTT), between clients or from a client to the depot (CTT). In a merge trip, a container is delivered at a client and another container is returned from another client. Here, the containers are uncoupled at the client. Figure 10 visualises the individual and merged trips (Bouchery et al., 2015).

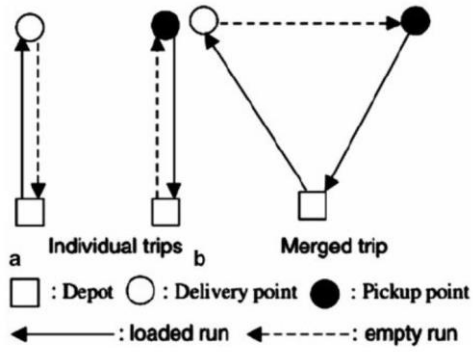


Figure 10: Individual trips and merged trips.

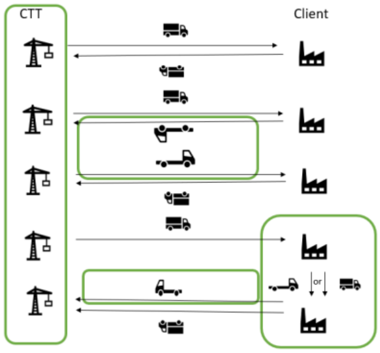


Figure 11:Transportation types of CTT.

Figure 11 summarizes the transportations types of CTT. In the last two types of transport, a merged trip occurs. Trucks can drive with or without a container. The green blocks indicate the possible assignment moments. Containers can be unloaded or loaded or uncoupled or coupled at the client.

- Loading/unloading. This activity is dependent on the load that must be loaded or unloaded. The driver and truck cannot leave in the meantime. The container stays on the truck.
- Uncoupling/coupling. This activity means that a container is uncoupled or coupled on a truck. The average uncoupling time and coupling time are both 20 minutes, based on the experience of planners from CTT. If containers are uncoupled at the client, it is necessary to consider the expected moment of the earliest pick-up time. After uncoupling, trucks are available to pick up another container (merged trip).

Figure 12 summarises the steps of assigning a container to trucks.

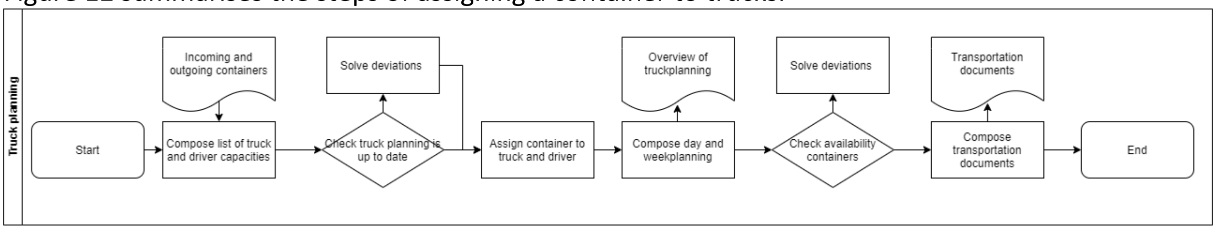


Figure 12: Overall trucking planning process.

Within this research, the focus is on the assignment of containers to trucks. A possible assignment at the client is activated when a truck is uncoupled from its container at the client and has time left to pick up and return another earlier uncoupled container at another client to the depot (CTT). Figure 13 summarizes this process.

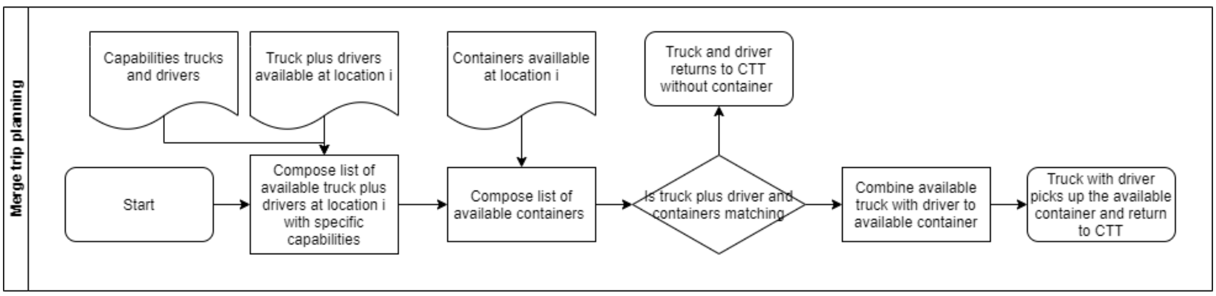


Figure 13: Merge trip planning process.

Within merging the trips, the restrictions are checked. According to planning personnel when multiple combinations are possible, the following aspects are considered:

1. The client requested to pick up the container at their location (approximately 5% of pick-ups is requested)
2. Export transport by barge or truck is planned for a specific container (not measured in the current situation)
3. Waiting time at the client (estimated in the current situation based on gate-in gate-out times)
4. Necessary truck for an urgent transport element (manually considered by human planner)

2.1.5 Truck application of CTT

Within CTT, a truck application has been developed, and the implementation has already started. This application combines truck data from different sources. The goal of this system is to create a better overview of all data that are present at CTT. The overview includes the capacities, available containers and trucks, and the status of different transport elements. Before CTT starts working with this app, CTT had only insight into the gate-out and gate-in times. The driving times are estimated based on experience. In this application, truck drivers insert the moment of departure and arrival times in the truck app. Human planners use this new information for planning decisions. It tracks smartphone locations of drivers. However, this is according to CTT not preferred because this tracking information uses a lot of processing power which delays the truck app.

Transportation data are available at a specific moment. Also, the transports where clients picks-up a container by themselves are handled by human planners. The expected moment that the truck is present at CTT is listed in the available truck list, which enables planners to combine these trucks with the right container. After that, terminal personnel know which container should be picked up and placed on the truck. A client that pick-up a container by themselves happens approximately 30 to 35 times a week. Compared to the total average weekly handlings (see Section2.2.1), this is less than 3 per cent.

According to CTT, approximately 40 per cent of the outgoing containers must be uncoupled and coupled at the client. The other 60 per cent are loaded or unloaded at the client. On expertise, planners schedule when a container is first uncoupled, unloaded by the clients and ready to pick up and couple to bring the container back to CTT to have the specific container available for the next transport element. CTT collaborates with Bolk Transport in truck planning. The trucks that are used by CTT are dependent on the number of planned transport elements. Bolk Transport decides the number of trucks that can be used by CTT. The steps taken within the truck application are summarized as follows:

1. The first data point is when an order is created in the modality system, which is manually inserted by customer service.
2. The driving time is calculated using expertise from planners. The number of kilometres and expected driving time is listed. These two data points can be changed by planners to make this more accurate at any time. These driving times are used to calculate the latest possible moment of departure from CTT to be on time at the client.
3. These data are inserted into the system. Here planners can combine containers to trucks and drivers that are available at a specific moment with the right restrictions to fulfil the transport to or from the client. It is estimated by CTT when the container is available to be picked up at the client location. If the number of trucks is insufficient, Bolk can provide more trucks.

4. A transport element is created in which represents the container the truck with driver, the expected departure, and the expected arrival time. This is manually inserted by planners in the truck application based the received times of the truckers. Two times are received from drivers:
   - The moment the container departs from depot or client.
   - The moment of arrival at the client or depot.
5. A container could have multiple planned transport elements. When all transport elements are executed, the container is deleted from the list of actual transport elements and the truck app.

2.1.6 Assignment decision moment

Human planners of CTT usually make planning decisions with limited information. Within the processes, not all data are immediately present. Therefore, assumptions should be made when this information is present. At some point in time, a decision should be made to accomplish restrictions like the latest moment of delivery and latest moment of departure. Figure 14 gives a representation of the moment of decision. The first available information, information 1 in Figure 14, arises when the client contact CTT. Later, more and more data become available to make the assignment decision. Figure 64 in Appendix B shows this decision moment using example activities of a container within the transportation process.

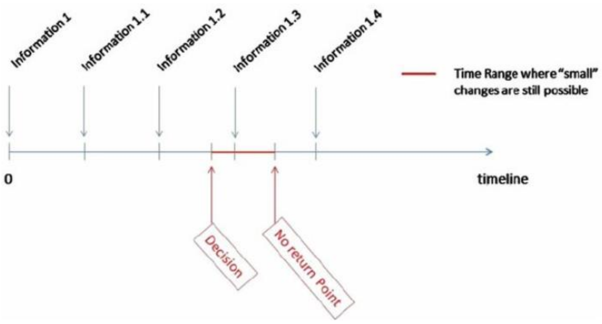


Figure 14: Representation of moment of decision in planning process (Bouchery et al., 2015).

Eventually, the present transportation data should be coupled to make decisions in the planning processes. CTT uses the program Modality to plan the transportations. This program is linked with Microsoft Power BI to store temporarily and analyse the performances. The data from the planning tool is real-time integrated within the database. However, this database focuses on the not-finished bookings and all fields can be updated at any time. For example, if an expected departure of a booking is delayed, planners update the expected departure date to the latest information. For real-time information and decision making, this is usable. However, for the analysis, this makes it hard to do several analyses on the time-related delivery performances.

2.2 What are the current performances and what is expected to change within the hinterland container transportation at CTT?

This section investigates the current performances. In Chapter 5, these performances and some added performances are used to measure and analyse different setups or levels of autonomy in the decision-making processes.

2.2.1 Containers throughput

The container throughput is an important measure in this research. The number of containers that are handled by CTT is retrieved from the barge performances. In the overview of Figure 15, the handled TEU per week is illustrated for 2018 and 2019. As can be seen, there is an increasing trend in these two years. Table 2, summarizes the throughput averages and standard deviation per week per year. The correlation coefficient is positive (33%), indicating an increasing demand.

[CONFIDENTAL INFORMATION]

Figure 15: Number of TEU handled by CTT Twente per week.

Table 2: Average and standard deviation number of TEU handled by CTT.

[CONFIDENTAL INFORMATION]

2.2.2 Type of container

As said, one container can have multiple dimensions, which results in different TEU per container. In Figure 16, represents the type of containers transported in 2019. Each type of container has its empty weight, which is the start value of weight for each transport. The two most used types are the 40HC and 20DV, having an empty weight of 4200 and 2300 kilograms, respectively.

[CONFIDENTAL INFORMATION]

Figure 16: Container type handled by CTT in 2019.

2.2.3 On-time percentage

[CONFIDENTAL INFORMATION]

2.2.4 Turnaround times

The turnaround times considers the time driving back and forth a client and the time staying at the client. The average driving times per client (single trip) and average time at a client are in the planning documents of CTT. As an indication, Table 3 shows the weighted average and standard deviation of these times. In the simulation model, the driving times per client are determined using historical data and an online route-planning app. The waiting time is for unloading containers.

Table 3: Average and standard deviation driving times of 2018.

[CONFIDENTAL INFORMATION]

These times are based on experience. The exact times are not measured precisely for every trip. In the current situation, the times are calculated by looking at the difference between when a truck leaves CTT (gate-out) and when the truck returns at CTT (gate-in). No real-time data are yet available to precisely distinguish the driving time to clients, handling times at clients, and waiting times at clients. Furthermore, no separation is made between (un)coupled containers and (un)loaded containers. In the truck application more of these data could be stored. According to human planners, (un)loading times differ a lot for each container. The average unloading time is estimated on experience at 25 minutes. The (un)coupling at CTT and the client is estimated at 20 minutes at the client.

2.3 How can data gathering from sensors be used within the hinterland container transportation planning of CTT?

Freight and logistics are complex and dynamic. In the consortium, multiple companies contribute to indicate the possibility of implementing self-organizing logistics in hinterland transportation. The consortium partner Pharox developed connected sensors that are usable in truck transportation. With these sensors, the supply chain planning can be made smart by generating more data related to different transportation processes.

2.3.1 Sensors applicability within a planning process

During the SOL-port project, it is intended to implement the Pharox sensors at the truck and containers. Pharox uses LoRa-sensors (low power wide area), which are sensors in a network in which objects and systems use a small amount of data to connect to each other. In this way, a small amount of data can be exchanged between the objects and systems. Using LoRa-sensors, real-time data can be gathered to improve openness, add local intelligence, and enable dynamic re-planning. A result of these three aspects should result in improved utilization, efficiency, alignment with global economic policy effectiveness customer service and satisfaction.

Figure 17: Illustration sensor on truck and container.

Figure 17 illustrates the placement of the sensor on a truck and container. Furthermore, it shows a sensor of Pharox. According to Pharox, the sensors can measure four types of data, namely:

- GPS location
- Shocks or movements
- Light intensity
- Temperature

Especially the first two datapoints are relevant within the container allocation planning because these could be useful input for the planning decisions. Using the GPS location of containers, events can be monitored like geofence-in and geofence-out. These measures can be extended with data as at-dock and left-dock. The shocks or movements is measured to indicate whether the container is currently moving and whether the container is loaded or empty. The time-frequency using these sensors can be reduced to once every minute. Next to the barge information also the truck information can be monitored closely. The sensor will be placed on the chassis of a truck. Using these sensors on chassis, different statuses of transport can be monitored.

These sensor data enable planners to have dashboards with real-time information on different transportation statuses by barges and trucks. In the current situation, not all data are filled in on the moment that they are available at a specific stakeholder in the process, which complicates the planning process. With the real-time data of these sensors, the planning database has the latest available data. This way, the planning system can be adaptive and agile on the latest updated data, resulting in a more self-organizing logistics system. Figure 66 in Appendix B shows the proposed communication IT architecture with the necessary system components using the sensors.

3. Literature review

This chapter evaluates the theoretical framework, and the knowledge to be acquired. Within this chapter, the acquired knowledge from the literature review is discussed and linked with this research. A literature review is needed to formulate the problem, know the present studies, and what aspects are under-researched. The goal of this review is to answer the following question: *"What is the state-of-art of developments in SOL-systems, and how can it be applied to the hinterland container transportation logistics at CTT?".*

3.1 What is a self-organizing logistic system, what is required for such a system and how does such a system use autonomous agents?

Continuing, the different innovation concepts, this section discuses self-organizing logistics. Furthermore, this section discusses the impact on the logistic processes and autonomy agents.

What is a self-organizing logistic system?

In the SOL-port project, the following definition of self-organizing logistics is used, formulated by Mes (2019): *"A hybrid form of logistics that contains both decentralized and centralized control elements and utilizes automated processes based on real-time system information".* Related keywords are multi-agent systems, decentralized control, distribution control, adaptive logistics, agile logistics, internet of thing, automated decision making, and physical internet (Mes & Gerrits, 2019).

A self-organizing system makes decisions automatically within an environment and should be able to undergo spontaneous changes in the internal organization to arrive at a state of equilibrium (Ashby, 2010). Self-organization uses the sense that local interaction eventually produces global coordination and synergy. Complex self-organizing systems can be modelled as a collection of interacting agents, which all have their role in the system (Heylighen, 2008). The underlying mechanisms and all agent interactions should be well declared in a non-linear process. If a system can deal and maximize synergy using a complex perspective, it is a self-organizing system (Heylighen, 2008).

The concept of self-organization is close to autonomy in the context of automated data analysis. According to Wagner and Kontny (2017), self-organizing adaptive logistics focuses on increasing the flexibility and reaction time using efficient data analysis and dealing with disturbances. It integrates processes in the end-to-end supply chain. Autonomous logistic components are connected and communicate to make independently optimized adaptive decisions, which eventually leads to a decentralized self-organizing logistics system (Wagner & Kontny, 2017).

What is required for a self-organizing logistic system?

Self-organization is expected to reduce the number of human interventions, which decrease personnel costs. Humans are bounded to deal with much information and uncertainties at the same time. According to De Roo (2016), four steps are necessary for creating a self-organizing system (Roo, 2016):

- Creation of a symmetry break, which means that small fluctuations acting on a system crossing can result in a different optimal configuration.
- This symmetry break should reach a specific critical point to change the optimal configuration.
- Agents should respond individually when this break occurs in terms of their resulting action.
- These agents' actions should eventually lead to an unintended but collective result.

According to Feng et al. (2014), a proper integral platform should be created which processes the information and communicates this information to the operational planner. This improves visibility and creates an advanced decision-making system to replace human planning jobs (Feng et al., 2014). The available data influences the tardiness and increases the flexibility in slack time. However, such a system is not yet implementable in current hinterland logistics because of the lack of scalability (Feng et al., 2014). The capability to handle the necessary amount of data is still a challenge within this system (Feng et al., 2014).

How does a self-organizing logistic system use autonomous agents?

A multi-agent system is a system in which multiple agents cooperate to achieve a system or agent-specific objective. Agents have joint behaviours with some degree of autonomy and the complexity arising from their interactions (Madureira et al., 2014). The complexity increases rapidly when increasing the number of agents or the characteristics of their behaviour. Objectives of the system or individuals can be achieved by communication and cooperation (Madureira et al., 2014). According to Jederman et al. (2007), the requirements to apply autonomous decision-making, on a system with limited resources, are (Jederman et al., 2007):

- Secure and cost-efficient communication.
- Extended sensor monitoring.
- Measurements support decision guidelines.
- Robustness of decision-making.
- Just in time communications.
- Decentral local processing networking of embedded systems.

An intelligent agent should not be overwhelmed by the flow of information. The local supervision system provides agents processing power to operate on distance. Adler et al. (2005) and Madureira et al. (2014), investigated a multi-agent approach to cooperative distributed systems to improve the dynamic routing and traffic management. A rule-based principled negotiation model between agents is used to have a more direct negotiation (Adler et al., 2005). All agents communicate within the cooperative zone. The size of this zone changes dynamically according to the changing needs of the agent. The efficiency increases when dealing with the infinite time horizon. Each agent executes the algorithm independently to gain the best possible schedule (Madureira et al., 2014).

Conclusions 3.1

Self-organizing logistics is a complex hybrid form of logistics that contains both decentralized and centralized control elements and utilizes automated processes based on real-time system information. Agents are locally interacting and communicate with each other to make adaptive decisions. A SOL-system should include secure and efficient communication, extended sensor monitoring, robustness, just in time communications and networking of embedded systems.

3.2 What are the definitions, applications and future expected developments of Physical Internet, Internet of Things, and Industry 4.0?

This section discusses and compare the different terminologies to know the relations between SOL and these technologies.

Logistics operations consist mainly of three elements: transportation, warehousing, and inventory operations. The current logistics systems are still not entirely efficient and sustainable in terms of economy, environment, and society. For innovating and improving these logistics systems, researchers investigate the implementation of different improvement concepts. Before diving into the capabilities and opportunities, first, the differences between the terminologies are described. Table 4 explains the definitions and terms, according to Maslaric et al. (2016).

Table 4: Definitions PI, IoT and Industry 4.0 (Maslaric et al., 2016).

Term	Definitions	Goal
Industry 4.0	"It describes the organization of processes based on technology and devices autonomously communicating with each other along the value chain."	End-to-end solutions by integration within the supply chain.
Internet of Things	"It refers to information technology systems connected to all sub-systems, processes, objects, and networks that communicate and cooperate with each other and with humans."	Connecting real-time data for better value chain driven big data and cloud computing.
Physical internet	"The metaphor of the (digital) internet in the way we move, store, handle, realize, supply and use physical objects all around the world."	Improving supply chains throughout the world in sustainable economically, environmentally, and socially.

The goal of Industry 4.0 is to enhance productivity through smart autonomous self-learning systems to decrease waste and improves yield (Spectral-Engines, 2018). Real-time monitoring logistics processes increase the sustainability and efficiency, resulting in less transportation cost and maintenance activities. The digitalization increases the agility, which enhances competitive benefits. Industry 4.0 is the fourth generation in the industrial revolutions. The four revolutions are summarized as follows (Spectral-Engines, 2018):

1. Mechanization and introduction of steam and water.
2. Mass production assembly lines using electrical power.
3. Automated production, computers, IT-systems, and robotics.
4. The Smart factory autonomous systems, IoT, machine learning.

The Internet of Things is a type of network to connect anything with the Internet. Through information sensing equipment, it can exchange information to achieve smart recognitions, positioning, tracking, monitoring, and administration (Patel & Patel, 2016). Using intelligent capabilities, IoT enables the interconnection of devices to get complete operational visibility and give better insights into the decisions in the logistics processes. According to Kim and Hoa (2018) the practical applicability of IoT is not given much attention yet. For the implementation, various issues should be tackled. Namely, an architecture must be created to share, exploit, and manage efficiently the information.

The physical internet is an open network designed with a long-term vision for the global logistics systems. It assumes that all related systems are open and connected to share information via the world wide web. With physical internet, it is intended to obtain a global efficient and sustainable global logistic system (Hoa & Kim, 2018). Physical internet provides tools to realize smart characteristics, like information and commutation technologies to improve the overall efficiency significantly in terms of physical flow management, security, and automation of processes. It enables and improves end-to-end visibility of a supply chain in terms of self-identification, context detection, service access, status monitoring and registering, independent behaviour, and autonomous decision making (Hoa & Kim, 2018).With this ability, optimization processes can start to avoid inefficient processes or congestion to create more sustainable supply chains compared to the traditional logistic systems (Hoa & Kim, 2018).

Application and future expectations of mentioned concepts

The terminologies should be mirrored to self-organizing logistics (SOL) to make the transportation plans more efficient. In the current literature, a more recent term used is "Zero-emission". Figure 18 represents many improvement terms. The roadmap shows an overarching view on logistics and supply chains planning and control to reach efficient and non-wasting logistics processes in container transportation (Liesa, 2020). Physical internet is an intermediate step towards zero-emission.

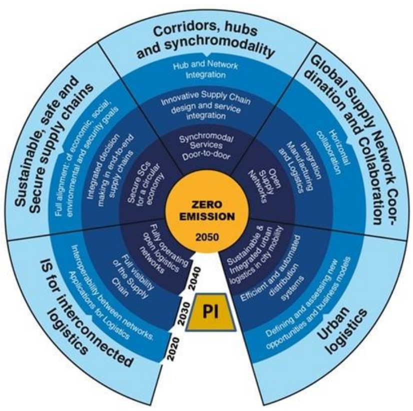


Figure 18: Alice roadmap (Liesa, 2020).

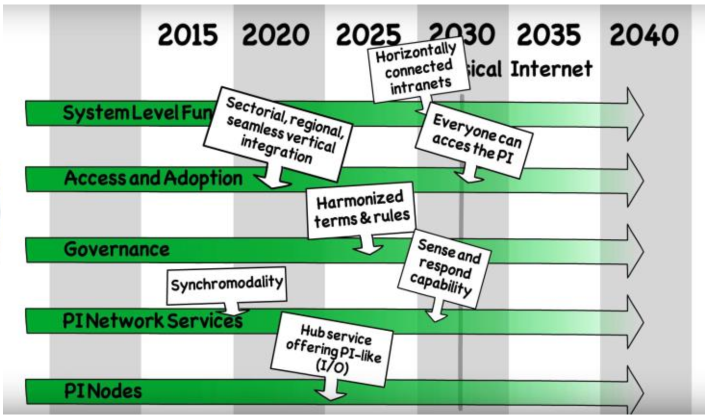


Figure 19: Future expectations P.I. (Alice, 2020).

Conclusions 3.2

Physical Internet, Internet of Things, and Industry 4.0 are different concepts in the innovation of logistic processes. Industry 4.0 focuses on end-to-end solutions by integration within the supply chain. IoT focuses on connecting information for a better value chain driven big data and cloud computing. Physical internet focuses on improving supply chains in a sustainable economic, environmental, and social context. These insights are used as background information. Eventually, the proposed method analyses the efficiency and sustainability.

3.3 How are self-organizing strategies used in the container supply chains?

To see the possibilities of using a self-organizing logistics system, first, a description is given about the supply chain and its intermodal transportation system. Second, this section describes briefly two implemented automated systems in hinterland container transportation. The focus is on the agent-based models, which is a type of a computational model. Computational models use mathematics to study the behaviour of a complex system.

Introduction to the container hinterland transportation

Container terminals are an essential part of the global container supply chain. Container terminal logistics systems (CTLS) are the backbone routing engines for the container transportation network (Li, 2016). Due to maximization policies and improvement in handling technology, decision-making at container terminals became very complicated. Crainic and Kim (2007) define intermodal freight transportation as transportation of items and crude materials from origin to destination by at least two combinations of transportation modes, such as land, rail, or maritime transport. Furthermore, complex and dynamic decision-making situations force human decision-makers to adopt cognitive heuristics, which add vulnerability to judgment and decision biases (Crainic & Kim , 2006).

Péres & Mes (2017) study the scheduling drayage request in a synchro modal network to minimize the assignment costs. Figure 20 classifies eleven request types. Some request types allow decoupling and do not need to wait for the container to be loaded or unloaded and that another truck can pick up the loaded or empty container later (Mes & Pérez-Rivera, 2017). In a pre-haulage request, an empty container is transported to a customer location and subsequently, after loading, transported to a long-haul terminal. In an end-haulage request, a loaded container is transported to a customer location and subsequently, after unloading, transported to the next terminal or customer.

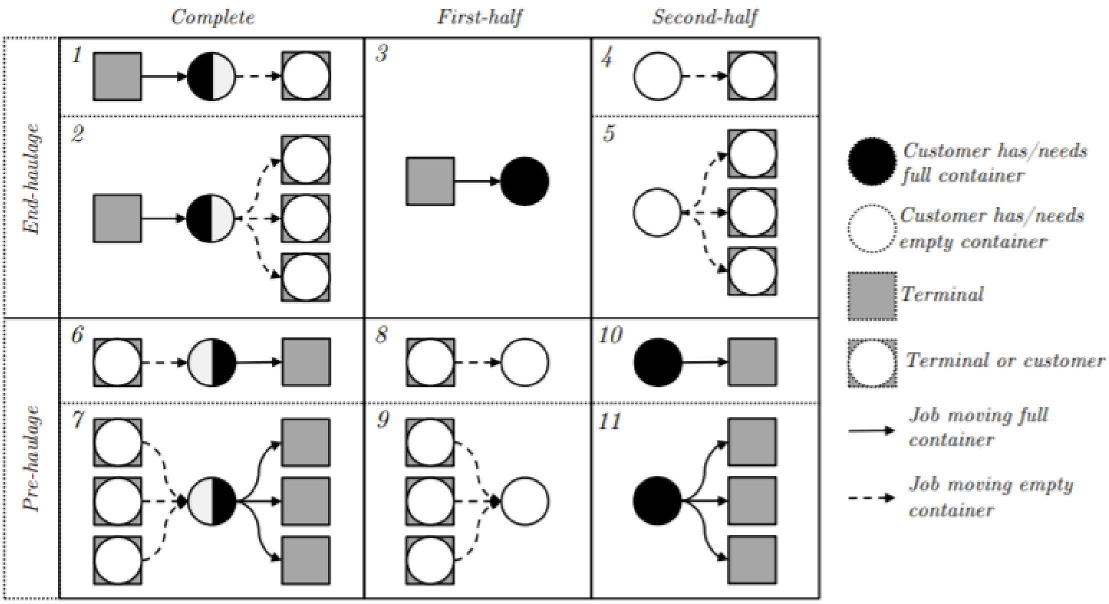


Figure 20: Request types of intermodal transport (Mes & Pérez-Rivera, 2017).

Current implemented self-organizing systems within container hinterland transportation

SOL-systems have been applied in different fields, namely in financial markets, supply chain management, fleet management for scheduling and dispatching, terminal management, and intermodal transportation (Irannezhad et al., 2020). It is useable to illustrate competition and interaction among various locations. Some agent-based self-organizing systems are already implemented at a regional level (Fazi et al., 2015). Multiple simulation studies examine different policies by changing the environment. The agents observe to learn how to behave in different environments. Results show that the number of unnecessary transports decreases, and the on-time arrivals increase using a SOL-system (Irannezhad et al., 2020). The focus is on the competitive advantage of inland terminals or gaining insight into the overall network (Fazi et al., 2015).

Rivas (2011) used a basic machine learning paradigm, which predicts the agents' behaviour to maximize the reward within a specific environment. Rivas (2011) used a heuristic with a set of if-then rules, with a choice probability. This choice probability changes over time when unexpected outcomes arise, which is called probability matching. Experiments confirm that human's adaptive behaviour or chance of changing a strategy is high when undesirable performances occur to prevent a similar event in the next case. Rivas demonstrates that in a reinforcement learning environment, the chosen choices made eventually converges to the best situation (Rivas, 2011). Diversification in decision-making is strong when agents do not know the possible actions. Consequently, it is weak for a real-life situation when individuals do know possible actions. Diversification is an instinct to seek information and learn about the environment.

Irannezhad et al. (2020) let agents learn independently and update the preferred transport after new information arises. The payoff of agents on a specific moment in time is the percentage of savings in transport costs. Having more agents implies that the number of possible bundling of resources and loading opportunities arises, resulting in more potential savings in the overall process (Irannezhad et al., 2020). The transportation costs are determined by summing the time-based, distance-based operational costs and fixed costs of the modality.

Fazi et al. (2015), assumes that the system has a specific planning horizon in which limited data are available for the scheduling. If the local search finds a better feasible solution, the system creates a new route with a determined probability. The local search initializes this procedure each delta hours. Delta stands for the frequency of the initialization (Fazi et al., 2015).

Conclusions 3.3

A computational model uses mathematics to study the behaviour of a complex system. A commonly used model is an agent-based model. Agent-based models seem suitable for container freight transport to illustrate competition and interaction among various agents. Some agent-based self-organizing systems are already implemented at a regional level. Published papers show promising results. Diversification in decision-making is strong when agents do not know the possible actions. Consequently, it is weak for a real-life situation when individuals do know possible actions.

3.4 How can last-mile logistics and container allocation be applied in vehicle routing problems?

This section discusses last-mile logistics and container allocating in the vehicle routing problem to seek applications in the case of CTT. Section 3.4.1 discusses last-mile logistics and the black hole algorithm (Banyai, 2018). This last algorithm indicates how a distance searching algorithm can be applied in the vehicle routing problem and container allocation problem. Other studies use other meta-heuristics within the container allocation problem. However, these are not evaluated within this research.

3.4.1 Last-mile logistics

Last-mile logistics concerns the final transportation of freight from a depot to the destination in a supply chain. In literature, first-mile and last-mile logistics is seen as the least efficient stage and covers approximately 28% of the total delivery cost (Ranieri et al., 2018). Nowadays, the system can be more efficient and sustainable. Already, many innovations are made in the logistic and transport systems, using ICT systems, focusing on (Ranieri et al., 2018):

- Location technologies.
- Retrieving and providing information from the user.
- Developing a mobile application with an interface.
- Using the advantages of IoT and big data tools.

Last-mile logistics is described as the process of planning, implementing, and controlling of transportation, and storage of goods from the order penetration point to the final customer (Olsson et al., 2019). The last-mile locations can be categorized into three aspects or facets (Olsson et al., 2019):

- Last-mile fulfilment focuses on making an order ready for delivery.
- Last-mile transport focuses on the movement of goods.
- Last-mile delivery focuses on physical delivery to the destination.

Last-mile logistics connection with real-time information

Banyai (2018) uses real-time information in package supply chain operations. Due to developments like Industry 4.0 and the internet of things, it is possible to control and optimize energy-consuming resources by hyperconnected logistics. Real-time processing of open tasks in a network reduces the order fulfilment time to face objectives in having a more efficient supply chain (Banyai, 2018). Banyai developed a model in which the first-mile and last-mile logistics focus on energy efficiency. It integrates the assignment of open tasks to scheduled routes, scheduling of open tasks, and rescheduling of existing delivery routes, considering time and capacity restrictions (Banyai, 2018). Banyai (2018) used the black hole algorithm-based optimization heuristic, which belongs to the swarm intelligence paradigm. This type of paradigm uses adaptive strategies to search and optimize in its environment. This optimization strategy uses the idea of dying stars where a gravity force pulls everything in the neighbourhood to them. The event horizon is a search radius, which is called the Schwarzschild radius. Figure 21 illustrates moving behaviour of the stars. The closer to the black hole, the stronger the gravity force.

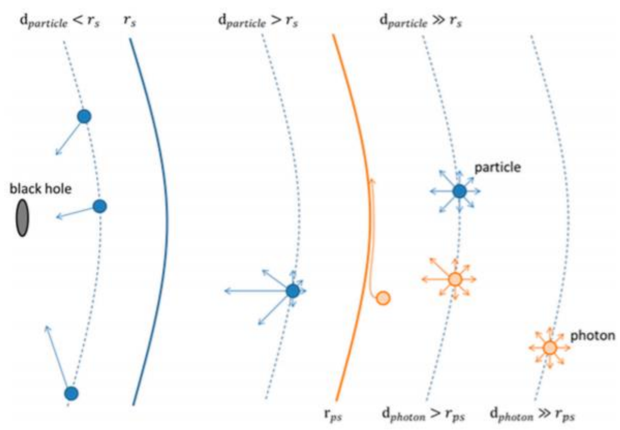


Figure 21: Moving behaviour of different particles depending on the distance between particle, event horizon and photon sphere (Banyai, 2018).

The black hole optimization has four phases (Banyai, 2018):

- Initialization of location and stars characteristics in the search radius.
- Evaluation of potential solutions.
- Selection of the best star.

- The fourth phase is moving or swarming of stars towards the black hole. When stars reach the event horizon, they are absorbed, and the black hole searches for a new star in the search space. The search radius is constant or a permanently decreasing value.

3.4.2 Container allocation in the vehicle routing problem

This section focuses on dynamic vehicle allocation and routing problem in a time-varying network with time windows. Furthermore, this sections briefly explains the cheapest insertion algorithm. Yang et al. (2004), defines the vehicle routing problem as the assignment of vehicles to jobs in an appropriate order, considering the time and vehicle restrictions (Yang et al., 2014). The jobs are the physical object to transport to another location. The objective function is to minimize total travel costs to serve all routes. Constraints ensure that customers are served by one vehicle only, the same number of vehicles goes in and out the depot, and all routes connect with the depot (Yang et al., 2014).

The vehicle routing problem can extend with additional restrictions for clients or transporting vehicles. Desrochers et al. (1992) proposed an algorithm for the vehicle routing problem with time window restrictions. Varying over the width of a time window and the vehicle capacity makes the system complex to simulate. For considering the time windows, four conditions should be evaluated (Desrochers et al., 1992):

1. Minimal arrival time from predecessors
2. Minimal arrival time to successors
3. Maximal departure time from predecessors
4. Maximal departure time to successors

The container allocation problem uses the vehicle routing problem to achieve a proper allocation of jobs to resources. The container allocation problem is a stochastic integer programming problem. The overall objective is to determine an efficient allocation schedule at the operational planning level in which all vehicle routing problem constraints are satisfied (Xu et al., 2015). An efficient allocation of containers aims to minimize the transportation costs in the transportation network. The travel times and travel distances have an impact on the total transportation cost. Travel times considers four times: empty and loaded travel times and loading and unloading times. Improvements can be analysed using meta-heuristics like tabu search and simulated annealing. Koo et al. (2005) introduce a makespan, which is the time needed to fulfil all jobs. The swap with the highest reduction in the makespan is accepted (Koo et al., 2005).

Vehicle routing problems are examined using different improvement algorithm to improve the system performance. An example is the cheapest insertion algorithm. This algorithm focuses on the least extra cost or time needed to fulfil a job or transport. According to Rosenkrantz et al. (1977), the cheapest insertion method runs in polynomial time. The algorithm uses three steps to identify and select the cheapest de-route in a vehicle routing problem (Rosenkrantz et al. , 1977):

1. Start with a route from location i to destination j, with route cost c_{ij}.
2. Evaluate all alternative routes from location I to new destination r, with route cost c_{ir}.
3. Choose the new route with the minimal sub-route cost $c_{ir}+c_{rj} - c_{ij}$.

3.4.3 Auction mechanism in the vehicle routing problem

In the last decades, there has been an increasing interest in collaborative logistics to be more efficient and cooperative. Wooldrich (2009) describes an auction as a mechanism between an agent known as the auctioneer and a collection of agents known as bidders. Auctioneers attempt to achieve their desires by designing an appropriate auction and bidders attempt to achieve their desires by using an effective strategy. An auction mechanism has three dimensions, namely (Wooldridge, 2009).:

- *Winner determination*. This dimension covers which bidder wins the good of the auctioneer.
- *Sealed or open cry auction*. This dimension covers whether the other placed bids are known.
- *The number of rounds*. This dimension covers whether bids can be placed in successive rounds.

English auctions are the most commonly used type of auction. The auctioneer starts with a reservation price (can be zero) which can be overbid by bidders. Bidders are invited to bid more than the current highest bid. The bidder with the highest bid is allocated to the auctioneer (Wooldridge, 2009).

Mes et al. (2007) described a Vickrey auction, in which the auction is sealed and assigns transportation jobs to trucks. It has a decentralized decision making principle where agents only have information from its neighbourhood. This bidding strategy enables trucks to bid on the jobs considering the additional pick-up, transportation, and delivery costs. In this sealed-bid auction, every bidder submits his bid without knowing other bidding agents. The auctioneer selects the best bidding agent. It can change an existing assignment if a better deal of another truck arises. It focuses on profit allocation and less on the efficiency of assignment decisions (Mes et al., 2007).

The bidding mechanism starts when a job arrives. It opens an auction by asking a bid from all vehicles within the environment. All trucks create a bid, consisting of a price, expected departure time, and expected arrival time. The auctioneer communicates whether it accepts or rejects the bid. However, it can also wait to receive a better bid at a later moment in time. The acceptance of a new assignment leads to a new schedule. In this Vickrey auction, the bid price depends on the minimal additional costs (Mes et al., 2007). The additional costs of the concerned schedules are determined using the additional waiting time needed to move to the container and the change in the total penalty costs for tardiness (Mes et al., 2007). An advantage of this auction mechanism is that the focus can be laid on the transport control variables instead of the learning and rationality of agents. The focus of improving such complex systems should lie in the interactions between agents in the multi-agent system (Mes et al., 2007).

Winner determination in an auction mechanism

Gansterer and Hartl (2017), proposed a combinatorial auction mechanism. Carriers have paired pick-up and delivery requests with each an origin and destination location. A carrier starts at a depot and handles a given set of pick-up and delivery jobs (single or bundles) before returning to the depot. The objective is to minimize total travel time. The jobs are selected from an auction pool. Bids are created considering the carriers' marginal profit (value of job minus exclusion value). Here the tour length restrictions are considered. After that, the winner determination problem is started, which maximizes the total system profit by selecting the best allocation of bundles and carriers (Ganserter, & Hartl, 2017). The restrictions concern that a carrier wins or loses a bundle, each bundle is allocated once. The carrier can only win a bundle if it submitted a bid. Each request is allocated once, and this problem has only binary decision variables. Using the auction mechanism, four standard properties should be aimed for efficiency, budget balance, individual rationality, and incentive compatibility. Efficiency is covered by the winner determination problem in which the total profit of the network is maximized (Ganserter, & Hartl, 2017). The budget balance is covered by the fact that the exchange does not run at a loss. Individual rationally is covered by the fact that the bid placed equals the paid amount. Incentive compatibility is reached when each auctioneer and carrier act or creates bids according to their true characteristics.

Sadoui and Shil (2016) proposed a multi-attribute auction mechanism. Four phases are needed to determine which buyer wins the auction (Sadoui & Shil, 2016).
Phase 1: Specifying constraints on attributes.
Phase 2: Specifying qualitative preferences on attributes.
Phase 3: Specifying qualitative preferences on attribute values.
Phase 4: Specifying constraints on bidding.

After these phases, the winner determination process is initialized. This process is defined as a weighted set cover problem where the winner is determined using weights and scores over a set of attributes. It used the utility function of the buyers to maximize the buyers' expected payoff. The score of the bid is calculated by using the sum-product of variable weight and variable score. After each pre-set round the highest score bidder wins the auction. Using successive rounds, sellers can improve their highest bidder by letting better bids overrule the current configuration. The auction mechanism considers five phases (Sadoui & Shil, 2016):
Phase 1: Calculating the attribute scores.
Phase 2: Revealing the scoring rule and submitting bids.
Phase 3: Checking the constraints.
Phase 4: Defining the attribute value functions.
Phase 5: Generating partial feedback information about sellers.

Conclusions 3.4

Last-mile logistics concerns the final transportation of freight from a depot to the destination in a supply chain. The last-mile logistics can be described as the process of planning, implementing, and controlling efficient and effective transportation and storage of goods from the order penetration point or depot to the final customer. The vehicle routing problem is defined as the assignment of vehicles to jobs in an appropriate order such that time and vehicle restrictions are not exceeded. With minimal arrival times and maximal departure times, the vehicle routing problem can be extended to multiple allocations over time. A Vickrey auction can be used to assign trucks to containers based on characteristics within the neighbourhood. In this way, the number of communications decreases. The winner determination problem (WDP) allocates the bidders over the good of the auctioneers to maximize the total system profit. Auction mechanisms should have the properties of efficiency, budget balance, individual rationality, and incentive compatibility. Using multiple attributes, each having an own specified weight, the bid function can be calculated. In this way, pairwise comparisons can be made in which the individual utilities are compared. The individual with the highest utility can be selected as the winner.

3.5 What are the different decision control hierarchies and what is their role in self-organizing systems?

Supply chains can be managed by adopting different levels of centralization. In current logistics, many decisions are made with limited rationality because of the lack of complete information. Besides, many number of parameters, criteria, nonlinear relationships, fluctuations decisions are stated with relative uncertainty (Hongler et al., 2010). The choice of the level of centralization to manage the supply chain is a critical theme because it affects supply chain performance. Different degrees of demand uncertainty results in that not every supply chain has the same desired level of centralized decision making (Giannoccaro, 2018). Higher demand uncertainty means more adaptive decision making. To investigate which hierarchy is suitable for the truck planning of CTT, the decentralized decision hierarchy is compared with the centralized decision hierarchy.

High centralization occurs when decision-making power is concentrated in one party or single decision-maker. A high level of centralization of inventory control is beneficial for supply chain performance since it can improve overall efficiency and reduces a possible bullwhip effect (Giannoccaro, 2018). An example of the bullwhip effect is the swings in inventory levels to be adaptive towards uncertainties. When solving problems, cognitive ability is used to conceive alternative solutions. High centralization is associated with improved efficiency, thanks to the possibility of handling in an integrated way all the interdependencies exciting among the supply activities. It allows resolving conflicting aims among supply chain actors thanks to the integrated approach (Giannoccaro, 2018).

The difference between high-central and low-central (decentral) decision making is that within decentralization decision making, multiple independent decision-makers or agents are present within the supply chain. These agents make local decisions to optimize their local performance. In central decision making, the focus is on the overall performance of the supply chain. In decentralized decision making the focus is on individual performances. Feng (2014) describes centralized control as a hierarchy in which all related information integrated at one point. In decentralized control, multiple local controllers communicated by a point-to-point mechanism. The most important disadvantages are summarised by Feng (2014) in Table 5.

Table 5: Disadvantages of centralized and centralized control.

Disadvantages of centralized control	Disadvantages of a decentral control
All related information is needed simultaneously at one point (decentral).	A certain level of coordination is necessary to couple information from different parties to make feasible decisions.
All parties should give up their possession of control.	Not with all interest could be dealt.
Data privacy cannot be guaranteed, which undermines individual competitive positions.	

According to Hongler et al. (2010), the most cost-efficient decision hierarchy depends on the time horizon. In the short time horizons, the agent-based decentral self-organization beats the optimal effective centralized controller in terms of cumulative costs and effectiveness. In this agent-based self-organization, agents interact with each other to find improvements. If the time horizon increases, these interactions become less effective, resulting in higher cumulative costs (Hongler et al., 2010). Figure 22 illustrates this relation. However, the question remains, which control hierarchy or a mix of decentralized and centralized is most beneficial per supply chain activity (Hongler et al., 2010).

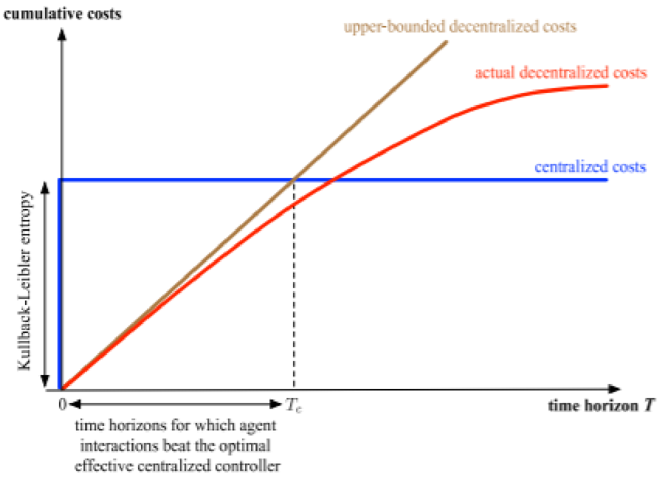


Figure 22: Qualitative sketch of the global cumulative costs incurred by decentralized and effective centralized control.

Hybrid decision making

Feng (2014) examined a hybrid system as an information exchange mechanism for planning at a container terminal. It involves a multi-agent system in which soft agents have three features: autonomy, adaptability, and coordination. Here, the user defines the behaviour attributes of each agent. Furthermore, negotiation strategies and the amount of data that are shared.

Feng (2014) represents the overall architecture system in three layers. Firstly, the decentral agent layer, which gives real-time updates for the schedule database. Secondly, the knowledge layer involves all tasks and activities to specify the functionalities of the agents. It provides ontologies and software engines that combine expert knowledge-based software with the acquired information. Thirdly, the central agent layer, which involves the coordination agent community.
To enable a hybrid decision-making system, three steps are defined (Feng et al., 2014):

1. Creating the agent-based web application system platform to ensure interoperability.
2. The programming language should be platform-independent and portable.
3. The system should be universal, which means that more stakeholders within the container transportation sector could join the platform to prove a complete solution for hinterland planning.

Conclusions 3.5

Supply chains can be managed by adopting different levels of centralization. High centralization occurs when decision-making power is concentrated in one party or single decision-maker. Low centralization occurs when multiple independent decision-makers or agents are present, who make local decisions to optimize their local performance. The most suitable decision hierarchy is different for each supply chain and planning situation. The demand uncertainty and time horizon are two main aspects to decide which decision hierarchy is most suitable. Higher uncertainty and a short-time horizon prefer a more decentral decision hierarchy and a low uncertainty and long-time horizon prefer a central decision hierarchy. Hybrid systems can use the strengths of both hierarchies in which agents have three features: autonomy, adaptability, and coordination.

4. Solution design

This chapter describes the solution method for the problem by examining how the different levels of self-organizing logistics can be implemented and support the human planner. Chapter 3 provided background information for this chapter. Scenarios are defined in which the impact and effectiveness are evaluated using different levels of self-organization to support the human planner. This chapter discusses how to mimic the planning system and answer the main research question. It focuses on the design of the mechanisms and the interpretation of the transportation elements. The different scenarios are used to generate outputs with different inputs to investigate causal relationships and find remarkable findings. This section is divided into multiple subsections. Firstly, the goal proposed multi-agent model is evaluated. Next, the four important mechanisms are introduced and explained. Figure 23 shows these mechanisms and the corresponding subsection. The arrows indicate the interrelationships between the mechanisms. The routing mechanism is only active or called when a (new) assignment is made. Chapter 5 explains the routing mechanism and the model map in more detail.

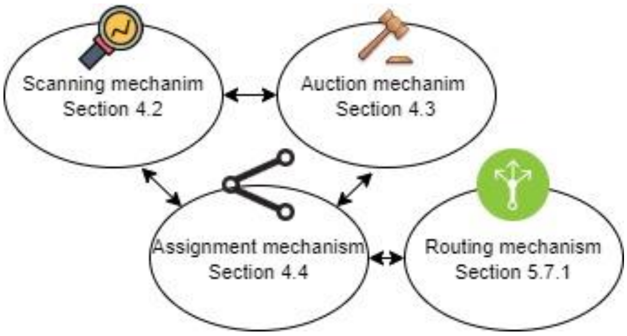


Figure 23: Model mechanisms and the interrelationships.

4.1 Goal of designed multi-agent model

The goal of this research is to indicate the possibilities using a SOL-system with real-time information, gathered by sensors, to support the last-mile assigning process. A multi-agent system is designed to mimic the planning system and answer the main research question. A multi-agent system is a system which contains a number of agents, which communicate with one another. The agents are able to act in an environment (Wooldridge, 2009). An agent is an autonomous "entity" that can sense its environment, including other agents, and use this information in making decisions. Agents have attributes and behaviours in specific situations (Law, 2015). This research focuses on the assignment of trucks with containers, which are both considered as agents in the multi-agent model. These agents interact in a changing degree of centralized decision-making environment using a scan radius to find each other in the scanning mechanism. This model indicates the effect on transportation performances using different levels of self-organizing logistics. Chapter 5 continues with the implementation of the multi-agent model in a simulation study.

4.2 Scanning mechanism

The scanning mechanism in this study is inspired by the black hole optimization and the visualization in Figure 21 and animal behaviour considering a 'scenting' and a 'smelling' property to match the two subjects.

The designed scanning mechanism determines the available agents in the neighbourhood by considering other agents within a search radius. The search diameter of the container depends on specific attributes, like urgency and waiting time. Both radii can be compared with a 'scent' that is spread by an agent from its current position. This 'scent' can be 'smelled' by other agents to enable local decision-making. Both types of agents only have information from their neighbourhood in the scanning mechanism, indicating a decentralized decision-making environment.

The scanning mechanisms of both agents are initialized in the following situations:

- Containers start scanning when the container is delivered at CTT by a barge. The scan mechanism is turned off when the container is unloading at the client, coupled on a truck or returns at CTT. The scanning is activated again when the container is ready for the next transport.
- Trucks start scanning when the working day is started and stops when they enter the night parking. The trucks return to the night parking when the working day is closed, and it has no assigned containers anymore. Furthermore, a truck scans continuously for better assignments when it is not currently transporting a container, or the truck has less than 2 current assigned containers.

So, both agents initialize the scanning mechanism. When two agents find each other, the scanning mechanism activates a bilateral communication where the agent-specific attributes of both are stored for the auction mechanism. Figure 24 shows a simplified representation of the idea of the scan radius of both agents. The chosen diameters of the search radii do not correspond to a real-life distance.

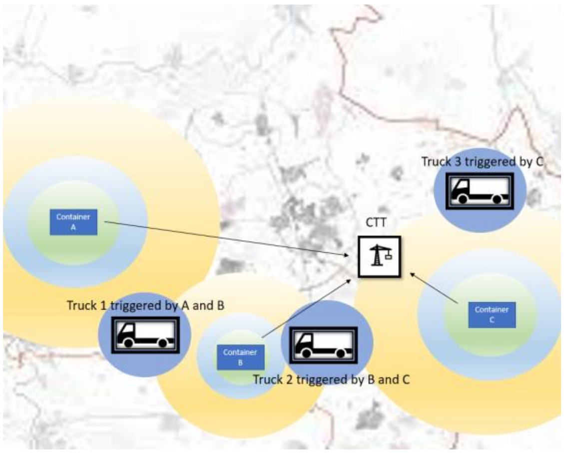


Figure 24: Idea of radius of containers.

Figure 25: Radius visualisation of container and truck.

The scan areas of both agents are spread over a map with a spread location as the centre. The spread location of the container is always its current location. The spread location of the truck is the location where it is available for the first time. The truck is available when it is not transporting a container. Hence, if the truck is transporting a container, the next available location is the location where the container is uncoupled. The truck can only be assigned to a maximum of two containers. Section 4.4 explains the assignment mechanism in more detail. Besides the different spread location determination, the diameter is also different for both types of agents. Figure 25 illustrates a simplified radius determination. The trucks have a non-changing radius diameter. The diameter of the radius of containers is based on three priority rules, which are based on the experience of the human planners in assigning trucks with containers. The three priority rules are summarized below.

1. *Requested by the client*

   In the assignment at of containers CTT, this variable is not applicable. In the assignment of containers at the client location, human planners approximate that 5 per cent of the containers are requested to pick up by the client. This request increases the scan radius of the container.
2. *Planned deadline at the next location*

In the assignment of containers at CTT, the planned deadline is the agreed delivery time with the client. In the assignment of containers at the client, the planned deadline is the time the containers should be present at CTT. For the export transportations, the deadline to deliver at the client is always available. However, the deadline for returning containers is not always available. On estimation, this is only 10 per cent of the returning containers. This returning deadline increases the search radius of the container.

3. *Waiting time*

   This rule indicates the current waiting time of the container. The waiting time of a container is the current time minus the first available time to pick up. Higher waiting time results in a bigger search area.

Equation 1 shows how the search diameter of the container is determined. The first two priority rules are true or false, with a score of 2 and 1, respectively. The priority rule waiting time is the day number. For example, using a start radius of 100, the client requested the container, the container has no returning deadline, and the container waits for 4-days, the radius becomes 800 (=100*2*1*4).

$$Search\ radius\ container = Start\ radius * Score\ priority\ rule\ 1 * Score\ priority\ rule\ 2 * waiting\ days$$

Equation 1: Search radius equation.

Possible situations in scanning using radius

Both agents scan every five minutes for a possible assignment. This is chosen to limit the computational time of running the scenarios. The radii of containers and trucks can overlap or not. Two agents find each other when having overlapping radii. To examine the overlap of the search radii, the scanning mechanism increases the search radius at the beginning of the search mechanism. In this way, the mechanism also triggers agents just outside the search radius of the searching agent. If a container does not find an available truck with overlapping radii, it waits for the next scanning moment. If a truck does not find an available container with overlapping radii, it is routed or remains at the parking of CTT. Intuitively, having a bigger search radius, the chance of triggering another agent increases. The scanning mechanism calculates the Euclidean distance between the agents by the square root of both positions. If this distance is less than the sum of both radii, the scanning mechanism initializes the auction mechanism. Figure 26 gives an example of this overlap determination. Here, the container searches for a truck. By the increased radius, the container finds truck 1, truck 2 and truck 3, but only truck 1 and 2 have overlap. So, these two trucks are making bids to pick up the container. The winner depends on the scores on the four variables in the auction mechanism. Section 4.3 explains the auction mechanism and auction variables in more detail.

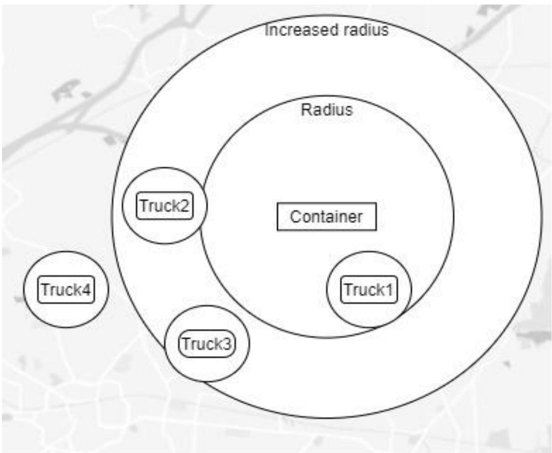


Figure 26: Overlap example.

4.3 Auction mechanism

The auction mechanism determines the bids and indicate possible assignments between truck and container an auction mechanism is designed. This auction mechanism is inspired by the Vickrey auction of Mes et al. (2007), see Section 3.4.3. The auction mechanism is triggered when two agents find each other by the scanning mechanism. As mentioned in Section 4.2, the scanning mechanism results in bilateral communication. Bilateral communication is activated when the radii of two different types of available agents overlap each other. The scanning mechanism and auction mechanism of an agent remain active until an agent is coupled. A container is available when it waits for the next transport at its current location (CTT or client). A truck is available when it is not transporting a container. However, a container can trigger trucks that are transporting containers. The first available location of the truck is the location where the coupled container should be uncoupled. In this case, it takes time to be available. The time to be available of trucks is defined as "Currently scheduled time". The next paragraph explains this variable in more detail. Only trucks create bids on containers. Due to the stochastic nature of the logistic system, better assignments or combinations can arise over time. Therefore, the scanning mechanism scans every five minutes to find better alternatives within the auction mechanism. In this way, an assignment can overrule a previously assigned agent. Section 4.4 explains this overruling process in more detail.

Auction variables

The bid of the truck determines whether the agents become assigned to each other. The bids are calculated using four time-related variables of the current state of the truck. The variables are penalty times or extra time needed to transport the container or return to CTT. In this way, possible pick-ups can be compared with each other. For simplicity, the weights of the variables are set equal to one. Figure 60 in Appendix B shows an example calculation. The following variables are used for creating a bid:

- The Euclidean distance divided by the system average driving speed.
- The expected extra driving time that is required to pick-up and transport the container. More time needed lowers the bid. The expected driving times are calculated using a route planner for the considered destinations and estimated for the unknown clients in a specific direction. Furthermore, this variable includes container-specific activities times.
- Overtime needed for the transport. Coming closer to overtime hours or overstepping the overtime the bid of the truck decreases.
- Currently scheduled time. Having scheduled transports assigned to the truck will lower the bid. This variable is only relevant for a truck that is currently transporting a container. The currently scheduled time indicates the time until the truck is uncoupled plus a penalty time per to-be-executed activity. This penalty time covers a possible deviation from the average duration of the transport activity. The number of scheduled activities depends on the transport type and the remaining transport activities. Each routing, unloading and uncoupling activity is considered as an activity. Each to-be-executed activity has a penalty time of 5 minutes. In this way, a truck with many scheduled activities creates a lower bid than a truck on the same location without scheduled transport activities.

Bid calculation

As mentioned, four variables are considered as time penalties because this concerns the extra time to transport a container. In the auction mechanism, trucks bid on containers that should be transported. In the designed system, both agents scan every five minutes for better combinations. As mentioned, four variables are considered as time penalties because this concerns the extra time to transport a container. In the designed system, both agents scan every five minutes for better assignments. When agents find each other by overlapping radii and both are available to be assigned, trucks create a bid on the container. For the calculation of a bid, a starting bid is used as a starting point. This starting bid equals 5 hours. It is assumed that a transport element should not be more than 5 hours in the auction variables. The auction variables are expressed in seconds. Therefore, 5 hours equals 18000 in the bid creation. The time-related auction variables scores are subtracted from the starting bid. If the penalty time is higher than 5 hours, resulting in a negative bid, the bidding truck is excluded in further steps. With this restriction, the system only accepts assignments which need too much time for transportation. Equation 2 shows the bid calculation in a formula.

$$Bid\ truck\ on\ container = SB - \sum_{i}^{4} S_i * W_i$$

$$SB = Starting\ bid\ in\ each\ bid\ calculation$$
$$S = Score\ on\ auction\ variable\ i$$
$$W = Weight\ on\ auction\ variable\ i$$

Equation 2: Bid truck on container calculation.

4.4 Assigning mechanism

The assigning mechanism in this study is inspired by the assigning mechanism used in the research of Mes, et al. (2007). In the designed scanning mechanism, agents trigger all agents with overlapping radii. However, not all agents are included in further evaluations because only the best options are considered. An agent can trigger zero up to and including four agents in the assignment mechanism. The agents are divided into current and new agents. The new agents are the best option following from the scanning and auction mechanism. Current agents are the assigned agents of the new agents. Figure 27 visualizes the determination of the number of agents. The new truck or new container initializes the scanning mechanism.

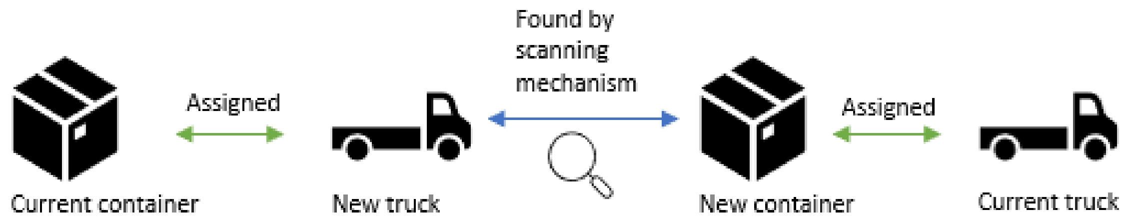


Figure 27: Number of agents in a scan moment.

To determine the assignment between agents, several procedures should be executed to determine the best assignment. After the scanning and auction mechanisms, nine situations can occur. Figure 28 gives an overview of these situations and show the resulting actions. The current agents can be overruled in three situations by the newly found agent. Figure 28 indicates these situations (5, 8 and 9) in green boxes. The next paragraph describes overruling in more detail, focussing on the bundling of two container assignments of trucks.

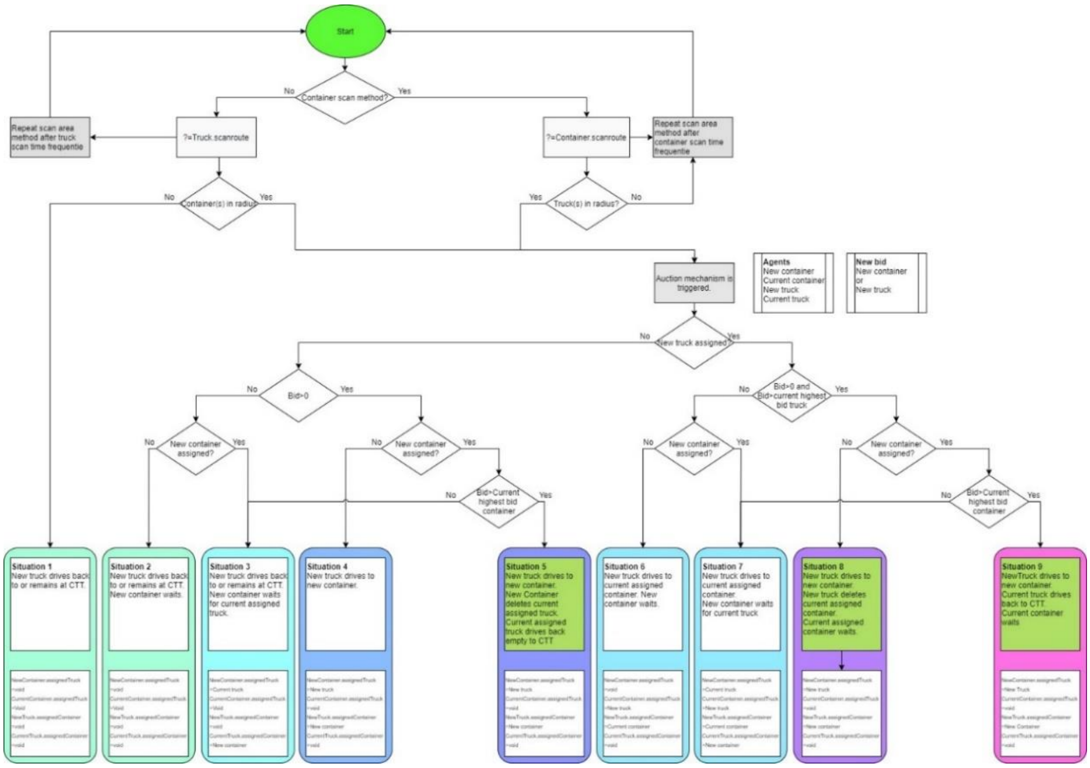


Figure 28: Determine assignment method situations.

Scanning and auction mechanism illustration - container perspective

Figure 29 shows the seven steps of a scanning process and auction mechanism with the perspective of the container. The boxes in the illustration briefly explain the steps. Figure 61 in Appendix B gives the same illustration with a truck perspective.

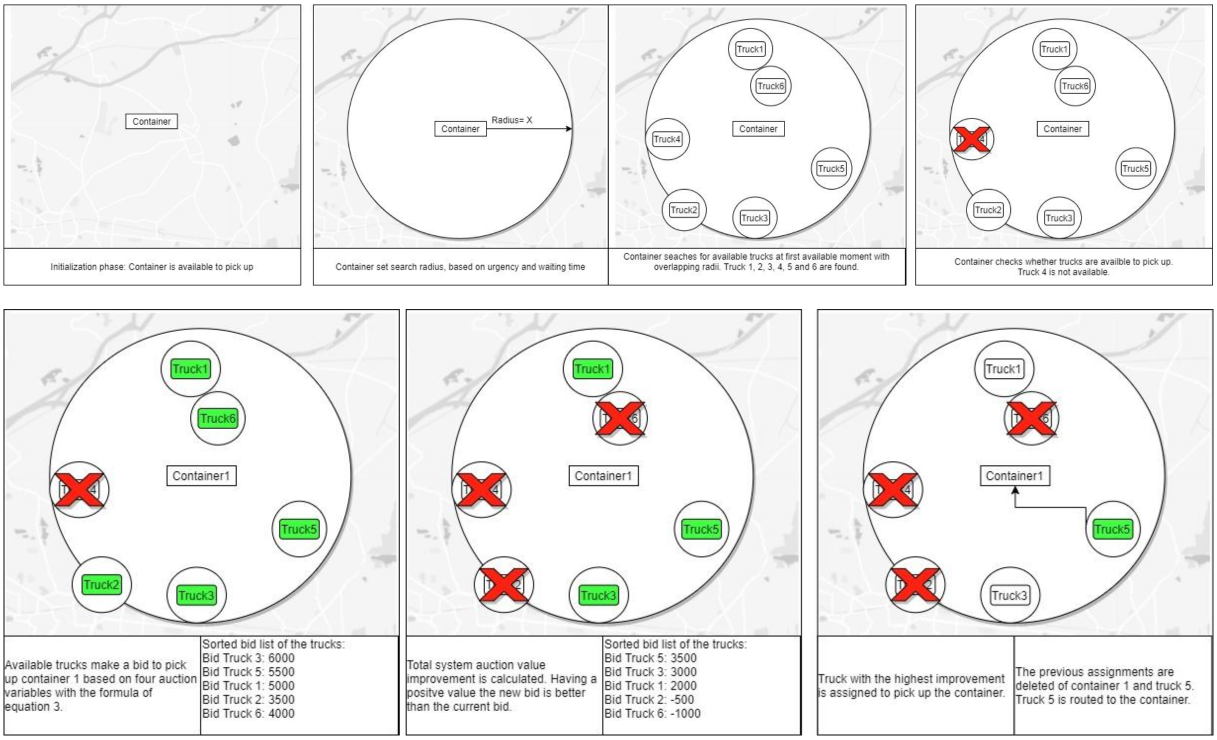


Figure 29: Scanning and auction mechanism illustration - container perspective.

Overruling

Continuing with Figure 29, both agents are continuously searching for better assignments. If an agent is assigned and it finds a better assignment, the overruling mechanism is started. An overrule happens if an agent overbids a previous assignment. The agents get a new assignment and trucks are re-routed. Section 5.7.1 explains the routing in more detail. To overrule, the new bid should increase the total system auction value. This total system auction value is the sum of all current highest bids of trucks and containers (see Equation 3), where i is the total number of trucks and j the total number of assigned containers. In a made assignment, the current highest bid of the container (CHBC) equals the current highest bid of the truck (CHBT). The idea of this total system auction value is that an overrule should improve the overall system.

$$Total\ system\ auction = \sum_1^i CHBT_i + \sum_1^j CHBC_j.$$

Equation 3: Total system auction value.

Figure 30 shows a simple example, in which truck 1 is assigned to container 1 and truck 2 creates a bid for container 1. The total system auction value is increased from 20 to 80, which is an improvement. Therefore, truck 2 overrules truck 1. Truck 1 is routed to CTT and truck 2 is routed to container 1.

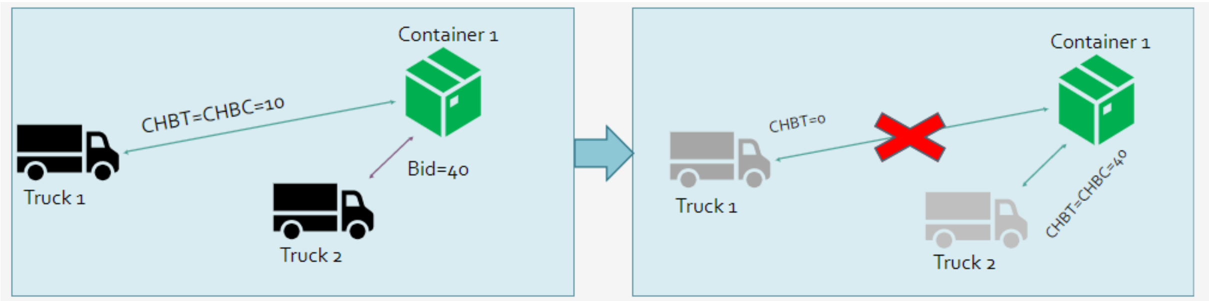


Figure 30: Overruling: simple example.

Important to consider in the overruling mechanism is whether none, one or both new agents are already assigned to another agent, as represented in the flowchart in Figure 31. If a new auction round starts and the same assigned truck wins the auction, both agents receive an updated current highest bid. In the case that both agents are previously assigned, the new bid should be more than the current highest bid or current highest bids. In the case that no agent is previously assigned, a positive bid leads to an assignment. In the case only one of the new agents is previously assigned, the new bid should be evaluated whether it improves the total system auction value. After an overrule has happened the current highest bids of the agents are updated, which is used in next scanning moment. Figure 31 shows the different situations in a flowchart.

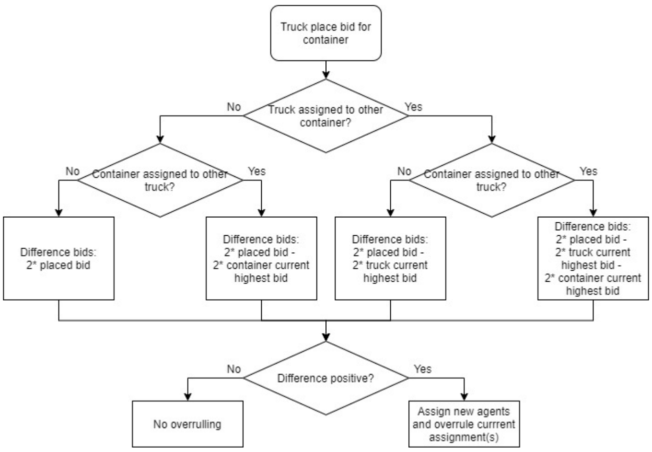


Figure 31: System improvement calculation.

Bundling of assignments for trucks

If the truck is not transporting a container, it is available to be assigned and can follow the assignment mechanism of Figure 28. However, as mentioned before, a container can find a truck that is transporting another container. The maximum assignments of trucks and containers are two and one, respectively. The time to be available is considered in the creation of the bid. This is necessary to evaluate whether a truck should be assigned to a second container. Figure 32 shows this bundling procedure in a flowchart. If the container is already the second assignment of the truck, no action is required. If a new container finds an unavailable truck, the difference in the total system auction value is evaluated to determine whether the container should be the second assignment of the truck. When the truck uncouples its currently attached container, the truck checks whether the second assigned container is still assigned to the truck. If so, the second container becomes the first assigned container of the truck, the current highest bids are updated and the truck routes towards the current location of the container. If the second container has found a better truck in another auction round, the truck deletes the second assigned container, routes towards the parking of CTT and the truck activates the search Booleans to initialize the scanning mechanism.

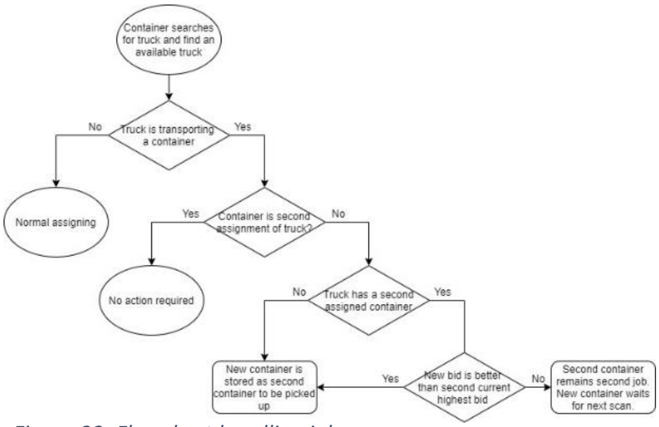


Figure 32: Flowchart bundling jobs.

Next available location of a truck

As stated, a truck can be assigned to zero, one or two containers. The uncouple location is the next available location of the truck. Figure 33 gives an example of this. In this example, container 3 is searching for a truck. As can be seen, using the search radius of the container 3, truck 1 and truck 2 are triggered. However, truck 1 is transporting container 2 to client 2, which is the next available location of truck 1, which is outside the search radius. Therefore, truck 1 is not considered in the auction mechanism. However, truck 3 is currently outside the search area, but the uncouple location is inside the search radius, resulting in overlapping truck and container radii. So, truck 3 should be included in the auction mechanism. The auction of container 3 is held between truck 2 and truck 3. If truck 3 wins the auction, container 3 is assigned as the second assignment of truck 3. If truck 2 wins the auction, container 3 is the first assignment of truck 2.

Figure 33: Second assignment example.

4.5 Conclusion

This chapter discussed the multi-agent model and used methods to search, scan, bid and assign trucks and containers to mimic the planning process of CTT. The agents in the multi-agent model are the containers and trucks. Every five minutes, the scanning mechanism initializes a scan which could lead to a bilateral communication between agents to fulfil a transport. The container search radius is based on the urgency level and the total waiting time. The search radius of the truck is a fixed constant. Both radii are not based on a real-life distance. Trucks bid on containers in an auction mechanism in which the best bids are evaluated using the overall system auction value. The goal of the auction mechanism is to improve the total system transportation performances. The bid is calculated using a starting point or starting bid. This is subtracted by four time-related auction variables or time penalties. These time penalties link with the amount of time needed or uncertainty present to assign a truck to a container. Overruling means that a previous assignment is deleted, and a new higher bidding agent is assigned to the currently assigned agent. Containers can be assigned to one truck. Trucks can be assigned to maximum two containers. After an assignment, the data of both agents are updated, and the truck is routed to the current location of the container. If a truck does not find containers, it returns to the parking of CTT and initializes the scanning mechanism every five minutes. If a container does not find any truck, it waits for the next scanning moment.

5. Simulation model

This chapter discusses the simulation model using the explained mechanisms of Chapter 4. Section 5.1 discusses the conceptual model, covering the requirements, methodology and type of simulation. Section 5.2 covers the problem situation and objectives. Section 5.3 explains the designed scenarios, covering the assignment decisions using different thresholds to determine the decision-maker. Section 5.4 discusses the simulation model inputs and outputs. Section 5.5 discusses the assumptions, and simplifications, including how the human planner in the model is interpreted and simulated. Section 5.6 discusses the promising variables for a sensitivity analysis. Section 5.7 explains the implemented model. It starts with the explanation of the routing mechanism, as mentioned in Chapter 4. Next, it explains and shows the 2D and 3D simulation model. Finally, Section 5.8 discusses the verification and validation of the proposed simulation.

5.1 Conceptual simulation model

This section answers the following question: *"How to build and align a simulation model on the current situation and how to apply different levels of self-organization within this model?"* The important elements within a simulation study are discussed and these are used for the rest of this report. Furthermore, the type of simulation is determined. This section supports the layout of the next sections of this report.

5.1.1 How to build a valid model for the multi-agent self-organizing logistic system?

A simulation model enables to predict how the system will perform under scenario-specific operational conditions. First, the study should design a conceptual model which includes a non-software specific description of a computer simulation model. This description covers the objectives, inputs, outputs, content, assumptions, and simplifications (Robinson, 2008). This conceptual model helps to validate the simulation model and understand the outcomes. The system inherits the concept of multi-agent decentralized coordination between different parties (Feng et al., 2014). The key requirements of a conceptual model are validity, credibility, feasibility, and usefulness. Robinson (2008) created a methodology for a simulation study with interconnections between different concepts. As can be seen in Figure 34, it is a cyclic concept in an interactive perspective to better refine the simulation study.

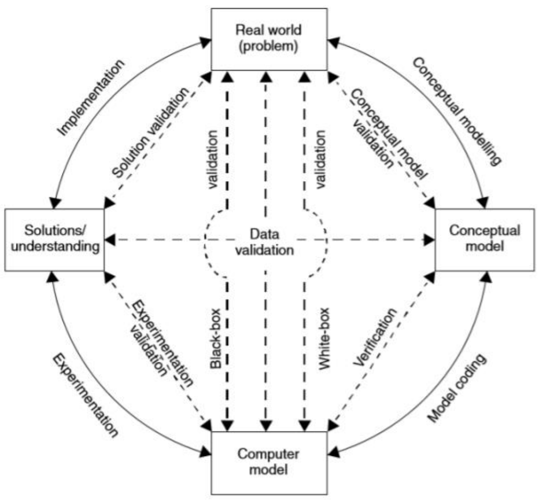


Figure 34: Practice of model development and use (Robinson, 2008).

5.1.2 Type of simulation

A simulation is a mathematical representation of a system to investigate the impact on chosen performance indicators. Law (2014) classifies three dimensions of simulation models, namely:

- Static versus dynamic models.

Static models show the system on a specific moment, and a dynamic model represents the system over time. Dynamic models are more useful for evaluating performances.

- Deterministic versus stochastic models.

Deterministic models have the attribute that the system output is determined once the input is specified. Stochastic models have inputs that are determined using variable components.

- Continuous versus discrete models.

Continuous models have a continuously changing system over time. In discrete models, the system attributes only changes upon a specific event.

In this research, the best-linked choices for the three dimensions are: dynamic, stochastic, and discreet. It is a dynamic model because the system situation changes over time due to the continuously changing attributes. It is a stochastic model because every time a container arrives in the system, the agents' attributes are determined using specific distributions or probability functions. It is a discrete model because the actions or decisions are event-based. After starting or finishing an event, the model initializes follow-up actions.

Furthermore, Law (2014) describes the types of simulation regarding the output analysis. The desired type of simulation depends on the objectives of the study. It can be a terminating or a non-terminating simulation. A terminating simulation has a predetermined end event, resulting in a specific run length. A non-terminating simulation has no natural event that stops the simulation. This makes it not possible to determine the run-length in advance. The designed system can be modelled as a non-terminating simulation because it has no natural terminating event. However, it can also be modelled as a terminating simulation because working days include 16 hours. This simulation study is interpreted as a non-terminating simulation because the ending situation of each day is used as the starting point for the next day. Furthermore, the arrivals of barges continue.

5.2 Problem situation and modelling objectives

This section discusses the problems in this simulation model and the desired experimental objectives. The goal of a simulation study is to gain insight into the impact and effectiveness of using different levels of autonomy in the last-mile transportation decision-making processes. Following from this, the modelling objectives are:

- Provide accurate insights into the impact and effectiveness on the outputs, using different scenarios.
- Allow SOL-port partners to use this report and its outcomes, using a visually attractive representation of the model.
- Be feasible to build within the given time and data constraints and limitations.
- Be useful for further evaluation and sensitivity analysis to evaluate more scenarios, transportation processes or companies, in other supply chains or using different inputs.

Chapter 2 has already explained the problem situation. Summarizing, the possibilities and opportunities of different levels of autonomy in the decision-making process are unclear, scoping on assignments in the export and import transportations. With a decentralized approach, the goal is to delegate the decision-making from human planners to an autonomous planning system. This study examines the impact of the chosen inputs on the outputs. Accurate insights and valid outcomes are necessary. The model should be based on current decision trade-offs and should be understandable by a moderately experienced modeller. In this way, the model can be used for extensions or more experiments in further research.

5.3 Scenarios

Multiple scenarios are designed to indicate and see the impact of using different levels of self-organization logistics. These scenarios use different values for the inputs and delegation of decisions in the last-mile transportation process. Six scenarios are formulated together with the consortium partners. Furthermore, a benchmark scenario is added using a proven heuristic, namely the cheapest insertion algorithm (see Section 3.4). All these scenarios use the mechanisms of Chapter 4.

The first scenario corresponds with the current situation, using multiple simplifications and assumptions. The next scenarios gradually increase the level of self-organization. All have different settings to search and assign the transports to see the impact on the outputs. In this way, the scenarios diversify over the number of decisions made by the SOL-system and decisions made by human planners. Human planners should focus on complex decisions, and the SOL-system focusses on the more logical decisions. This study investigates the desired amount of delegation. A complex decision is defined as a situation in which multiple good alternatives are present within an auction round. The boundary depends on the chosen variables or thresholds within the scenarios. Assuming that it is undesirable that more complex decisions be fully self-organizing because humans can oversee uncommon information. Therefore, the different scenarios consider a stepwise process in which the role of the SOL-system is increased, and the role of the human planner is decreased.

As mentioned in the literature review, the winner determination covers the question which bidder wins the good of the auctioneer. In the designed simulation model, the truck is the bidder, and the container is the auctioneer. The scenarios have certain thresholds in the auction mechanism to consider the winning agents. In the scenarios, the assignment decisions should be delegated more and more from human planners to the more autonomous SOL-system. For this, the system examines situations in which multiple alternative assignments occur in an auction round. The system uses two thresholds to compare the alternatives, namely the bid threshold and the difference threshold. The difference threshold (Equation 4) compares the highest bid placed by a truck with the second-highest bid in one auction round. This threshold is only triggered if multiple trucks compete for the same container or if multiple containers compete for the same truck. The bid threshold (Equation 5) compares the highest bid placed with the highest possible bid (or starting bid).

$$Difference\ threshold = \frac{Highest\ bid\ truck - second\ highest\ truck}{highest\ bid\ truck}$$

Equation 4: Difference threshold calculation.

$$Bid\ threshold = Highest\ placed\ bid / highest\ possible\ bid$$

Equation 5: Bid Threshold calculation.

Table 6 shows the seven designed scenarios. Furthermore, the table indicates the role of the SOL-system and human planners. It is expected increasing in scenario number the role of the human planner decreases and the role of the SOL-system increases. Further research can focus on other improvement heuristics or adaptions in these scenarios.

Table 6: Scenarios.

Scenario	Description	SOL vs human
1.	Human planners make **all** assignments based on the highest bidding agent, without allowing overruling.	SOL: N.A. Human: Complete
2.	If **multiple agents** compete for the same agent, the *human planners* make the assignment. If **only one agent** competes for an agent, the *SOL-system* makes the assignment.	SOL: Very low Human: Very high
3.	*SOL-system* makes the assignment if the highest bidder scores much better than the runner up (***Difference Threshold)*** and the highest bidder scores above the ***Bid Threshold***, otherwise, the *human planners* make the assignment.	SOL: Medium Human: Medium
4.	*SOL-system* makes the assignment if the highest bidder scores much better than the runner-up (***Difference Threshold***), otherwise, the *human planners* make the assignment.	SOL: Medium Human: Medium
5.	*SOL-system* makes the assignment if the highest bidder scores above the ***Bid Threshold***, otherwise, the *human planners* make the assignment.	SOL: Medium Human: Medium
6.	*SOL-system* makes **all** assignments based on the highest bidding agent.	SOL: Complete Human: None
7.	*SOL-system* makes the assignment considering the **least extra driving time** needed, without allowing overruling. This corresponds to the cheapest insertion algorithm.	SOL: Complete Human: None

Figure 62 in Appendix B shows the mentioned scenarios from Table 6 in a flowchart with the corresponding decisions in specific situations. The stated thresholds in this flowchart are the bid threshold and difference threshold. As can be seen, in scenario 1 the assignment is always made by CTT and in scenario 6 and 7 always made by the SOL-system. To simulate the human decision, the radius of the container is set very large, resulting in that the containers always see all trucks. Furthermore, the highest bidding agents is always chosen. However, having a human evaluation results in a small evaluation penalty time for the truck agents. This penalty time influences the time performances of both types of agents. Section 5.5.2 explains the human evaluation and the role of the human planner in more detail. Scenario 6 seems the most promising scenario because it always chooses the best assignment option, and no human evaluation is needed. However, this scenario is expected to have many overrules and many autonomous decisions, resulting in an unstable system. Chapter 6 evaluates these performances and other performances in detail.

5.4 Identifying model inputs and outputs

This section explains and discusses the model inputs variables and model output variables. Defining these variables is crucial for a good analysis of the system.

5.4.1 Model input variables

Within the simulation study, several input values are chosen to represent the reality and the designed scenarios. These inputs must be in line with the real world to test the impact on the system performances. Furthermore, some of the chosen input variables are included in the sensitivity analysis (see Section 5.6). Table 7 shows the main input variables for the simulation model. The truck costs distribution is based on the distribution from Volvo (2017).

Table 7: Input variables.

Input variable	Explanation for this research	Value
Interarrival time of containers	Arrival rate at the Port of Rotterdam.	[CONDIFDENTAL]
Number of available trucks	Trucks transport containers.	45
Number available barges	Barges transport containers.	7
Number of clients	Possible destinations for containers. See Figure 68 for the distribution per client.	13 clients. Consisting of 7 clients according to the dataset of CTT and 6 for each area of Figure 36.
Route specifics	Routing, driving times and distances in a from/to table.	Appendix F explains this route specifics in more detail.
Capacities of barges	If 104 containers are arrived at the Port of Rotterdam, a barge is called to transport these containers to CTT.	104 containers, without weight constraints.
Duration working day trucks	Operating time per day.	16 hours.
Duration working day barges	Operating time per day.	24 hours.
Personnel costs	Human planner wage and truck driver wage.	Human planner hourly wage is 30 euros. Truck driver wage is 20 euros in normal working times and 30 in overtime working times.
Truck costs distribution	On top of the driver wage, fuel costs and other costs are based on driving hours. Only the first three elements are considered for the output calculation, because the fourth element does not change by driving activities.	Distribution used (Volvo, 2017): • 46% truck driver wage. • 24% fuel costs. • 17% other costs. • 13% Insurance, depreciation, and interest costs.
Deadlines to be on the next location	Assumed fixed interval after arriving in the system using a uniform distribution, symbolising the requested time of the client (export) or barge export transportation (import).	Export: *U* (182 hours,254 hours) and Import: *U* (91 hours,127 hours).

5.4.2 Model outputs

Table 8 explains the nine main outputs. Furthermore, the table describes the goal of the defined outputs briefly. All outputs are considered for each scenario to see the impact of the chosen scenario-specific input variables.

Table 8:Main outputs explanation.

KPI	Explanation for this research	Goal in this research
1.On-time percentage	This percentage indicates how the planning decisions result in whether containers reach before the agreed delivery time. This percentage is calculated by the on-time deliveries divided by the total deliveries.	Provides insight into the impact of the input configuration per scenario on the on-time delivery of containers.
2.Average turnaround times per type of container	The time necessary to transport a container from CTT to a client and back to CTT. It consists of driving times, handling times, and waiting times. The performances of (un)loaded and (un)coupled containers are separated.	Provides insight into the time-related performances per scenario.
3.Containers in process	This output sums the total number of containers at CTT and client locations.	Provides more insight into the average number of transportation jobs are still be executed and to see the correlation with other outputs.
4.Transportation costs in euro	The total transportation costs to deliver and return the container. The transportation costs consider the truck costs, penalty costs and assignment costs.	Provides insight into the resulting costs of different configurations in the scenarios.
5. SOL-system percentage	This percentage considers the number decisions made by the SOL-system with the total number of decisions. With more autonomous assignments, the system goes step-by-step to a more self-organizing system.	Indicates the number of decisions taken by an autonomous planner versus a human planner.
6.Number of overrules	The number of assignments that are overruled by a better bidding agent in the auction mechanism.	Indicates how many overrules occur. It is unfavourable to have continuously overruling agents, because of the many communications and unnecessary driving.
7.Number of merged trips compared to the number of single trips	This output considers the number of transportations, considering single trips, in which the truck transports one container, and merged trips, in which the trucks transport multiple containers. This output indicates the utilization rate of trucks.	Provides insight into the resulting numbers using different configurations in the different scenarios. More merged trips are intuitively better than empty returns.
8. Total truck driving time	The total time that was needed to fulfil the transportation after the working day.	Give insight into the concerned times using different configurations in the different scenarios.
9. Total truck driving distance	The total distance travelled that was needed to fulfil the transportation after the working day.	Give insight into the concerned driving distance using different configurations in the different scenarios.

5.5 Identifying assumptions, simplifications and level of detail

It is necessary to define the assumptions and the simplifications to cope with the complexity of the system. This section describes the main assumptions and simplifications. Section 5.5.1 discuss the assumptions and simplifications made in the simulation model. Section 5.5.2 gives an extra explanation on how the role of the human planner is interpreted and simulated.

5.5.1 Simulation model assumptions and simplifications

The model assumptions and simplifications are listed below, excluding the human planner assumptions and simplifications.

- Both agents scan every five minutes for better assignments. It is assumed that the performances do not change much when having a lower time-frequency of scanning.
- CTT uses a homogenous fleet of trucks and only one available and empty truck at CTT can search at a time to decrease computational time.
- The searching containers at CTT are sorted based on the first departure time. The number of searching containers at CTT is set at 10 to decrease computational time.
- Average assigning, unloading and uncoupling times are pre-determined, based on experience from planners.
- Total driving distance and driving time are retrieved from the statistics of the trucks in the simulation model.
- The truck search radius is a fixed constant, and the radius of the container is determined using the urgency parameters: requested, the next transportation element and waiting time.
- One truck can handle one container of each size (1 or 2 TEU) and weight.
- Trucks do not break down.
- Maintenance, resting of drivers and refuelling of trucks is carried out during system downtime, the night or waiting at a specific location.
- Each variable in the auction mechanism has an equal weight of 1.
- Three container attributes are known when the container arrives in the system:
    - Client determination is based on pre-determined client division.
    - The deadline at the client is determined using a uniform distribution with pre-defined time windows.
    - The activity type (uncoupling or unloading) is based on historical data and experience of the planners.
- Deadline to be returned at CTT is determined using a uniform distribution with pre-defined time window.
- The first assignment determination of container and truck follow the same bid determination process.
- Trucks can be assigned to two containers and container to one truck.
- New arising bids should be 10% better than the current bid to be considered to overrule the current assignment. In this way, truck drivers are not continuously re-routed for small improvements. This decreased the amount of unnecessary driving and communications.
- If the working day ends, no further assignments can be made. A working day consists of 16 consecutive hours. The available containers remain at the location and searches again the next day.

- In-port activities are negligible.
- Each day the requested attributes of the to be imported containers are evaluated. There is a 5% chance of being requested by the client and a 10% chance of having a deadline at CTT, symbolising the planned return transport by barge. Both attributes remain true once the attribute becomes true.

5.5.2 The role of the human planner, simplifications, and assumptions

This research simulates the decision of the human planner in a model. The specific decision paths or decision processes are evaluated using the experience from the human planners of CTT. However, due to the complexity of many assignments, there is no uniform decision path to follow to assign containers to trucks. Therefore, the model uses the commonly used trade-offs based on logical thinking using the priority rules of Section 4.2, which are also used for the determination of the scan radius of the container. To simulate the human planner, several simplifications and assumptions are made. This is necessary because the human thinking and manual assignment cannot be fully integrated into a pre-programmed model. The assumptions and simplifications are listed below.

- In Scenario 1 the current situation is simulated with only human decisions, disallowing overruling. Figure 62 in Appendix B shows the decision flowchart. Human decisions in further scenarios are evaluated continuously with possible better options. Therefore, in these scenarios, the decision of a human planner can be overruled.
- Using knowledge based on experience of the human planner, the priority rules are used to see the importance of the transport and search radius of the container.
- In scenario 1 and scenario 7, once agents are assigned, it is not allowed to overrule even when the new arisen option is much better than the previous assignment. In this way, the assignment of agents is static for these scenarios.
- To consider a centralized decision-making environment, the search area of containers is considered very large. In this way, containers can see all trucks. Agents could access all necessary and available data to consider the best assignment.
- All relevant data are known by the human planner, once called to make an assignment.
- The human planner needs a short time to assign and communicate with the truck drivers. This covers two simplifications:
    - Human planners need, on average, 2 minutes to consider an assignment.
    - The human evaluation time per assignment is added as a penalty time for truck agent.

5.6 Identifying factors for sensitivity analysis

This section lists the main variables for the sensitivity analysis in Table 9. Because many variables are selected based on approximations, the evaluation and impact of these variables are interesting. It shows to impact of the chosen input variables on the outcomes. Figure 9 shows the ranges per variable. These variables are only evaluated one-factor-at-a-time. Section 7.3 gives recommendations for further research, including the promising adaptions or combinations. With an interarrival rate of five minutes for containers at the source of the system, the number of barges is insufficient to transport containers to CTT. The number of containers at the Port of Rotterdam continuously increases, which indicates that the number of barges or the system cannot handle and transport the arising containers, resulting in non-stable time-related performances. Therefore, this experiment also increases the number of barges by one.

Table 9: Settings sensitivity analysis.

Variable	Explanation	Initial value	Low value	High value	Increment	Number of extra experiments
Winner percentage	The minimal different to be considered to overrule another assignment.	10%	15%	25%	5%	2
Difference threshold	The difference with the runner up for an autonomous assignment.	10%	5%	15%	5%	2
Bid threshold	Threshold to be considered as a good bid.	50%	40%	60%	10%	2
Start radius truck	Starting search radius of a truck.	100	50	150	50	2
Start radius container	Starting search radius of a container.	500	400	600	200	2
Scan frequency	The time interval of the scan mechanism.	5:00	4:00	6:00	1:00	2
Starting bid	Start point in the bidding procedure.	18000	14400	21600	3600 (1 hour)	2
Number of trucks	Maximum capacity of trucks to transport containers.	45	40	50	5	2
Throughput container	The interarrival rate of containers at the source of the simulation model.	[CONDIFDENTAL]	[CONDIFDENTAL]	[CONDIFDENTAL]	1:00 (1 minute)	2

5.7 Implemented model

After having the necessary information and properties for the simulation model considering the mechanisms of Chapter 4 and the simulation model specifics of Chapter 5, the simulation model is built in Tecnomatix Plant Simulation. The model is built using a dashboard and model map. The model uses different stations, tracks, markers, tables, methods, variables, generators, MU-elements, and automated guided vehicles (AGVs) to mimic reality.

Appendix F shows and explains the used dashboard or control panel to vary over the scenarios and experiments, containing the specific input variables, methods, and output tables. This section focusses on the model map and the routing mechanism.

5.7.1 Routing mechanism

In the simulation model, the reality is simulated using routes concerning markers and tracks. After the assignment is accepted by the assignment mechanism or the container is loaded on the truck, the truck is routed to the concerning location to pick up or drop-off the container. Multiple events could trigger the initialization of a new route. This happens when a truck gets a new destination. This happens in five situations:

- A truck gets a new container assignment that is located at a different location.
- A container is loaded on a truck and ready to transport to the next location.
- Truck finished its current assignment.
- Truck overrules or is overruled by another truck.
- A working day is ended, and the truck has no assignments left.

After the truck gets a new destination and the destination does not equal the previous destination, the truck-specific Boolean ('Routed') is set on true in the simulation model. This Boolean activates a truck user-attribute method which initializes the creation of a route. If the previous destination equals the new destination, this is indicating that the truck is overruled by another container on the same location as the previously assigned container. The initialization of a route is shown in Figure 35 in a flowchart.

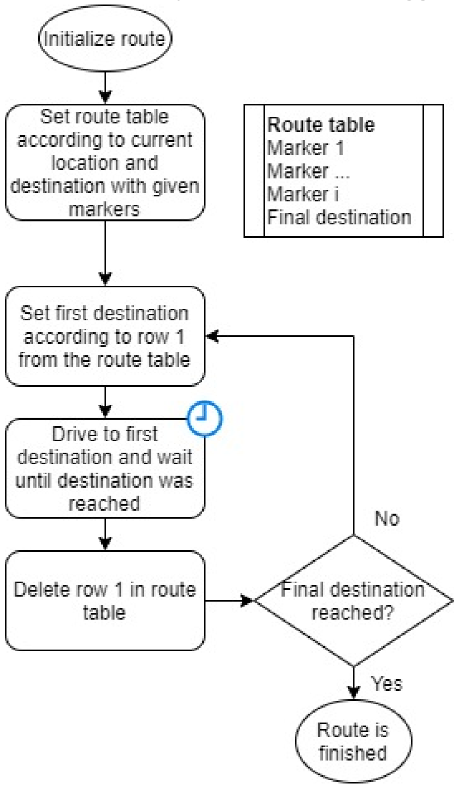


Figure 35: Route initialization flowchart.

In the first step of the flowchart, the route is set based on a route table. This route table is placed in the dashboard (see Figure 71 in Appendix F). This route table includes all possible clients, locations, and driving areas. Each of these relates to a from-to-route which is called and used in the creation of the route for the truck. Figure 36 shows the model map with the locations and driving areas.

5.7.2 Simulation model map

Figure 36 shows the simulation model map. Multiple representations are given in this screenshot. The green circles mark the thirteen used clients in this research. Figure 68 in Appendix D shows the client distribution. The blue circles mark the ports within this research, namely the Port of Rotterdam and Terminal in Hengelo. As can be seen, the location of the Port of Rotterdam is not on the real location. This is chosen to focus on truck routing in the simulation model. Furthermore, the trucks are visualized by the red automated guided vehicles (AGVS) and containers by small brown squares.

For the routing mechanism of Section 5.7.1, this simulation model considers a free-routing automated guided vehicle mechanism supported by the modelling program Tecnomatix Plant

Simulation. After the assignment is accepted by the assignment mechanism or the container is loaded on the truck, the truck is routed via markers to the concerning location to pick up or drop-off the container. Figure 65 in Appendix B shows how the markers are placed. Due to the fixed routes by the markers, indicating the roads between locations, it is important to consider the expected driving time within the auction mechanism. These markers create routed from the current location or region to the destination. Figure 69 in Appendix D shows the locations of the different clients.

Figure 36 shows the multiple driving areas that are used in the routing by the brown frames. If a truck enters one of the areas, this area is stored as the current location of the truck. Once, it enters the client location or CTT Hengelo parking, the current location is updated to this location name. The driving area and client location are used for the creation or evaluation of new routes or assignments. In Figure 36, the blue circles indicate the inland terminal and seaport, and the green circles indicate the client locations.

[CONFIDENTAL INFORMATION]

Figure 36 Simulation model map.

5.7.3 3D visualisation of the simulation model

Figure 36 shows the simulation model in 2D. However, this simulation model is also modelled in 3D. Figure 37 shows a 3D visualisation of CTT and a client location. Furthermore, Figure 38 gives a more zoomed out screenshot of the 3D model. These 3D visualisations are used for meetings within the SOL-port project and CTT to present the preliminary model and outcomes attractively.

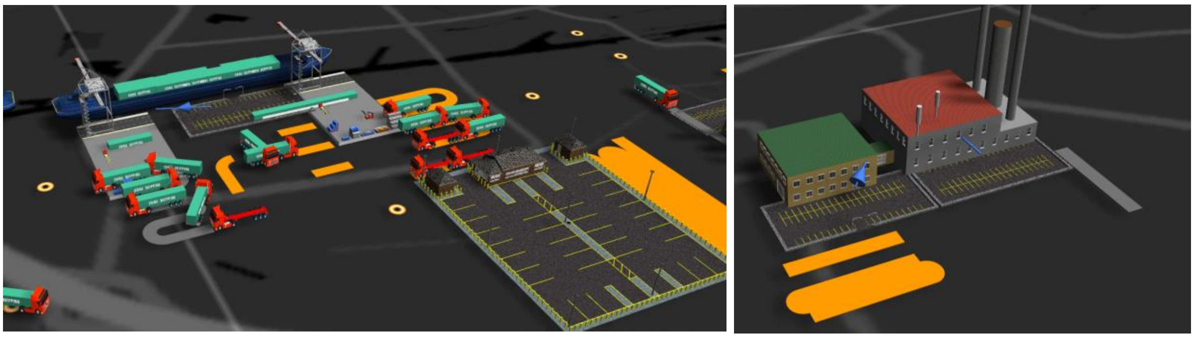


Figure 37: 3D visualisation of CTT and Client location.

[CONFIDENTAL INFORMATION]

Figure 38: 3D representation of simulation model.

5.8 Validation and verification simulation model

This study focusses on simulating a possible situation using sensors in the current practice. Verification is the procedure that checks whether the conceptual model is translated properly to the simulation model. Validation is the procedure that checks whether the model is sufficiently accurate for the objective of this simulation study (Law, 2015).

Scenario 1 is designed to simulate the current situation as good as possible. The input parameters, preliminary outputs and assumptions of the proposed model are discussed with the relevant business developers, customer service and human planners of CTT and Bolk Transport. Furthermore, meetings were planned with Pharox to discuss the possibilities and applicability of using the sensors. Unfortunately, the implementation of the sensors and measuring of the real-time data were delayed due to the COVID-19 circumstances. Due to this fact, it was not possible to validate the outcomes with real-time data. However, in other meetings with Pharox, other already implemented system were discussed to indicate the opportunities. The mentioned related parties are positive about the results, but the practical application and implementation remain a future action point. For this actual implementation, a larger role is reserved for Pharox. After that, this report and designed model should be evaluated again to increase the content value.

In scenario 1, the outputs that are calculated in this situation should approximate the real current situation. However, due to many necessary simplifications and assumptions, it should not be stated that scenario 1 corresponds exactly with reality. However, it should reflect the complexity of the processes. Therefore, it is more difficult to validate this study and its outcomes. As mentioned before, some performances depend on the chosen input variables. However, the verification can be evaluated in more detail. As mentioned, the verification of a simulation considers whether the conceptual model is translated correctly to the computer model. Law (2015) defines several general verification techniques to verify a simulation model:

- Write and debug in modules or subprograms and tracking of agents.

The dashboard frame stores the input variables, which are pre-defined per scenario and results per run and experiment. With multiple methods and dividing multiple events, each situation and each event is checked and verified. These activities are necessary to make sure that the model is incorporated correctly. Multiple tables are created in the simulation model. These tables check whether model is doing what it is supposed to do and keep track of the agents. Debug statements are used to consider whether a trigger or agent has not the right attribute for that specific situation or code.

- Run the simulation under a variety of settings and inputs.

In addition to the previous technique, all simulation runs should run under a variety of settings using the variables on the dashboard or method-specific chosen values or distributions. This is used in the scenarios which have different settings. Next, in the sensitivity analysis input variables are varied. All events and methods are debugged and checked whether it considers the right information and calculated or returns the intended outputs. Furthermore, several outputs are calculated to verify the calculations and the simulation model. For example, a counter variable counts the number of containers in a specific phase, as the number of containers at client locations. The dashboard screenshot in Figure 71 in Appendix F shows all these counters. Furthermore, tables are created. These tables store the relevant data for the simulation methods. These tables must show the right values and update them when necessary. Most of the tables are used to calculate performances and to determine the next desired activity.

- Use animations.

The simulation model is created in a 2D and in 3D environment. A model map is used which visualises the concerned road network. In this way, the truck positions correspond approximately to reality. Exact position determination does not add too much improvement to the analyses. The visual animations are continuously checked to see whether all agents follow the right steps in the process. Furthermore, debugs statements are included that helps this animation verification technique. Arriving in specific situations, information of that specific agents is checked and verified using the desired state or next activities.

- Use a commercial simulation package.

In this research, the system is modelled in the software package of Tecnomatix Plant Simulation version 15.1 of Siemens. This software package provides pre-set tools, enabling experimentation and optimizing within pre-determined logistics or producing models and processes. In this way, it reduces and simplifies programming and visualizes the transporting process in 2D and in 3D. This visualization is not possible in many open-source programs.

6. Experimental settings and analysis of results

This chapter discusses the experimental settings and analyses the results. Firstly, Section 6.1 briefly explains the objective of experimenting. Secondly, Section 6.2 discusses the experimental settings. Section 6.3 explains the experimental factors. Section 6.4 presents the main scenario outcomes of the simulation study. This section describes each performance indicator of Table 8 separately, focussing on the differences per scenario. Finally, Section 6.5 examine the results of the sensitivity analysis.

6.1 Experimental objectives

This section explains the experimental objectives and experimental settings. The goal of experimenting is to get insight into the impact and effectiveness of using different setups using different input values. he experiments compare multiple situations to see notable results and outcomes for further evaluation and possible implementation. This chapter analyses both the individual performances as the combination of performances.

6.2 Experimental settings

The experimental settings are separated into three sections: warm-up period, replications and run length. Due to the many different model setups per scenario, each scenario can be evaluated separately. However, having different experimental settings, it is not possible to compare the different scenarios. Therefore, the experimental settings are determined with the results of scenario 1. It is assumed that the other scenarios do not differ much. The goal of the experimental setting is to generate reliable outcomes per scenario and experiments. For this evaluation, the first scenario has run five times.

6.2.1 Warm-up period

Considering the warm-up period, the observations that depend on initial conditions are deleted. After the warm-up period, the results are stored. However, it is important to consider how many output values should be ignored before starting the performance measurement for the conclusions and recommendations. Another trade-off is to reduce the impact of the initial state using an appropriate run length to decrease variability in the outcomes. In this research, it is necessary to create a situation where the spread of the containers and the average turnaround times are constant. After the container arrives at CTT, the container starts searching for trucks and eventually the truck transports the container to the client. At a certain moment, the scanning mechanisms of truck agents should sense a relatively stable number of containers at CTT and client locations in the designed scenarios. This moment indicates a good warm-up period. The next paragraph investigates the warm-up determination using three related performances. The determination is graphically determined using the resulting graphs of scenario 1.

Graphs of performances indicators

Three performance indicators are used for the determination of the warm-up period:

- The number of containers in the process is defined as the total number of containers arrived at CTT and client locations plus the containers on trucks. Figure 39 shows a stable state after the first couple of days. The peaks represent the arriving barges at CTT, which unloads 104 containers to storage station of CTT.

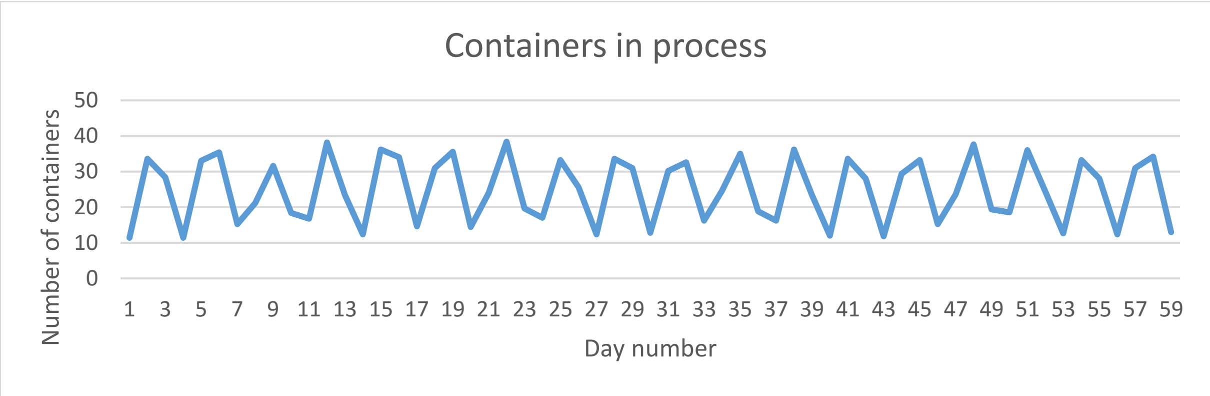


Figure 39: Determination warm-up period: Containers in process.

- Average turnaround time per day per type container is defined as the average time from entering CTT to leaving CTT by barge. This performance indicator seems also stable from the beginning. For the same reason as containers in-process indicator, the turnaround times also show peaks. The fact that during the night no containers can be picked up by trucks influences these performances. Figure 40 shows the continuously updated means of the turnaround times. As can be seen, it takes a couple of days to flatten the line.

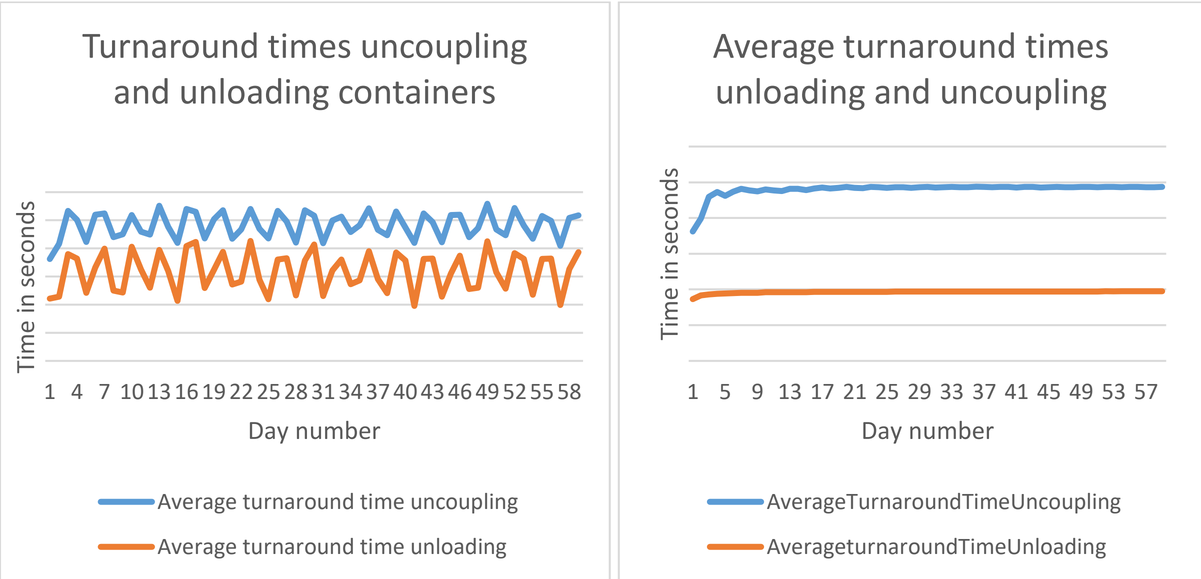


Figure 40: Determination warm-up period: turnaround times.

- The on-time percentage is calculated using the on-time delivered container compared to not-on-time delivered containers. In contrast to the two previous indicators, the on-time percentage shows performances which indicate the necessity of a warm-up period. Logically, containers are delivered on time at the beginning of the run because the moment the first barge arrives, all trucks are available to pick up and transport the arriving containers. The moment when the containers are spread over the system and the truck finds a stable number of containers at CTT and client locations indicate a sufficient warm-up period.

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Figure 41: Determination warm-up period.

Selection of warm-up period

As stated in the explanation at the three performance indicators, the system seems almost directly in a stable state. However, considering the on-time percentage indicator, it is wise to include a couple of days as the warm-up period to decrease the effect of the initial conditions. For this research, a 6-day warm-up period is chosen. This is chosen because from day number six all examined performance seems stable enough. Appendix H briefly examine these performances for the warm-up length in more detail, resulting in similar results.

6.2.2 Run length

The run length of the simulation is based using the rule of thumb of 10 times the minimum warm-up length. In Section 5.2.1 the warm-up length was determined on 6 days. Therefore, the run-length becomes 60 days. The run-length includes the warm-up period.

6.2.3 Replications

Multiple replications per scenario are necessary to obtain reliable results. Calculating the averages per output the relative error per scenario can be calculated. Having more replications, the relative error is below the threshold which is required to have reliable results. Replications use a different common random number. Without adapting this number, the experiments will be the same, because the variable determinations will be the same for each experiment, resulting in the same outputs. The desired number of replications is determined using five replications with run length of 60 days.

Selection number of replications

For determining the required number of replications, the relative error is compared to the gamma prime (see Equation 6). The number of replications should be performed until the width of the confidence interval, relative to the average is sufficiently small. For this determination, the relative error must be compared to the relative error with a chosen confidence interval level, which is chosen to be 95%. The number of replications necessary can be calculated using the formula of Law (2014):

$$\frac{t_{n-1,1-\alpha/2}\sqrt{S^2/n}}{\overline{X}} < \gamma'$$

Equation 6: Determination number of replications.

First, the left side of the above equation should be calculated. In this equation the t stands for the t-value, S for the standard deviation, n for the number of runs and X for the average of the run and y' stands for the gamma prime. Table 10 shows the results. Appendix C presents further calculation outcomes of the determination of the number of replications.

Table 10: Relative error per run for determining number of replications.

N	On time percentage	Average uncoupling turnaround time	Average unloading turnaround time	Containers at client location
1	N/A	N/A	N/A	N/A
2	0.0446	0.0171	0.0249	0.0363
3	0.0101	0.0071	0.0060	0.0090
4	0.0054	0.0044	0.0089	0.0051
5	0.0036	0.0043	0.0063	0.0156

Choosing a confidence interval of 95% the gamma prime equals= (1-0.95)/ (1-(1-0.95) =0.04762. As can be seen in Table 10, the required number of replications is 2, because for all examined indicators the relative error is below the gamma prime at run 2. Two runs are considered as a low number of runs for a simulation study. The run length and number of replications do influence each other. A relatively long run length requires fewer replications than a simulation with a relatively short run length. For example, one day can also be used as one replication. However, the run length is not changed, because the impact on the performances using a long run length is interesting to analyse.

In this research, two types of evaluations are executed, namely: simulation with the initial set variables and sensitivity simulation using an adaption on one of these variables. Despite the results, the simulation runs with the initial variables use five replications to have less variability in the outcomes. For the sensitivity experiments, the determined number of replications is followed, so two replications per run.

6.3 Identifying model experimental factors

This section determines the experimental factors. Here a division is made between scenario-specific factors and the experimental factors used in the designed sensitivity analysis.

6.3.1 Experimental factors in scenarios

Table 11 shows the variables in the experiments focusing on the auction mechanism. As can be seen, some of the experimental factors are only used in specific scenarios. A overrule percentage of 100% indicates that it is not allowed to overrule an assignment. The start scan radius of 10000 indicates the searching area in a human planner-based central-decision environment because this covers the whole model. The radius used in the simulation model is not linked to reality. The thresholds influence the amount of decision by the human planner and SOL-system. Without the possibility of overruling and having a value of 1 at the threshold, the human planner always makes the decision (scenario 1). A threshold is not used when it has a value of zero. Having both thresholds on zero, the human planner is never asked for an assignment. The chosen values are assumed and further evaluated in the sensitivity analysis (see Table 12). As mentioned before, scenario 7 only focuses on the extra driving time auction variable.

Table 11: Experimental factors per scenario.

Scenario	Start radius container	Overrule percentage	Difference Threshold	Bid threshold	Weights variable (distance/extra driving/overtime/ Scheduled time)
1.	10000	100%	1	1	1/1/1/1
2.	500	10%	1	1	1/1/1/1
3.	500	10%	0.1	0.5	1/1/1/1
4.	500	10%	0.1	0	1/1/1/1
5.	500	10%	0	0.5	1/1/1/1
6.	500	10%	0	0	1/1/1/1
7.	10000	100%	0	0	0/1/0/0

6.3.2 Experimental factors in sensitivity analysis

Table 12 shows the experimental factors in the sensitivity analysis. Not all variables must be considered in each scenario because not all variables are used in each scenario. Initializing the experiment, the model initializes the scenario and experiment variables. Table 12 shows the experimental factor of the experiments, relevant scenarios, and the number of necessary runs. Summing the number of runs, this results in 204 runs in the sensitivity analysis.

Table 12: Sensitivity analysis experimental factors.

Scenario	Exp 1	Exp 2	Exp 3	Exp 4	Exp 5	Exp 6	Exp 7	Exp 8	Exp 9
Experimental factor	Overrule percentage= 0.75	Overrule percentage = 0.85	Difference Threshold =0.05	Difference Threshold =0.15	Bid Threshold = 0.4	Bid Threshold = 0.6	Start radius truck= 50	Start radius truck= 150	Start radius container= 200
Considered in scenarios	2,3,4,5,6	2,3,4,5,6	3,4,6,7	3,4,6,7	3,5,6,7	2,3,5,6,7	2,3,4, 5,6	2,3,4,5, 6	2,3,4,5,6
Number of runs	10	10	8	8	8	10	10	10	10

Scenario	Exp 10	Exp 11	Exp 12	Exp 13	Exp 14	Exp 15	Exp 16	Exp 17	Exp 18
Experimental factor	Start radius container = 600	Scan frequency = 4:00	Scan frequency= 6:00	Start bid= 14400	Start bid =21600	Number of trucks = 30	Number of trucks =40	Inter-arrival rate = 7:00	Inter arrival rate =5:00 & Number of barges = 8
Considered in scenarios	2,3,4,5,6	All	All	All	All	All	All	All	All
Number of runs	10	14	14	14	14	14	14	14	14

6.4 Analysis of experimental results

This section evaluates the selected desired outputs for all different scenarios, using the warm-up length, number of replications and run-length from Section 5.2. The simulation model has generated outputs of values per day per run per scenario and stored these values in a table. With these tables, comparisons are made, and notable results are evaluated.

Before starting with the experimental results, the throughput and average level of containers at the Port of Rotterdam (source of model) are summarized in tables and graphs. Using a fixed interarrival rate and number of barges to transport these containers to CTT, the results are the same for each scenario and each replication. As can be seen, both graphs seem to be stable with top peaks and down peaks. These peaks are because of the barge transportations, considering 104 containers per departure or arrival. In experiment 17 and 18, the interarrival rate is changed to see the impact on the system. These graphs change because of this adaption.

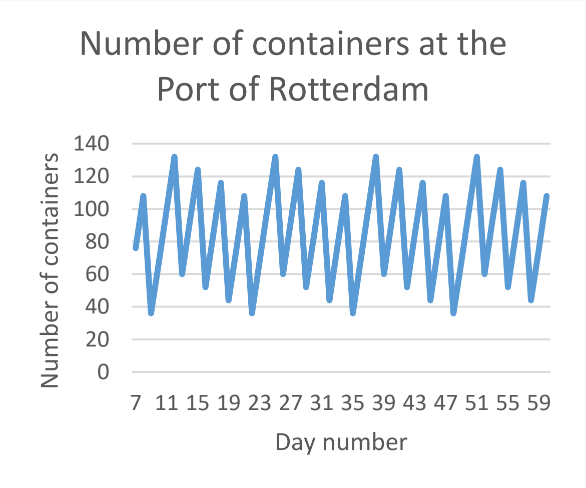

Figure 42: Number of containers at the Port of Rotterdam.

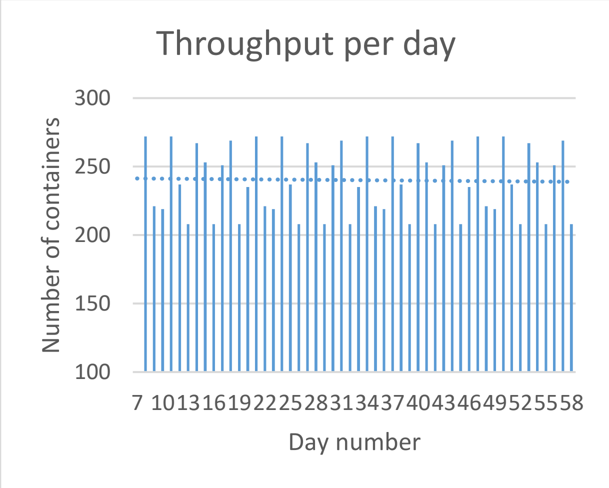

Figure 43: Throughput per day.

6.4.1 Decision-making SOL-system versus human planner

As stated in the simulation model setup, the number of decisions is an important output to evaluate the role of the human planner. The first important finding is that the number of human planner decisions is not a negative linear with the number of decisions of the SOL-system. This is due to the scanning frequency of 5 minutes in which overruling is allowed, which increases the total number of decisions compared to scenario 1. The human planner can be called to make another decision for the same agent.

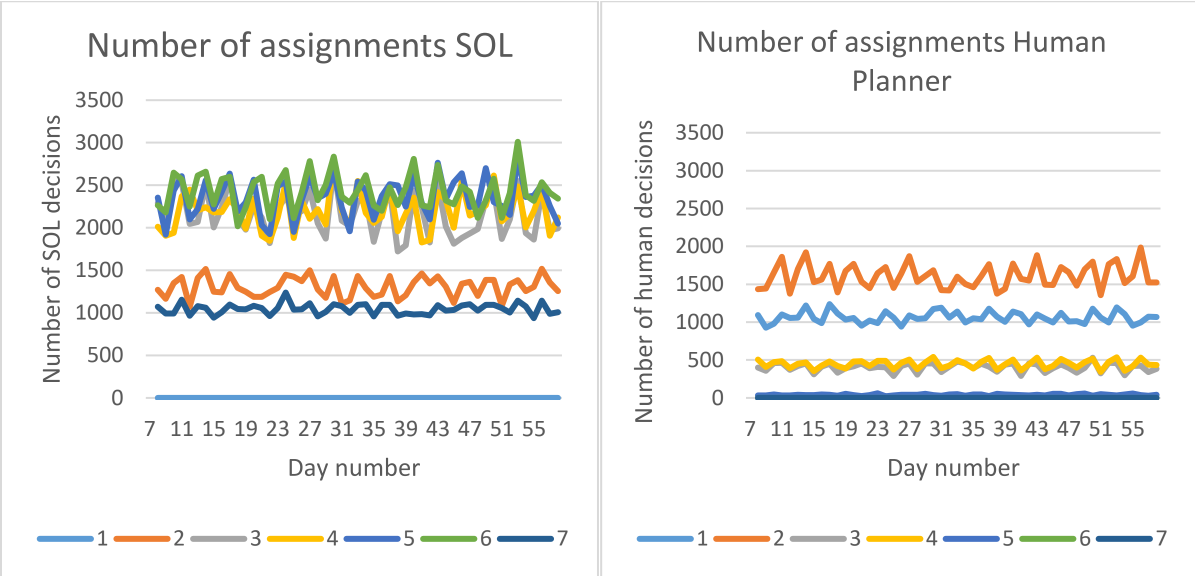

Figure 44: Number of decisions per scenario per type decision.

As can be seen in Figure 44, the decisions per days seem stable for the rest of the simulation using a warm-up period of 6 days. The averages of both indicators from five replications are summarized in Table 13. Furthermore, the table shows the resulting SOL-decision percentage.

Table 13: Average human decisions, SOL decisions and SOL-percentage.

Indicator	Scenario 1	Scenario 2	Scenario 3	Scenario 4	Scenario 5	Scenario 6	Scenario 7
Number of decisions	1061	2910	2566	2652	2406	2428	1046
Human decisions	1061	1610	404	451	40	0.00	0.00
SOL decisions	0	1309	2162	2201	2366	2428	1046
SOL-decision percentage	0	44.81%	84.27%	82.94%	98.34%	100%	100%

It was expected that the number of human decisions decreases while increasing the role of SOL-system. However, this is not true for scenario 2. The total of decision increase almost by 200% in which the human planner makes 55% of the decisions, resulting in the 1610 decisions per day on average. The increment is due to the activated scanning mechanisms. Every five minutes the scanning mechanisms of both agents are triggered in which a human planner or the SOL-system could be asked to make an assignment. If two agents, that are already assigned to each other, are reassigned, the decision is not considered as a new assignment. As can be seen, the bid threshold is almost always reached, resulting in a high SOL-percentage for scenario 5. With the designed difference threshold, human planner activities are more than halved. Increasing in the scenario number, also the number of SOL-decisions and the total number of decisions increase.

As mentioned before, it was expected that if the scenario number increases, the role of the human planner decreases and the role of the SOL-system increases. As can be seen, this is true for the number of SOL-decisions. However, the number of human decisions increases relatively more, considering scenario 3 and scenario 4. A reason for this could be that decisions could be made earlier, resulting in that the SOL-decisions of scenario 4 do not have to be made. Only scenario 7 has approximately the same number of human decisions as in scenario 1. This is logical because the number of containers that should be transported in the same and overruling and therefore the scanning mechanism is not triggered every 5 minutes for both agents.

6.4.2 On-time percentage

The model determines the client- and return deadline with a pre-defined time window. In the real situation, the deadline is not always known by CTT or no deadline is considered with the client. Therefore, with these outcomes, no major conclusions should be drawn. Furthermore, it is interesting to see, how much too late a specific not-on time delivery is delivered at the client or at CTT. Therefore, this extra evaluation is added in this section. *Table 14*Table 14 summarizes the averages per scenario.

Table 14: On-time percentage.

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As can be seen, the results show almost no difference in the on-time percentages. The differences between the scenarios are less than one per cent, therefore, considered as neglectable. Figure 44 shows the average hours too late per scenario.

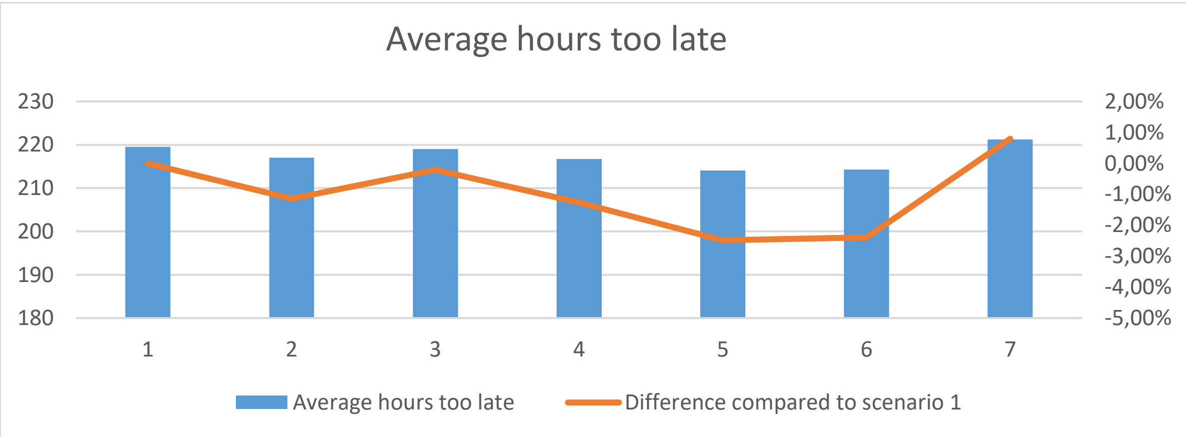


Figure 45: Average hours too late.

As can be seen, the average too late does not differ much from between the seven scenarios. However, scenario 5 and scenario 6 scores best on this indicator with respectively 2.48 and 2.39 per cent. A logical explanation for this is that these scenarios continuously search for better assignments in terms time performances and have less human evaluation (penalty) time needed for the decision-making.

6.4.3 Average turnaround times

The average turnaround times are divided per type of container because these two would be unfair to compare. Turnaround times consist of waiting times, driving times and handling times. Waiting time at the client is only relevant for the uncoupled containers, without considering the unloading time at the client location. Once a container is placed on a truck it is directly transported to the client location. However, due to the assumption of a fixed number of uncoupling and unloading places per client, the truck must wait before the attached container can execute its specific activity. This time is included in the time driving towards the client. Furthermore, the human evaluation time (penalty time) of trucks is included in the driving time from and to the client. In Table 15, the driving time indicator is the average of the driving time towards and from the client.

Table 15: Average turnaround times (hours).

Indicator (hours)	1	2	3	4	5	6	7
Time at client	42.87	58.00	55.51	54.90	53.26	52.77	41.12
Time at CTT	11.50	10.98	10.92	10.93	10.90	10.88	11.53
Turnaround time uncoupling	67.54	82.81	79.88	79.19	77.24	76.68	65.32
Turnaround time unloading	26.93	26.49	25.67	25.54	24.92	24.86	25.70
Driving time	2.17	2.25	2.10	2.07	1.95	1.94	1.93

Remarkable from these results is the time at the client, which also influences the average turnaround time of the uncoupled containers. The time at CTT remains relatively stable, indicating that the number of CTT pick-ups and throughput of CTT does not change much while increasing the level of autonomy in the scenarios. Scenario 1 and scenario 7 both have significantly lower average results. This can be explained by the fact that the scanning mechanism cannot overrule. In this way, the first good match that is found is selected considering all available agents. Evaluating the scenarios in between, the average time at the client is much larger. However, the time at CTT location is decreased. However, the number of pick-ups at CTT is of course much larger. Appendix E shows two tables with an additional evaluation, namely, the number of pick-ups per location and the average time at those specific locations. The number of pick-ups converges to the client distribution. The average time at client locations is approximately in line with the scenario-specific weighted averages, in which the performances of locations at longer distances have a higher average waiting time, which is logical because this is due to the lower placed bids due to time needed to fulfil the transport. These long-distance locations depend more on trucks uncouple another container at that specific location. The average driving time shows a decreasing trend, increasing the SOL-percentage, starting from scenario 2. This means that increasing the role of the SOL-system the average driving time decreases.

6.4.4 Containers in process

This performance indicator considers the number of containers at CTT and the client location. After each day, the model calculates this indicator. These outcomes indicate whether the system can handle the number of containers and how well the scanning method operates in specific scenarios. It gives useful insight into considering the output values over time.

Table 16: Number of containers at specific location.

Indicator	1	2	3	4	5	6	7
Containers at CTT	60.93	60.80	60.50	60.60	60.45	60.45	60.74
Containers at clients	14.91	19.24	18.79	18.77	18.32	18.45	14.86
Containers in process	24.91	29.44	28.85	28.77	28.47	28.45	28.45

The containers in-process are not equal to the sum of containers at CTT and container at client locations. Containers in-process are counted when it starts searching for trucks. The difference indicates the average amount of containers at CTT which are not searching yet. For this performance indicator, the same conclusion can be drawn as in the conclusion of the average times at specific locations. Concluding, autonomous decisions transit storage and waiting times to the client locations.

6.4.5 Transportation costs

The transportation costs indicate the cost given assumed costs, like wages and truck-specific costs. Therefore, before doing major conclusions, these assumed input values should be considered and mirrored in the real world. It is assumed that the values are valid enough to indicate the differences per scenario and situation. As stated in previous sections, the transportation costs are divided into three components: the total truck cost, fuel costs and other costs, the assignment costs of the human planner, and the penalty costs of delivering containers too late. Figure 45 shows the average too late per scenario per run. Figure 46 shows the sum of the three components and Table 17
shows the averages of the transportation costs per day.

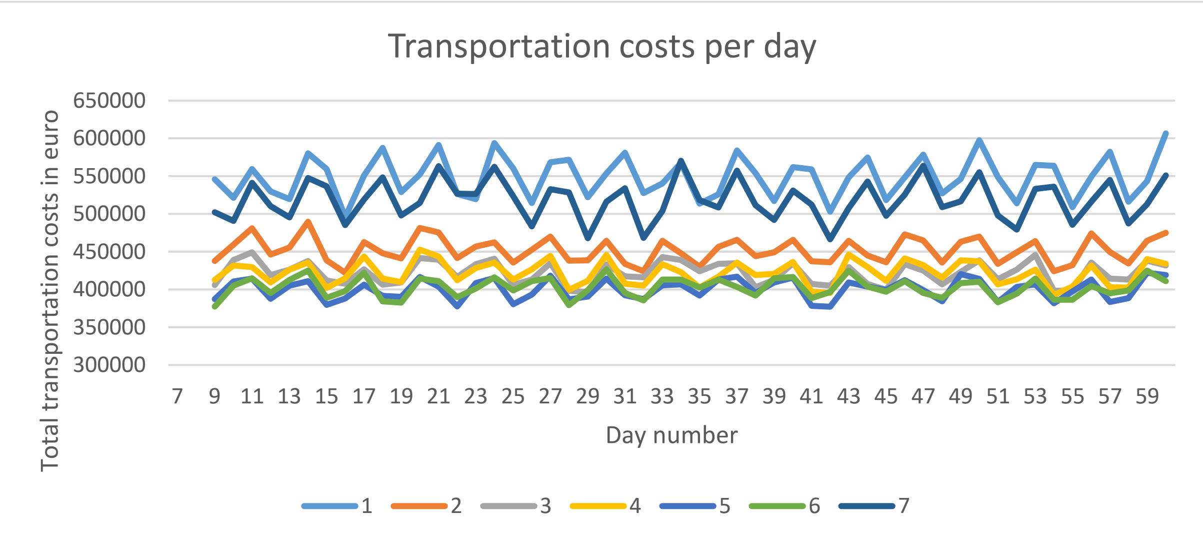


Figure 46: Total transportation costs.

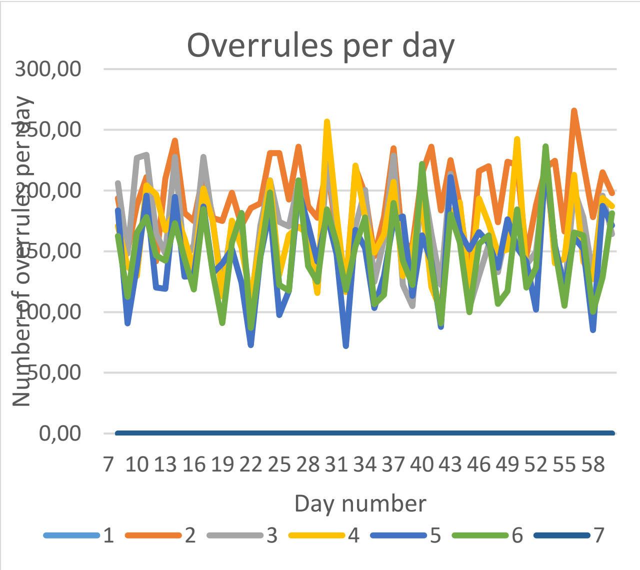
Table 17: Average costs.

Average costs in euros	1	2	3	4	5	6	7
Average transportation costs	548619	452083	421986	422036	400185	402734	518449
Average truck costs	539073	438681	416702	416496	397360	400127	515903
Average penalty costs	2472	2638	2583	2531	2545	2597	2540
Average assignment costs	7070	10732	2693	3006	267	0	0

Table 17 shows that the total truck costs have the largest share of the total transportation costs. The total truck costs consist of the driver wages, fuel costs and other costs. The assignment costs are only triggered when the human planner should decide, having an average of 2 minutes per assignments. Therefore, this output gives just an indication of the amount of time the human planner is asked to decide. However, in the real world, this is difficult because the flexibility cannot be planned on forehand. As can be seen, the assignment costs are linear with the number of assignments by the human planner, and penalty costs are approximately linear with the number of containers delivered too late. The penalty costs are not linear with the containers delivered too late because of the difference between the costs of being too late at the client location and CTT.

6.4.6 Number of overrules

The total number of overrules indicate how much assignments are taken over and re-routings of the trucks. Since the trucks are controlled by a human truck driver, continuous overruling is not preferred. In the simulation model, a truck can immediately drive to another direction. However, in the real world, this is not always possible. Therefore, drawing conclusions should also be done carefully. Figure 47 shows the number of overrules per day.



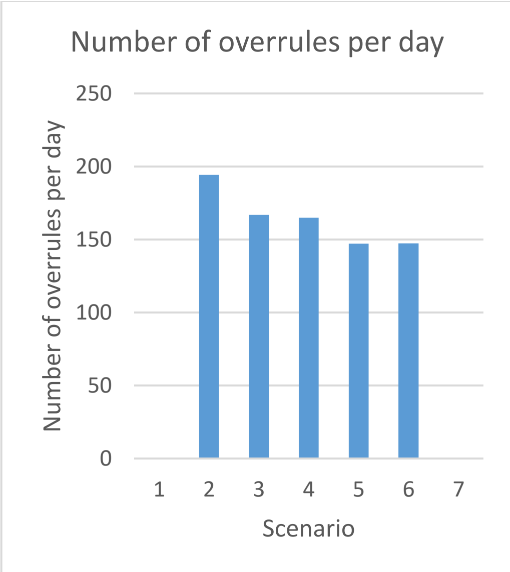


Figure 47: Number of overrules per day and average number of overrules per day.

As can be seen, scenario 2 up to and including 6 have a similar number of overrules per day. As programmed, scenario 1 and scenario 7 do not allow overrules. Scenario 2 shows a higher number of overrules. Therefore, it can be concluded that only using thresholds and the one-option assignment the number of overrules can be decreased. Figure 47 shows that the overrules of scenario 3 are close to scenario 4, and the overrules of scenario 5 are close to scenario 6.

6.4.7 Number of merged trips and loaded driving percentage

The number of merged trips sums the transportations in which a truck delivers a container at a client location, uncouple the container, picks up another container and return this container to CTT. Knowing that scenario 1 and scenario 7 are not allowed to overrule and scenario 2 up to and including scenario 7 scan frequently for possible assignments, Figure 48 shows the results of this performance indicator. Furthermore, an extra line is added in the graph representing the percentage of driving distance transporting a container, indicating loaded driving, of the total driving distance. The higher this average value, the more efficient the transport of the containers was in terms of driving distance.

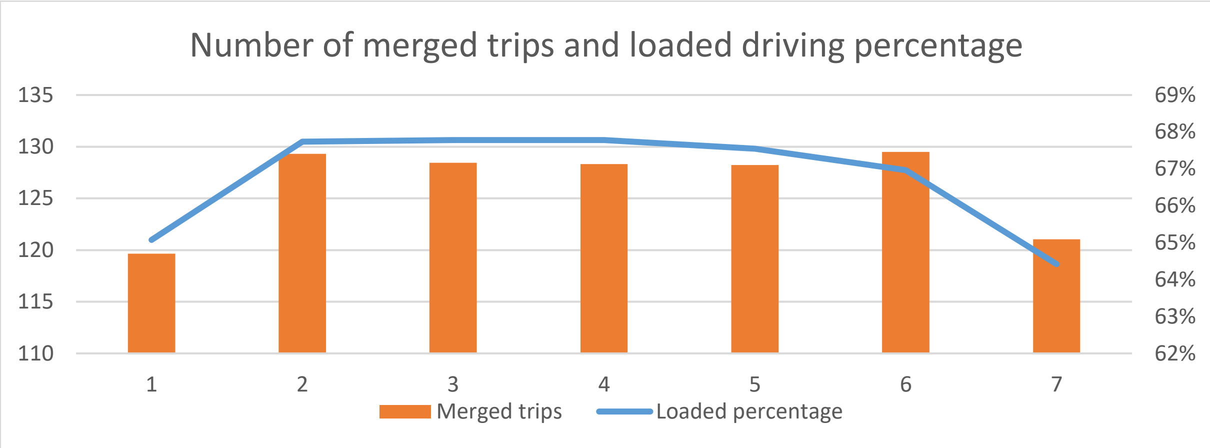
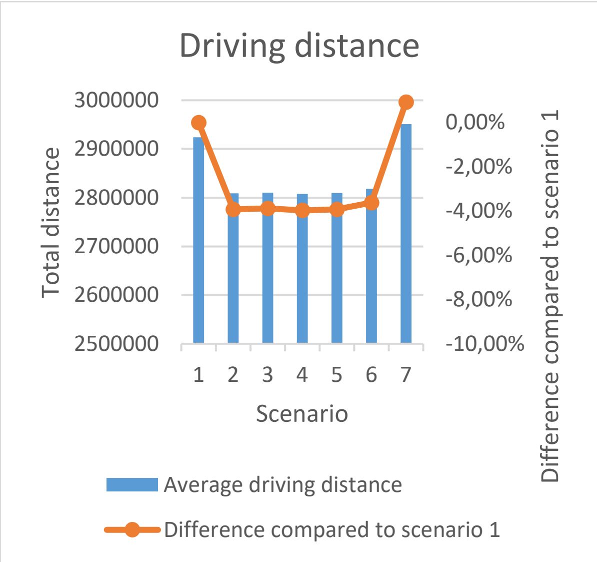


Figure 48:Merged trips per day.

As can be seen in Figure 48, these two indicators seem to be correlated. Having more merged trips increases the percentage of loaded driving time. This is logical because driving back empty without a container is less efficient than returning with a container from another location. Despite that, the percentage difference is small. The result is logical for the scenarios. Scenario 2 up to and including 6 are continuously scanning for better options for a merged trip. As can be seen, having more merged trips results in higher efficiency in transporting a container. In scenario 1 and 7, trucks prefer more to pick-up containers compared to other scenarios, which was also concluded at the turnaround time performances of Section 6.4.3.

6.4.8 Total truck driving time and total truck driving distance

Section 5.4.5 shows that the truck costs were the main costs component in the total transportation costs. Therefore, this section evaluates more the total truck driving time and travelled distance. The driving time is calculated by the sum of driving time towards a client and the driving time towards CTT Hengelo. The travelled distance is calculated as user-attribute in the simulation model. Figure 49 shows both indicators in the graphs. In both graphs an extra line is added, that evaluates the difference with scenario 1. Furthermore, Figure 50 shows the average hours in overtime per day. This graph shows the average hours added in overtime for all trucks per day.



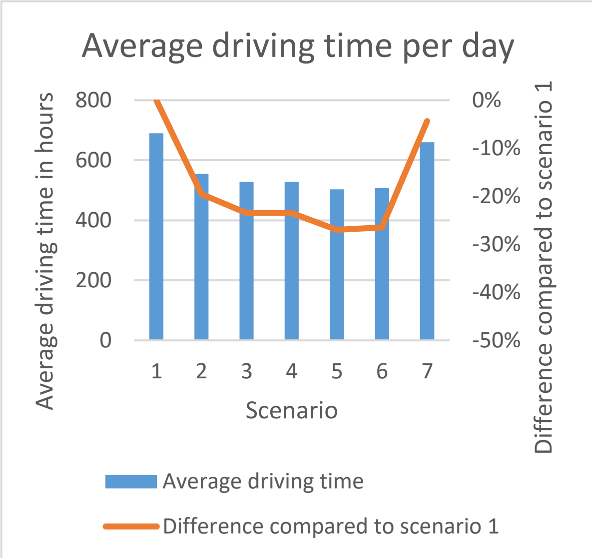


Figure 49: Average driving distance & Average driving time.

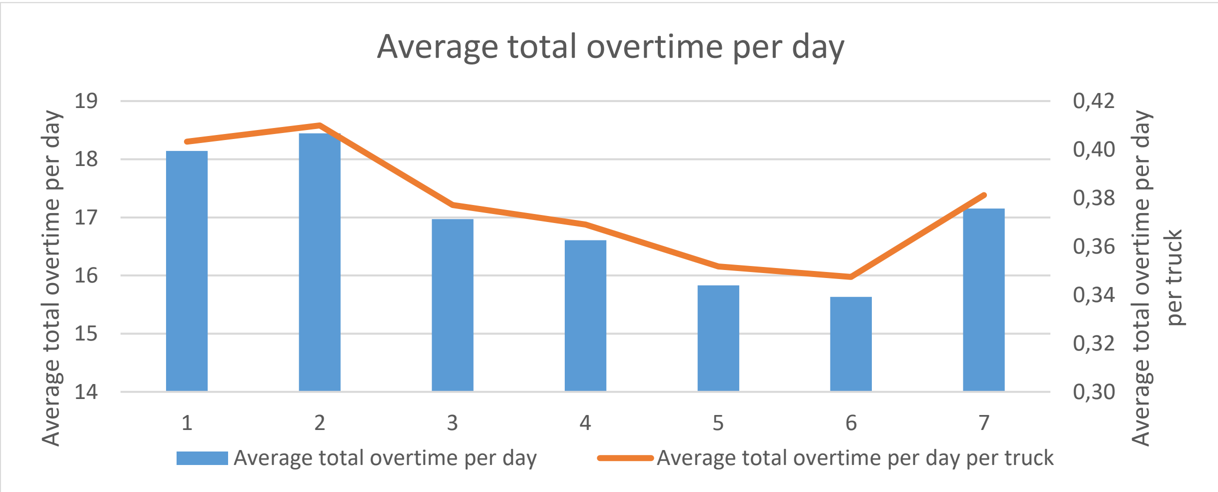


Figure 50: Average total overtime per day.

Figure 49 shows that the average driving time and driving distance decrease when increasing the role of the SOL-system. Furthermore, scenario 7 travelled more distance (+0.92%), and the driving time shows a small decline (-0.04%). Therefore, this scenario seems to be not an improvement compared to the current situation (scenario 1). However, compared to scenario 2, scenario 3 up to and including scenario 6, these performance indicators improve. Figure 50 shows that the total time driven in overtime also decreases increasing the role of the SOL-system. Due to the overtime variable in the auction mechanism, this extension of worktime is a negative effect on the bid of the truck on the container. This variable is excluded in the cheapest insertion scenario, in which the average is higher than scenario 3 up to and including 6.

6.5 Sensitivity analysis

Due to the many experiments in the sensitivity analysis, the tables show only the highlights and selected performances. Section 6.3.2 discusses the chosen factors in the sensitivity experiments. As mentioned before, this analysis has not the goal to optimize the chosen input variables. This research gives indications and causal relations on the performance indicators. Appendix H shows all numbers for all performances per experiment. Section 6.5.1 up to and including 6.5.9 discusses the results of the designed sensitivity analysis. Due to the changing ranges at the y-axis, consider this carefully. The chosen initial averages are determined considering only the relevant scenarios of that specific sensitivity analysis. As mentioned before, the shown distances are model-specific distance and not linked to reality. Therefore, only relative differences should be considered.

As mentioned before, the necessary scenarios for the sensitivity analysis are run two times. One run consists of 60 days, including a warm-up period of 6 days. Like section 6.4, first, the throughput and number of containers at the Port of Rotterdam are evaluated. Only experiment 17 and experiment 18 differ in the arrival of containers. Therefore, only for these two experiments, the difference is compared with the previous averages.

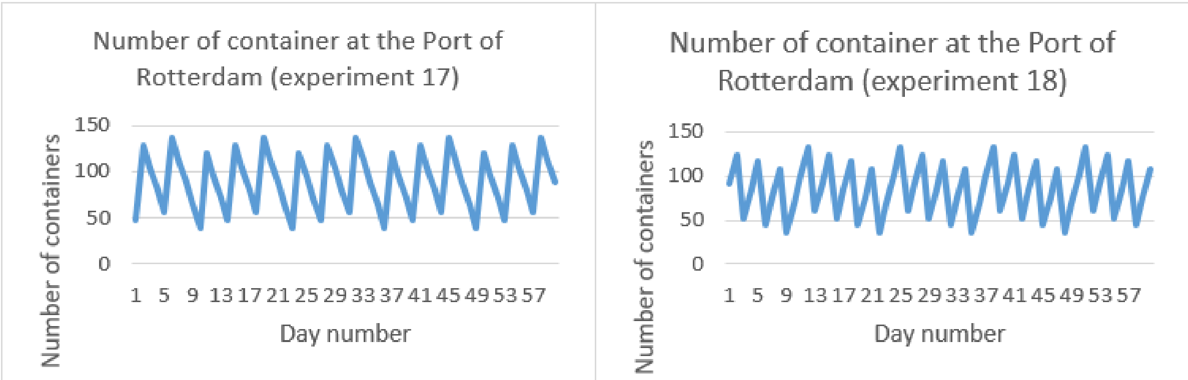


Figure 51: Number of containers at the Port of Rotterdam per experiment.

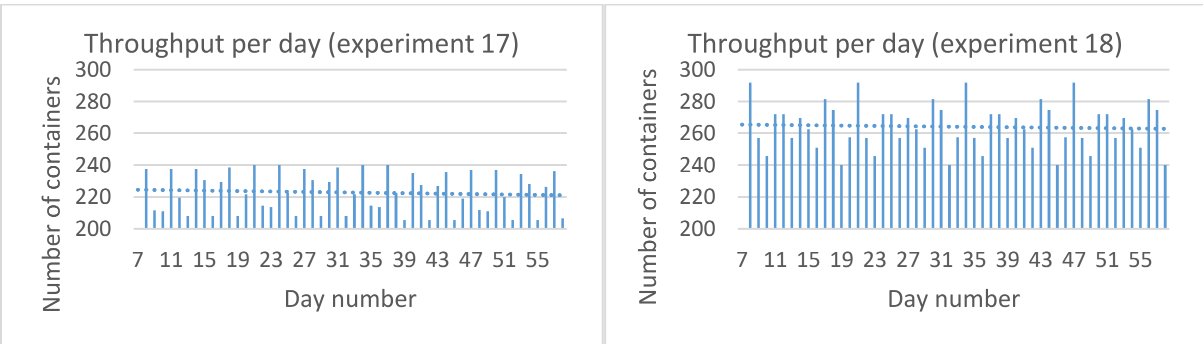


Figure 52: Throughput per day per experiment.

As can be seen in Figure 51, the number of containers remain stable. In experiment 18, the number of barges had to be increased by one. The number of pick-ups by barges increased, which can be seen by the larger number of peaks in the graph of experiment 18. Figure 52 shows the throughputs per sensitivity experiment. The averages of throughput of the normal configuration and experiment 1 up to and including 16. The throughput is 218 and 259 containers for respectively experiment 17 and 18.

6.5.1 Winner percentage

In experiment 1 and experiment 2 evaluates the winner percentage. The initial value was 0.9 and this value is changed to respectively 0.75 and 0.85. This factor is only relevant to the scenarios in which overruling is allowed. The most important trends are visualized in a dashboard.

Table 18:Sensitivity dashboard experiment 1 and experiment 2.

Experiment	*Containers in process*	*Number Merged Trips*	*Number of Containers at Clients*	*Number of Containers At CTT*	*Total driving time (seconds)*	*Number Of Overrules*	*Average transportation costs*	*Total Traveled Distance*
Initial	28.80	125.54	18.71	60.56	1842116.38	158.58	16479.94	2810922.42
1	29.53	126.06	19.53	60.55	1919003.43	96.49	16944.29	2778583.21
2	29.10	125.36	19.10	60.55	1831588.52	140.87	16423.09	2794472.26

The remarkable findings of experiment 2 can be summarized in two trends.

- Decreasing the winner percentage, decrease the number of overrules and total travelled distance.
- Containers in process, merged trips, containers at client number of client pick-ups, total driving time and transportation costs seems linked with each other. A winner percentage of 85% decreases the performances slightly. A winner percentage of 75% a larger difference can be seen in these performances.

6.5.2 Difference threshold

Experiment 3 and experiment 4 evaluates the difference threshold. The initial value was 0.1 and this value is changed to respectively 0.05 and 0.15. Only the scenarios are considered in which the difference threshold is used within the auction mechanism.

Table 19: Sensitivity dashboard experiment 3 and experiment 4.

Experiment	*Containers in process*	*Number of containers at clients*	*Number assignments CTT*	*Number assignments SOL*	*Total driving time (seconds)*	*Number of overrules*	*Average transportation costs*	*Total traveled distance*
Initial	28.80	18.70	499.16	2011.54	1838641.20	158.67	16552.21	2811709.27
3	27.88	17.88	175.71	1939.59	1958790.59	116.14	15069.92	2849709.15
4	28.04	18.04	234.16	1899.90	1966201.60	117.98	15492.03	2847337.92

The remarkable findings of experiment 3 and experiment 4 are summarized as follows:

- Using a lower difference threshold, the containers in the process decreases. This indicates that the containers are quicker through the process, given the same interarrival time.
- The number of assignments decreases much, changing the difference threshold. The main effect is the decrease in CTT assignment. In both experiments, the number of CTT assignments are more than halved.
- Both the total driving time and total travelled distance increases. This indicates that having more assignments (that should increase the bid), results in better truck performances. The initial seems to be the best scoring scenario in these two performances.

6.5.3 Bid threshold

Experiment 5 and experiment 6 evaluates the bid threshold. The initial value was 0.5 and this value is changed to respectively 0.4 and 0.6. Only the scenarios are considered in which the bid threshold is used within the auction mechanism.

Table 20: Sensitivity dashboard experiment 5 and experiment 6.

Experiment	*Containers in process*	*Number of containers at clients*	*Number assignments CTT*	*Number assignments SOL*	*Total driving time (seconds)*	*Number of overrules*	*Average transportation costs*	*Total traveled distance*
Initial	27.66	17.60	108.10	1949.23	1930829.10	111.66	14423.13	2847196.76
5	27.77	17.77	106.53	1953.16	1943577.73	110.43	14472.43	2851129.64
6	27.74	17.74	129.66	1957.16	1945857.69	113.99	14618.34	2851271.81

As can be seen in Table 20, these experiments do not impact the initial scenario much. Therefore, the impact of changing the bid threshold on the performances is low.

6.5.4 Start radius truck

Experiment 7 and experiment 8 evaluates the start radius of the truck. The initial value was 100 and this value is changed to 50 and 150. Only the scenarios are considered in which the search radius of the truck is relevant.

Table 21: Sensitivity dashboard experiment 7 and experiment 8.

Experiment	*Number of containers at clients*	*Number of containers at CTT*	*Number of assignments*	*Number of overrules*	*Average turnaround time uncoupling*	*Average turnaround time unloading*	*Total driving time (seconds)*	*Total traveled distance*
Initial	18.71	60.56	2522.88	158.58	7.92	2.55	1842116.38	2810922.42
7	19.05	60.53	2497.45	152.88	7.96	2.55	1840723.00	2803523.33
8	18.78	60.55	2589.95	164.68	7.94	2.55	1853687.70	2819016.43

The remarkable findings of experiment 7 and experiment 8 are summarized as follows:

- Decreasing the start radius (experiment 7), indicating more local searching, increases the number of containers in process, containers at the client, turnaround times. Furthermore, it decreases the total assignments, number of containers at CTT, total driving time, the number of overrules and total travelled distance.
- Increasing the start radius (experiment 8), indicating less local searching, increases the number of containers at CTT, total driving time, number of overrules, transportation costs, travelled distance. Furthermore, it decreases containers in-process and turnaround times.

6.5.5 Start radius container

Experiment 9 and experiment 10 evaluates the start radius of the container. The initial value was 500 and in the experiments this value is changed to 200 and 600. Only the scenarios are considered in which the search radius of the container is relevant.

Table 22: Sensitivity dashboard experiment 9 and experiment 10.

Experiment	*Number of containers at clients*	*Number of containers at CTT*	*Number of assignments*	*Number of overrules*	*Average turnaround time uncoupling (hours)*	*Average turnaround time unloading (hours)*	*Total driving time (seconds)*	*Total traveled distance*
Initial	18.71	60.56	2522.88	158.58	7.92	2.55	1842116.38	2810922.42
9	26.09	60.49	2262.27	131.78	9.53	2.55	1775055.01	2734272.67
10	17.80	60.51	2623.55	166.59	7.76	2.55	1858816.18	2831229.60

The remarkable findings of experiment 9 and experiment 10 are summarized as follows:

- Decreasing the container search area (experiment 9) increases the containers in process, the number of containers at CTT, turnaround times. It decreases the number of containers at client locations, number of assignments, driving time, overrules, transportation costs and travelled distance.
- Increasing the container search area (experiment 10) decreases the container sin process, the number of containers at CTT and client locations. It increases the total assignments, total driving time, number of overrules, transportation costs and distance travelled.

6.5.6 Scan frequency

Experiment 11 and experiment 12 evaluates the scan frequency. The initial value was five minutes, and this value is changed to respectively four minutes and six minutes.

Table 23: Sensitivity dashboard experiment 11 and experiment 12.

Experiment	*Number of containers at clients*	*Number of containers at CTT*	*Number of assignments*	*Number of overrules*	*Average turnaround time uncoupling (hours)*	*Average turnaround time unloading (hours)*	*Total driving time (seconds)*	*Total traveled distance*
Initial	17.62	60.64	2095.86	113.27	7.55	2.57	1993016.38	2847090.44
11	17.36	60.55	2266.17	115.97	7.46	2.56	2002642.11	2856287.97
12	20.14	62.88	2067.23	116.67	7.90	2.63	2054319.35	2849074.74

The remarkable findings of experiment 11 and experiment 12 are summarized as follows:

- Decreasing the search scan frequency (experiment 11) decreases the containers in the process, both at CTT as at the client and the turnaround times. However, it increases the number of assignments, driving time, overrules, costs and travelled distance.
- Increasing the search scan frequency (experiment 12) increases the containers in process, both at CTT as at the client, driving time, overrules, costs, turnaround times and travelled distance. However, it decreases the number of assignments.

6.5.7 Starting bid

Experiment 13 and experiment 14 evaluates the start bid. The initial value was 18000 and this value is changed to respectively 14400 (minus one hour) and 21600 (plus one hour).

Table 24: Sensitivity dashboard experiment 13 and experiment 14.

Experiment	*Number of containers at clients*	*Number of containers at CTT*	*Number of assignments*	*Number of overrules*	*Average turnaround time uncoupling (hours)*	*Average turnaround time unloading (hours)*	*Total driving time (seconds)*	*Total traveled distance*
Initial	17.62	60.64	2095.86	113.27	7.55	2.57	1993016.38	2847090.44
13	17.84	60.68	2102.67	125.90	7.61	2.57	1994389.52	2849263.89
14	17.93	60.65	2118.87	110.56	7.63	2.57	1996057.26	2844322.11

As can be seen, the starting bid has a small impact on most of the performances. The only performance which is impacted slightly is the number of overrules. Decreasing the start bid results in more overrules and increasing the start bid decreases the number of overrules. All other performances do not change much.

6.5.8 Number of trucks

Experiment 15 and experiment 16 evaluates the number of trucks. The initial value was 45 and this value is changed respectively to 30 and 40.

Table 25: Sensitivity dashboard experiment 15 and experiment 16.

Experiment	Number of containers at clients	Number of containers at CTT	Number of assignments	Number of overrules	Average turnaround time uncoupling (hours)	Average turnaround time unloading (hours)	Total driving time (seconds)	Total traveled distance
Initial	17.62	60.64	2095.86	113.27	7.55	2.57	44289.25	63268.68
15	31.91	355.24	3082.09	260.63	10.67	2.73	61903.89	92459.61
16	18.04	61.23	2288.58	142.39	7.74	2.58	48393.07	70877.65

For this analysis, the truck performances are scaled to the number of trucks used. The remarkable findings of experiment 15 and experiment 16 are summarized as follows:

- Setting the number of trucks to 30 (experiment 15) decreases empty returns, the transportation costs. However, it increases the container at the client and CTT, number of assignments, average driving time, number of overrules, turnaround times and average distance travelled. All these changes can be traced to the fact that fewer trucks should handle the same number of containers. Time-related performances decrease, but the effectiveness increases.
- Setting the number of trucks to 40 (experiment 16) visualizes similar results as in experiment 15. However, it seems that the system can easily handle the same amount of container. This can be seen at the average turnaround times, containers at the different locations and only small increases in the number of assignments and overrules, with a slightly more relative truck driving distance and time performances. Depending on the desired performances, the desired truck capacity can be determined.

6.5.9 Throughput containers

Experiment 17 and experiment 18 evaluates the interarrival time. The initial value was 6 minutes, and this value is changed respectively to 5 minutes and 7 minutes. For the 5 minutes interarrival time the number of barges is increased by one, so eight barges.

Table 26:Sensitivity dashboard experiment 17 and experiment 18 part 1.

Experiment	*Number of containers at clients*	*Number of containers at CTT*	*Number assignments CTT*	*Number of assignments*	*Number of overrules*	*Number Of client pick ups*
Initial	17.62	60.64	495.79	2095.86	113.27	93.27
17	16.68	52.91	447.21	1905.84	100.65	89.68
18	25.22	314.33	580.04	2660.59	188.50	93.53

Table 27:Sensitivity dashboard experiment 17 and experiment 18 part 2.

Experiment	*Average turnaround time uncoupling (hours)*	*Average turnaround time unloading (hours)*	*Total driving time (seconds)*	*Total traveled distance*	*Total overtime (seconds)*	*Average transportation costs*
Initial	7.55	2.57	1993016.38	2847090.44	60062.64	17364.47
17	7.53	2.55	1892774.51	2671568.29	53428.38	16239.32
18	8.30	2.64	2118302.47	3047317.25	89508.80	18852.13

The remarkable findings of experiment 17 and experiment 18 are summarized as follows:

- Decreasing the throughput of containers (experiment 17) shows outcomes as expected. For example, the assignments, number of containers at different locations and driving times and distances decreases.
- Increasing the throughput in experiment 18, the performances are developed the other way around, compared to experiment 17. This was also expected. Having more containers to handle by the system, the more efficient the trucks work and the worse the time-related performances of the container.
- Remarkable is the almost doubled overtime of the trucks at experiment 18. Many transportations finish after the closing moment of the working day. Furthermore, the number of containers in the process increase much, especially at client locations. This is almost four times the indicator value of the initial scenario. The assignment delegation is approximately the same. The average turnaround times indicate stable turnaround times for the containers.

6.5.10 Number of containers at CTT and client

Experiment 15 up to and including experiment 17 adapts the demand versus truck capacity ratios, considering the truck capacity and container interarrival times. Therefore, in these experiments, it is interesting to see the impact on the spreading of containers over time. Figure 53, Figure 54, Figure 55 and Figure 56 show the results of those experiments.

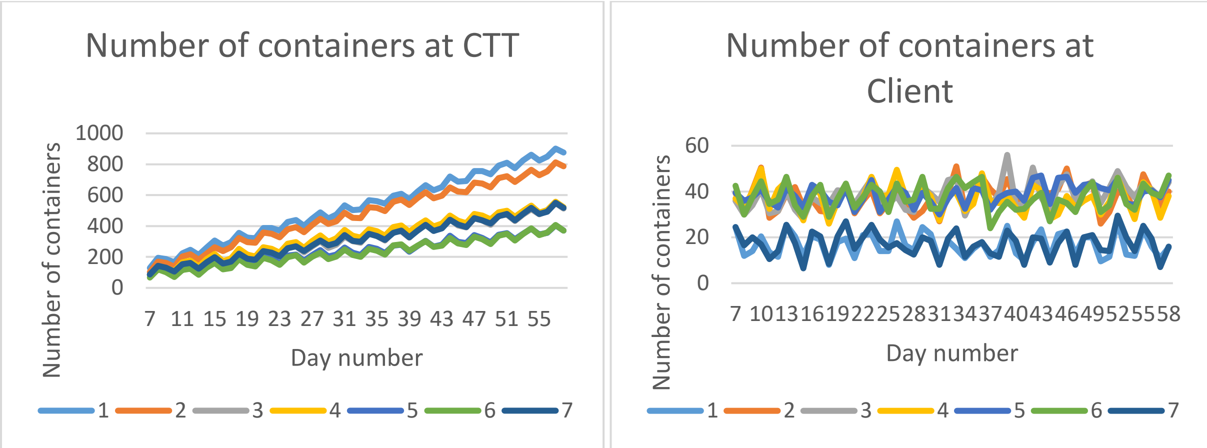


Figure 53: Number of containers at CTT and client experiment 15.

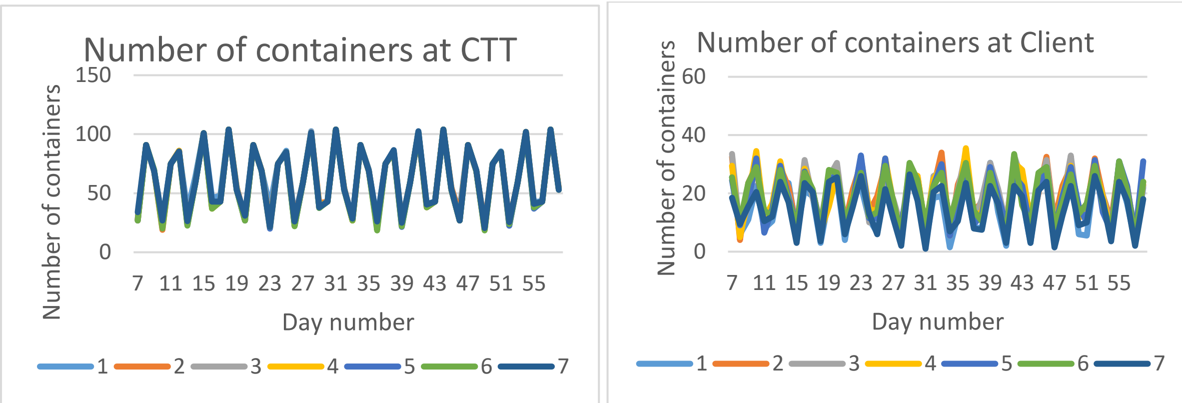


Figure 54: Number of containers at CTT and client experiment 16.

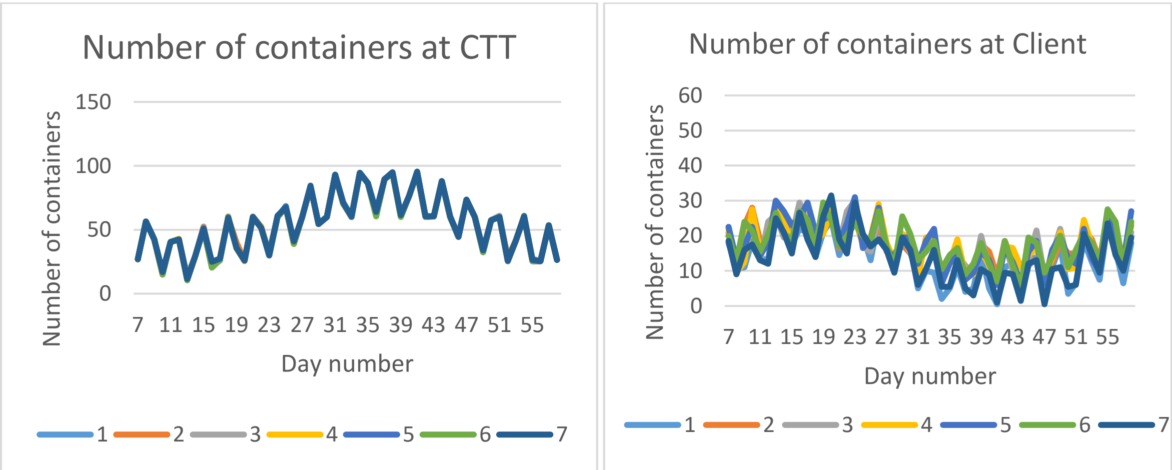
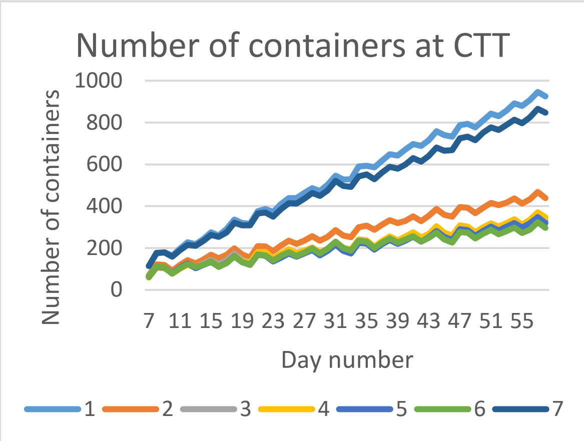


Figure 55: Number of containers at CTT and at client experiment 17.



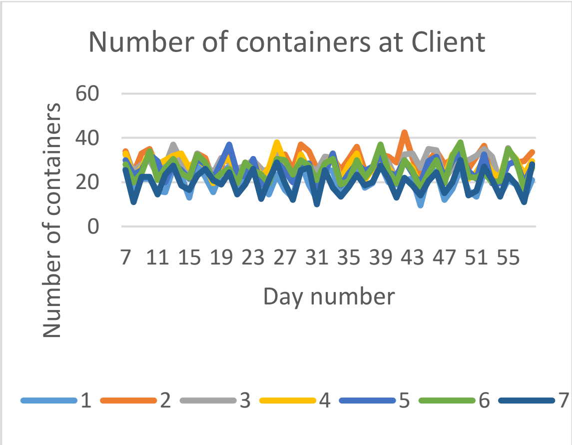


Figure 56: Number of containers at CTT and at client in experiment 18.

As can be seen, in the visualization of the results of the experiments, there is a relatively stable number of containers at client locations. More remarkable is the number of containers at CTT. Experimental 16 and experiment 17 show an equal relative stable number of containers at CTT with a sort of sinusoid movement, with almost the same results for each scenario. In experimental 15 and experiment 18, increasing lines are presented in the number of containers at CTT, indicating capacity problems, the system is tending to be overloaded, given the concerned input values. As can be seen, some scenarios score better than others. Especially in experiment 15, scenario 1 and scenario 2 score worse than the other scenarios on the number of containers at CTT. In experiment 18, especially, the initial scenario and cheapest heuristic scenario have a relatively bad score for this indicator. With these insights, it can be concluded that using a SOL-system is relevant to higher demand versus truck capacity ratios.

6.6 Conclusion analysis of results

This chapter visualizes, explain, discusses, and analyses the most important results of the experiments. An initial setup is analysed, and a sensitivity analysis is executed, analysing nine key initial settings to see the impact on the designed initial model outputs. The reliability of the outcomes depends on the chosen initial settings because some of these settings are crucial on the performances. This was also one of the main reasons for the designed sensitivity analysis. Furthermore, the human planner is simulated using some simplifications. A large search radius for the container symbolizes the centralized decision-making environment.

This research evaluates the causal relationships of the initial settings or decision-making processes. Table 28 gives a summary of the main outputs of the initial scenarios. This table uses conditional formatting, meaning that the good-scoring scenarios have by green colours and the worse scoring scenarios have red colours. The first column sums the number of containers at the client locations and CTT. This indicates, how fast the system can transport the containers. The second column indicates the amount of work for the human planner. The higher the number of decisions, the more work for the human planner. The third column shows the number of overrules executed per day. This indicates the sensitiveness of the system. The fourth column, the average transportation costs per day, indicates how much costs to transport the containers on average. This includes the assignment costs, penalty costs and truck costs. The fifth column consists of the weighted average number of hours a container is in the process. This is calculated by 0.4*average turnaround time of uncoupling containers plus 0.6* average turnaround time of unloading containers. The last column shows the amount of driving distance of trucks to transport the containers. This is not a real unit of length, but a simulation model-specific distance. However, the relative differences can be compared between the scenarios.

Table 28: Summary of important outputs of initial experiments.

Scenario	Average number of containers at Clients and CTT	Number of decisions human planner	Number of overrules	Transportation costs per day (in euros)	Average turnaround times (hours)	Average driving distance
Scenario 1	75.84	1035.60	0	23320.89	4.32	1021283.48
Scenario 2	80.04	1564.24	188.06	24346.96	4.90	906401.60
Scenario 3	79.29	393.55	161.66	15922.04	4.74	905607.22
Scenario 4	79.36	438.29	158.21	16190.90	4.70	904686.38
Scenario 5	78.77	38.85	142.267	13056.57	4.58	911631.96
Scenario 6	78.90	0.00	142.71	12883.26	4.56	937565.99
Scenario 7	75.59	0.00	0	15830.67	4.15	1049287.98

Using the visualizations of the graphs of the outcomes of the initial experiment and sensitivity experiments in previous sections, more remarkable and intuitive results arise. These are listed below:

- This research indicates the changing performances using the chosen input variables, assumptions, and level of detail of this simulation model. Multiple defined performance indicators visualize this impact.
- Introducing a SOL-system does not automatically indicate a decrease in the number of human evaluations. This is because of the more frequent decision moment per transport. In the initial scenario and cheapest insertion scenario, it is not allowed to overrule, which decreases the total number of decisions. Starting with delegating decision to a SOL-system and introducing the overrule possibility, first the human planner decision increase (scenario 2). Eventually, increasing in the scenario number, adding more thresholds, the number of human planner decisions decrease compared to the initial situation.
- Especially the truck-related performances indicate remarkable results. The driving time, driving time in overtime and driving distance improve compared to the initial scenario. This is a logical outcome because one of the main improvement perspectives is allowing overruling in which the time-related performances tend to reduce the time needed to transport containers.
- The average number of overrules per day indicates the sensitivity within the assigning process. It is not desired to have continuously overruling agents. Therefore, input variables are designed to limit this number, like: 'winner percentage', and included a restriction when it can overrule. The results show that the number of overrules increases when:
    - Lowering the truck capacity
    - Lowering the interarrival rate or increasing the throughput
    - Increasing the average placed bids
    - Decreasing thresholds in accepting bids

- The costs of trucks are the main factor within the defined performance indicator transportation costs. Therefore, the mentioned decreasing driving times impact the average daily costs per scenario. On average, the initial and cheapest heuristic scenario score worse on transportation costs. On the contrary, scenario 5 has the best score on this performance indicator.
- The choice of radii of both agents is an important consideration. Choosing greater search radii results in more found agents and more options in the evaluation. The results show that it does not imply that the to-be-picked up containers at client location results in linear decreasing turnaround times. However, considering the normal settings of scenario 1 and scenario 7 in which containers use the whole model to search trucks, it decreases the average turnaround times.
- Choosing the difference threshold is crucial for the results. As can be seen in the results in the sensitivity analysis of experiment 3 and 4 more remarkable results arise. Therefore, this input variable is a good further recommendation for further research.
- Bid threshold has only a small impact on the performances.
- The sensitivity analysis shows that expected changes occur in performances changing auction mechanism and capacity or demand input variables. However, some changes in performances are not linear with the change in the input variable. This is due to the complexity of the system. Many factors influence the specific performances.
- Changing demand versus truck capacity ratio indicates large correlations in the spreading of the containers. With a lower interarrival time or lower truck capacity, the number of containers at CTT seems not transported or too late delivered. The number of containers at client locations seems less vulnerable changing this demand versus truck capacity ratio.

7. Conclusions and recommendations

This section discusses the main conclusion, recommendations of the performed simulation study and the limitations of this research.

7.1 Conclusion

This research answers the following main research question:

What is the impact of different levels of self-organizing logistics to improve the last-mile transportation performances of Combi Terminal Twente?

This research indicates the changing performances using the chosen input variables, assumptions, and level of detail of this simulation model. Multiple defined performance indicators visualize this impact. The term self-organizing logistics is defined as a hybrid form of logistics that contains both decentralized and centralized control elements and utilizes automated processes based on real-time system information. The centralized decision-making environment is interpreted by the fact that containers can see all trucks by a very large search radius. A simulation model is designed in which the last-mile transportation is simulated. The sensitivity analyses examine the impact of the chosen input variables or designs within the searching and auction mechanisms. To investigate the opportunities of SOL seven different scenarios are designed. Each scenario is tested using multiple performance indicators to indicate and measure efficiency and measure the effectiveness. To which extent the decisions should be delegated is studied in the scenarios. The boundary depends on the chosen variables or thresholds within the scenarios. Table 29 gives a description of the scenarios.

Table 29: Scenarios.

Scenario 1	Human planners make **all** assignments based on the highest bidding agent, without allowing overruling.
Scenario 2	If **multiple agents** compete for the same agent, the *human planners* make the assignment. If **only one agent** competes for an agent, the *SOL-system* makes the assignment.
Scenario 3	*SOL-system* makes the assignment if the highest bidder scores much better than the runner up (***Difference Threshold)*** and the highest bidder scores above the ***Bid Threshold***, otherwise, the *human planners* make the assignment.
Scenario 4	*SOL-system* makes the assignment if the highest bidder scores much better than the runner-up (***Difference Threshold***), otherwise, the *human planners* make the assignment.
Scenario 5	*SOL-system* makes the assignment if the highest bidder scores above the ***Bid Threshold***, otherwise, the *human planners* make the assignment.
Scenario 6	*SOL-system* makes **all** assignments based on the highest bidding agent.
Scenario 7	*SOL-system* makes the assignment considering the **least extra driving time** needed, without allowing overruling. This corresponds to the cheapest insertion algorithm.

Within the analysis of the results, some findings and relations are discovered. However, firstly, the main insight into the number of decisions is illustrated per scenario. Due to the more frequent decision moment per transport, it does not result directly in a decrease in the number of human evaluations. Figure 57 shows the decision-making overview.

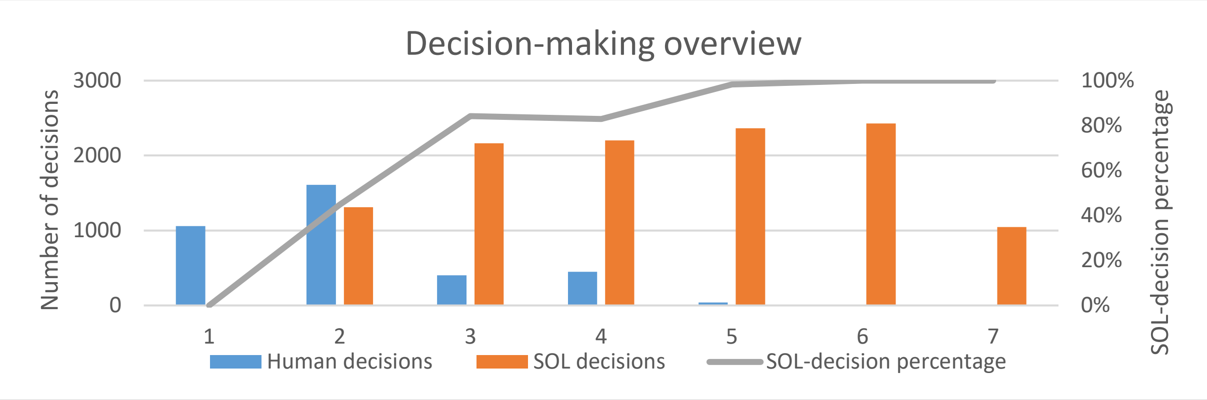


Figure 57: Decision-making overview per scenario

Moreover, multiple performance indicators are evaluated in the normal situation and within a designed sensitivity analysis on specific input variables. The main findings are summarized below.

- Especially the truck-related performances indicate remarkable results. The driving time, driving time in overtime and driving distance decrease compared to the initial scenario. This is due to the focus on reducing the time needed to transport containers in the auction mechanism.
- Truck costs are the main factor in transportation costs. On average, the initial and cheapest heuristic scenario score worse on transportation costs. On the contrary, scenario 5 scores best on this performance indicator.
- The number of overrules increases when lowering the truck capacity, lowering the interarrival rate, increasing the average placed bids and decreasing thresholds in accepting bids.
- Choosing greater search radii results in more found agents at greater distances resulting in more evaluations. The results show that it does not imply that the to-be-picked up containers at client location results in linear decreasing turnaround times. However, considering the normal settings of scenario 1 and scenario 7 in which containers use the whole model to search trucks, it decreases the average turnaround times.
- Choosing the difference threshold is crucial for the results. On the contrary, the bid threshold has only a small impact on the performances. This can also be seen in the delegation of decisions in scenario 4 and scenario 5 in Figure 57.
- Changes in input variables do not show linear changes in resulting performance indicators. This is due to the complexity of the system. Many chosen and unchosen factors, simplifications and assumptions influence the performance indicators, which makes concluding on the impact more difficult.
- Changing the demand or truck capacity indicates correlations in the spreading of the containers. With a lower interarrival time or lower truck capacity, the number of containers at CTT seems not transported or too late delivered. The number of containers at client locations seems less vulnerable changing this demand versus truck capacity ratio.

Concluding, the chosen impact of different levels of self-organizing logistics does indicate some interesting and promising results to improve the transportation process. To define the desired configuration, trade-offs should be made between the different performances within the last-mile transportation of containers to hinterlands locations. Increasing the role of a SOL-system and delegating decision from a human planner to a SOL-system, increases the total number of decisions but decreases the total driving time and driving distance. However, the amount of overrules and merged trips also increases, which results in a more changing and dynamic system. This increases the number of communications with truck drivers, which result in a more difficult system to manage in the real world. Moreover, this research indicates that the chosen scenarios do almost have no impact on the on-time performance indicator. The specific turnaround times do depend on the chosen configuration. Having scenarios with larger search radii, higher average bids, or lower thresholds in accepting bids, the average turnaround time decrease, especially the container waiting times. However, these system adaptions increase the number of decisions, overrules and average driving times towards locations. Therefore, before continuing or implementing a SOL-system in the real world, the preferred layout and performances should be considered. Furthermore, a system should be integrated using the data from sensors to manage, store, and analyse the necessary information for the decision-making process.

7.2 Limitations

As mentioned before, this simulation study contains limitations that need to be addressed. The model uses many assumptions and simplification to mimic reality as good as possible. Other model characteristics or input variables can influence the results and causal relationships.

Furthermore, the human planner is simulated with some simplifications. Th All thinking processes and decisions made cannot be simulated precisely or uniform captured in a simulation model. Smart flowcharts and uniform decision-making processes are created using the experience of human planners. However, specific situations are too complex or unique that it cannot be caught using these simplification steps.

It should also be stated that the simulation model input variables work with approximations due to the lack of necessary data or simulated data using the sensors. Since the input variables are approximated, it does not represent reality precisely. Furthermore, due to the COVID-19 circumstances, it was not possible to mirror the findings of this research with the situation in which the real-time data gathering of sensors is implemented in the decision-making process of CTT. However, this could be evaluated later when these sensors are attached and used for performance measuring. For this, it should be considered that the related companies do not want to lose their competitive advantage. Therefore, data gathering processes and analysis should be considered confidentially.

This approach to self-organizing logistics enables tweaking using multiple parameters and thresholds. The most preferred degree of SOL can be evaluated using more simulation runs. This can be evaluated in further research with different studies or other case studies.

Concluding, this research indicates of the possibilities and applications using different levels of self-organizing logistics in last-mile transportation.

7.3 Recommendations and further research

The outcomes of the simulation study show promising results, especially considering the amount of driving distance and driving time. However, a lot of aspects can be analysed in further research. Therefore, this section mentions five recommendations for further research.

Firstly, consider and examine the relevance and accuracy and relationships between the chosen input variables and output variables, before starting with a SOL-system. This research indicates some remarkable relationships between the chosen input variables and output variables. Especially, in the starting phase of such a system, the decisions should be considered with much human control to ensure the important performances of the system. Tests should focus on more common situations with commonly occurring clients, to check the made assumptions and simplifications. Another option is to create a digital twin or intelligence amplification to have two decision-makers. In this way, the decisions of both decision-makers can be compared. For the future, the most promising scenario is scenario 5. This scenario shows good results in the main performances, as shown in Table 21. Furthermore, it is a simple heuristic in which the human planners collaborate with the SOL-system. Furthermore, it requires only the setup of the auction mechanism and the height of the placed bid by the truck to compare alternatives.

Secondly, mirror this research more to reality to provide more accurate quantitative results. Evaluate more precise the defined assumptions or approximations or use real data to improve the simulation model. Eventually, or an end goal could be to design a decisions support system, which supports the human planner in its decision-making processes in assigning trucks with containers. In such a system, the human planner should be able to have control but should be supported in its assignment activities. The focus of human planners should be on more complex situations. Furthermore, the simulation model can be extended using more and real client locations based on the CTT dataset. More real clients in the model represent reality better.

Thirdly, evaluate and, if possible, optimise the specific chosen experimental factors and scenarios. Evaluate the correlations between variables to see the impact or predict the impact on the performance indicators using small adaptions in the designed simulated processed. Discuss adaptions with the related companies to consider the confidential information or competitive advantage of the concerned companies.

Fourthly, evaluate further improvements using the concepts of Physical internet, Internet of Things, and Industry 4.0. Many already executed studies have been performed and could be used or combined to indicate the possibilities in the last-mile transportation process of CTT.

Fifthly, consider and evaluate the used mechanisms in more detail. Consider different weight for the auction variables, determination of the search radius, penalties on overruling assignments. Furthermore, this research only uses one type per mechanism. These mechanisms can be replaced by or combined with other mechanisms with different procedures.

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Appendix

Appendix A

Acronyms

CTT Combi Terminal Twente

CHBT Current highest bid truck

CHBC Current highest bid container

DES Discrete Event Simulation

IEM Industrial Engineering and Management

MAS Multi-agent Simulation

TEU Twenty-foot Equivalent Unit, measure for capacity of container

SOL Self-organizing logistics

Appendix B

Appendix B focuses on additional visualisations or flowcharts for the simulation model.

Bid Example

The first two variables in the auction mechanism are related. If it is possible to drive the as the crow-fly distance to the container the distance dividied by the average speed correspond closely to the expected required extra driving time. An example of such situation is shown in Figure 58. In this situation, it is smarter to combine truck 1 over truck 2 because truck 1 needs only a relatively smaller detour.

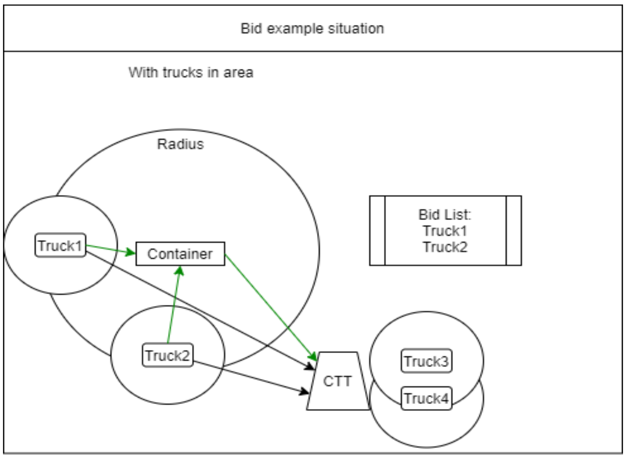


Figure 58: Illustration variable correlation in bid calculation

Present agents within decision

This flowchart indicates the possibility agents present in an auction mechanism. In this flowchart the "?" indicate the calling agent. This can be truck or container.

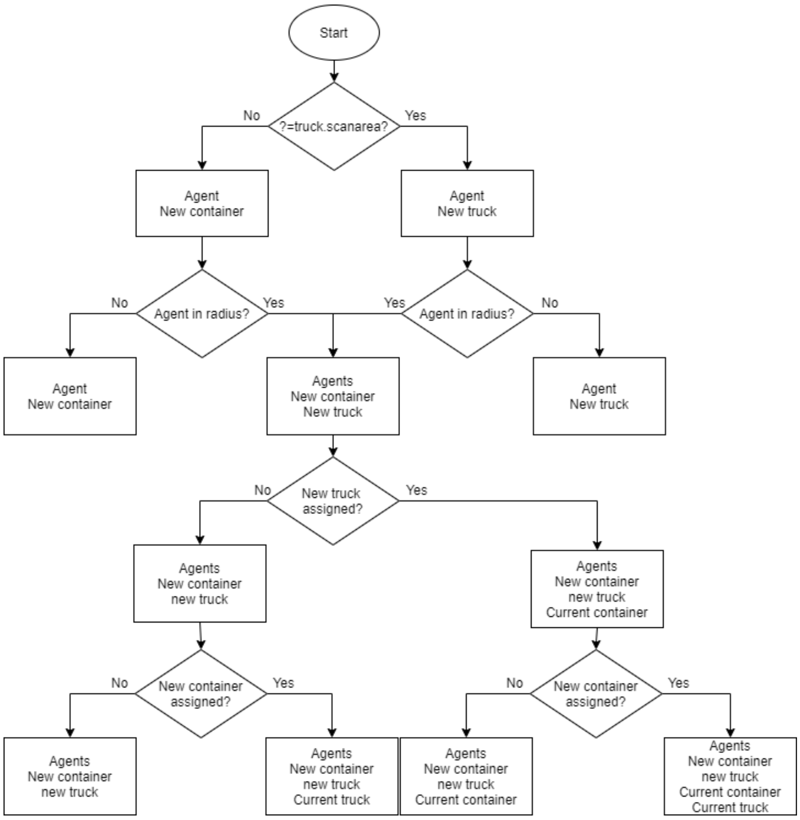


Figure 59: Determination of number of agents in bid evaluation.

Bid calculation example

In the example of Figure 60 three trucks compete for the container. Using the auction mechanism attributes three steps are followed. First, the attributes scores are determined. Second, the bid is calculated using the scores of the auction mechanism attributes. Third, the scenario specific attributes are calculated for the highest bidding truck. Currently, truck 3 transports a container and its next available location is indicated using the arrow. This takes 3000 seconds, as illustrated in the "Determine attributes" section. Using a difference threshold of 10% and bid threshold of 50% as in scenario 3, truck 2 is assigned to the container by the SOL-system.

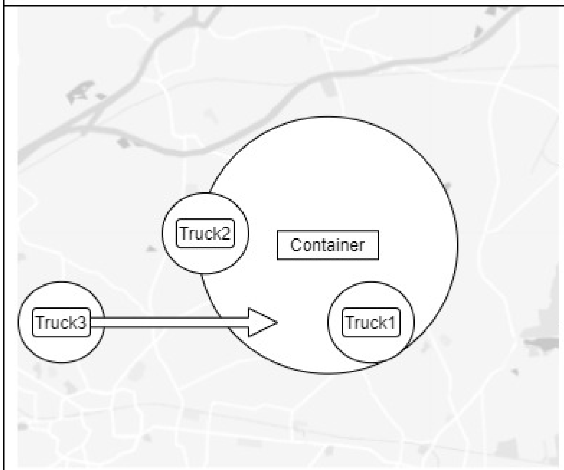
Represenation of situation	Determine attributes	Calculate bid	Consider thresholds
	Truck 1 attributes: Variable1: 1200 Variable2: 3400 Variable3:0 Variable4:0	Truck 1 Bid: 18000-1200-3400-0-0= 13400	Not applicable
	Truck 2 attributes: Variable1: 1400 Variable2: 2100 Variable3:0 Variable4:0	Truck 2 Bid: 18000-1400-2100-0-0= 15500	Difference threshold= (15500-13400)/15500=13.5% Bid threshold= 15500/18000=86.1%
	Truck 3 attributes: Variable1: 1200 Variable2: 1400 Variable3:0 Variable4:3000	Truck 3 Bid: 18000-1200-1400-0-3000 12400	Not applicable

Figure 60: Bid calculation example.

Scanning and auction mechanism illustration – truck perspective

In the Figure 61 the seven steps of a scanning process and auction mechanism is illustrated with the perspective of the truck. In the boxes below the illustration a small explanation is given.

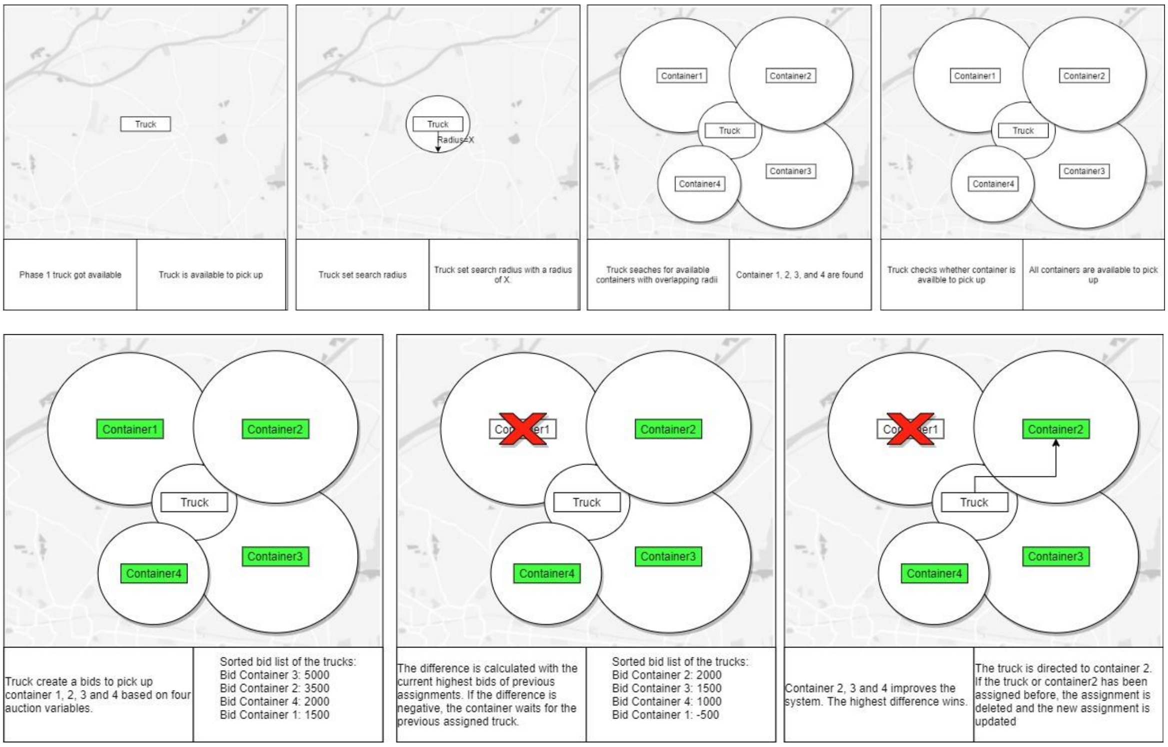


Figure 61: Scanning and auction mechanism illustration - truck perspective.

Decision flowchart

In this flowchart the delegation of decision is represented. Using the scenario specific variables or thresholds, it is decided whether the decision is made by a human planner (CTT) or a SOL-system. The bid thresholds differ per scenario. In scenario 4 and scenario 5 only one threshold is used.

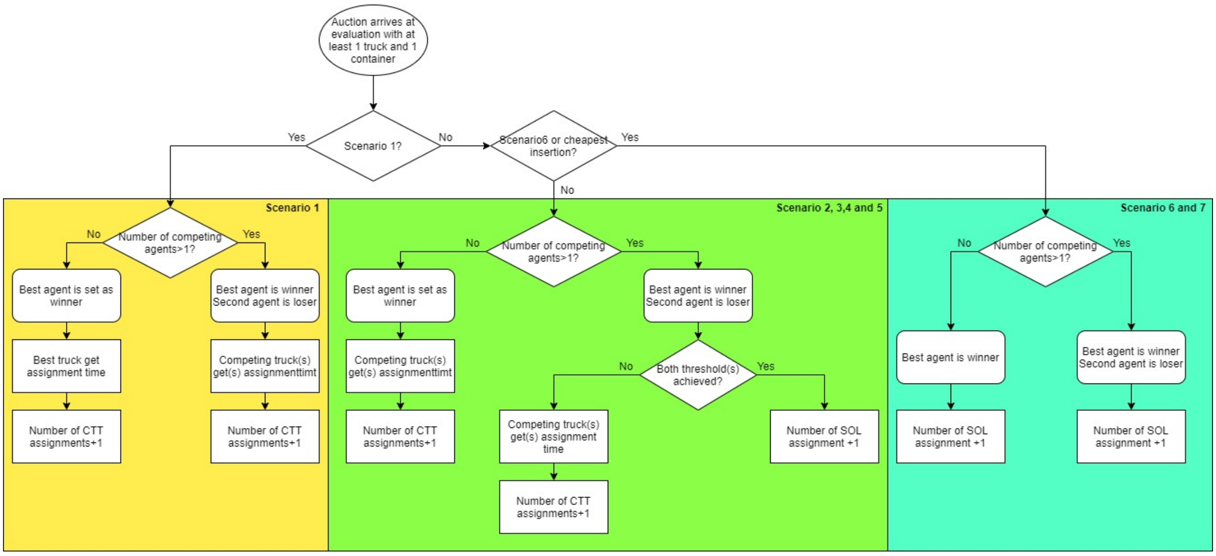


Figure 62: Decision-making flowchart.

Barge flowcharts

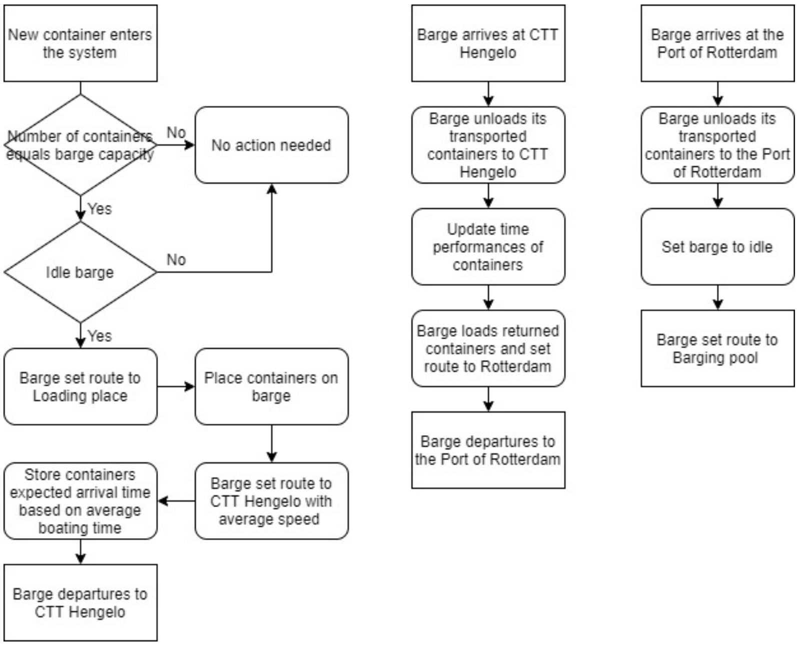


Figure 63: Barge related flowcharts.

Example activities container in deadline determination

Figure 64 shows an example of the activities of a container and truck within the transportation process considering the latest moment of departure of the truck to reach the agreed delivery time window of the client.

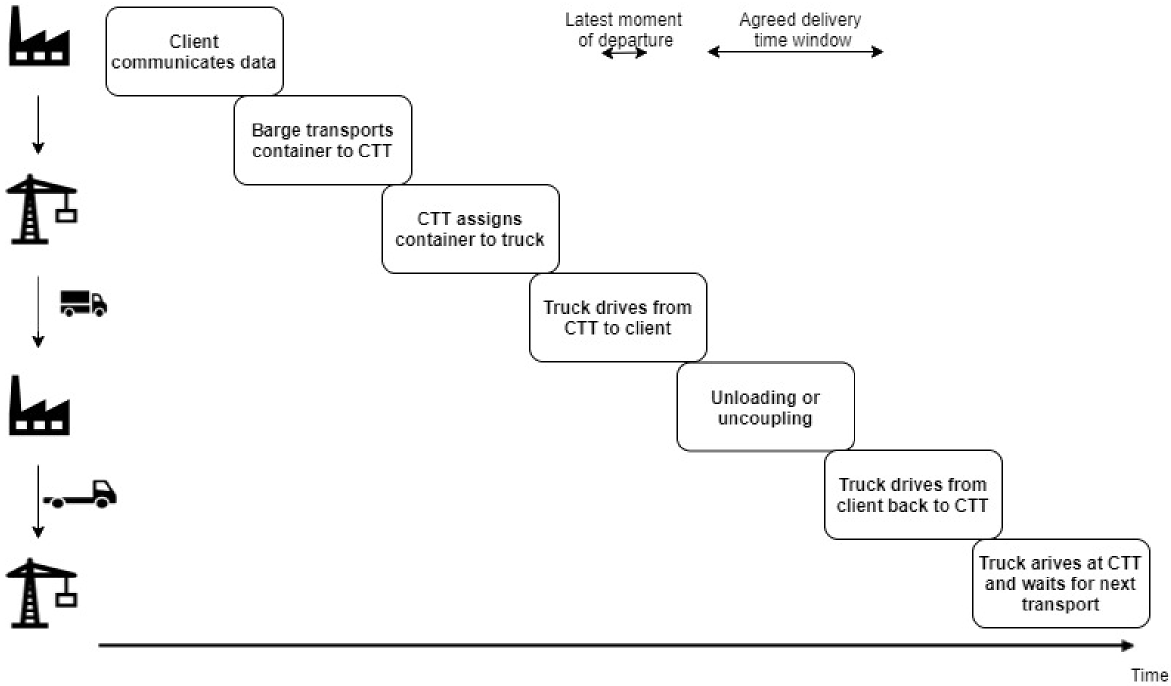


Figure 64: Example activities of a container in the deadline determination.

Routing by marker

In Figure 65 the routes are represented of the simulation model. These routes connect all location to each other. Each route consists of multiple markers which represent the roads in the hinterland supply chain of CTT. As can be seen, the rightest client locations (North Germany and South Germany) are the longest routes and therefore also the longest driving distance and driving time. These routes indicate highway connections and normal roads.

Figure 65: Routes by markers and tracks.

Communication IT architecture

As mentioned before, the system uses specific communication IT architecture using the LoRa sensors of Pharox between the agents, CTT databases, Human planners, SOL-system, and an auction system. Figure 66 gives a visualization of the interrelationships among all system components, which is used in the simulation model. In the auction system the assignments with corresponding current highest bids of the container and truck are stored. These current highest bids are also used in the overruling activities of Section 4.3. Truck communicates with containers and containers with trucks. The communication is about the agent-specific attributes, auction properties and the assigning properties. The yellow, green and arrows indicate an assignment communication, accepted assignment, and refused assignment, respectively. As can be seen containers have different search radii which do not always results in a found truck. When the human planner is called, the planner can see all retrieved information and is able to manually assign a truck to container. Therefore, all information should be stored on a central server, which is accessible by the human planner. In this example, truck 2 is assigned to container 2 by a human planner and truck 3 is assigned to container 4 by the SOL-system. Both current highest bids and assignment are stored in the Auction system. Container 1 and container 3 wait for the next auction round or passing trucks that initialize their own auction round.

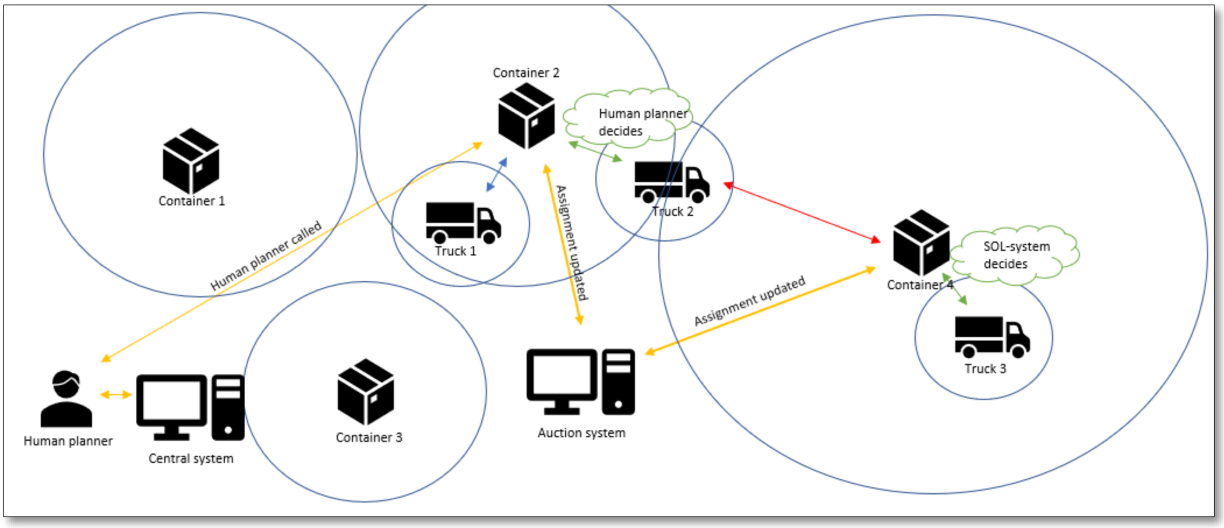


Figure 66: Communication IT architecture

Appendix C

Determination of number of replications

Following from Section 6.2.3, Figure 67 shows the result of the number of replications. For these the chosen four indicators are tested using a statistical test to calculate the relative error and to determine the required and desired number of replications running, using a run length of 60 days. The averages are calculated using all data point in these 60 days.

[CONFIDENTAL INFORMATION]

On-time percentage		N	**percentage**	Average	StDev	Tstatistic	Delta	Relative	Runs
run1					0	0	0	0	Wrong
run2					0.00446	12.7062	0.0401	0.04464	good
run3					0.00364	4.30265	0.00905	0.01008	good
run4					0.00302	3.18245	0.0048	0.00535	good
run5					0.00263	2.77645	0.00326	0.00363	good
Average uncoupling time		N	**Average uncoupling time**	Average	StDev	Tstatistic	Delta	Relative	Runs
run1	24348.5	1	**24348.54594**	24348.5	0	0	0	0	Wrong
run2	24414.2	2	**24414.22655**	24381.4	46.4432	12.7062	417.276	0.01711	good
run3	24274.7	3	**24274.68245**	24345.8	69.812	4.30265	173.423	0.00712	good
run4	24274.6	4	**24274.5722**	24328	67.2172	3.18245	106.958	0.0044	good
run5	24462.4	5	**24462.43649**	24354.9	83.6832	2.77645	103.906	0.00427	good
Average unloading time		N	**Average unloading time**	Average	StDev	Tstatistic	Delta	Relative	Runs
run1	9741.26	1	**9741.259024**	9741.26	0	0	0	0	Wrong
run2	9703.21	2	**9703.208308**	9722.23	26.9059	12.7062	241.74	0.02486	good
run3	9698.96	3	**9698.960012**	9714.48	23.292	4.30265	57.8606	0.00596	good
run4	9816.9	4	**9816.904937**	9740.08	54.6316	3.18245	86.9311	0.00893	good
run5	9704.35	5	**9704.345007**	9732.94	49.939	2.77645	62.0074	0.00637	good
Container at client		N	**Container at client**	Average	StDev	Tstatistic	Delta	Relative	Runs
run1	14.7797	1	**14.77966102**	14.7797	0	0	0	0	Wrong
run2	14.8644	2	**14.86440678**	14.822	0.05992	12.7062	0.5384	0.03632	good
run3	14.8793	3	**14.87931034**	14.8411	0.05375	4.30265	0.13352	0.009	good
run4	14.807	4	**14.80701754**	14.8326	0.04708	3.18245	0.07492	0.00505	good
run5	15.2414	5	**15.24137931**	14.9144	0.1873	2.77645	0.23257	0.01559	good

Alpha	**0.05**	Estimation		Mean	6966.75	Mean	6966.75
Gamma	**0.05**	**N**	**5**	StDev	0.00263	StDev	11896.5
Gamma'	0.04762	tValue(0.!	2.77645	StDevMe:	0.00117	Runs	**4940**
			1.95996	Halfwidtl	2.3E-06	Sequential procedure:	
				Runs	**5E-10**	2	
Alpha	**0.05**	Estimation		Mean	18864.7	Mean	18864.7
Gamma	**0.05**	**N**	**5**	StDev	83.6832	StDev	7577.41
Gamma'	0.04762	tValue(0.!	2.77645	StDevMe:	37.4243	Runs	**273.33**
			1.95996	Halfwidtl	0.02754	Sequential procedure:	
				Runs	**0.0669**	2	
Alpha	**0.05**	Estimation		Mean	6088.65	Mean	6088.65
Gamma	**0.05**	**N**	**5**	StDev	49.939	StDev	5029.73
Gamma'	0.04762	tValue(0.!	2.77645	StDevMe:	22.3334	Runs	**1156.1**
			1.95996	Halfwidtl	0.05092	Sequential procedure:	
				Runs	**0.2287**	2	
Alpha	**0.05**	Estimation		Mean	14.9144	Mean	14.9144
Gamma	**0.05**	**N**	**5**	StDev	0.1873	StDev	0.1873
Gamma'	0.04762	tValue(0.!	2.77645	StDevMe:	0.08377	Runs	**0.2672**
			1.95996	Halfwidtl	0.07797	Sequential procedure:	
				Runs	**0.5362**	2	

Figure 67: Number of replications determination.

Appendix D

Client distribution

The used client distribution is determined when the container is arriving at the Port of Rotterdam. The seven most occurring clients from the dataset of CTT are used. This is extended by consider one client per wind direction and two clients in Germany. Figure 68 shows the chosen distribution per client. The type of client is determined when the container enter the simulation model. In Figure 69 shows the locations of the concerning clients.

[CONFIDENTAL INFORMATION]

Figure 68: Client distribution.

[CONFIDENTAL INFORMATION]

Figure 69: Locations clients on simulation map.

Appendix E

Extra visualisations result analysis

Table 30 and Table 31 shows the average time at location in hours and the average total number of pick-ups per scenario.

Table 30: Average time at client location (hours)

[CONFIDENTAL INFORMATION]

Table 31: Number of container pick-ups per location

[CONFIDENTAL INFORMATION]

Appendix F

Main dashboard simulation model

In this research a main dashboard, or control panel, is designed. Figure 70 shows this dashboard.

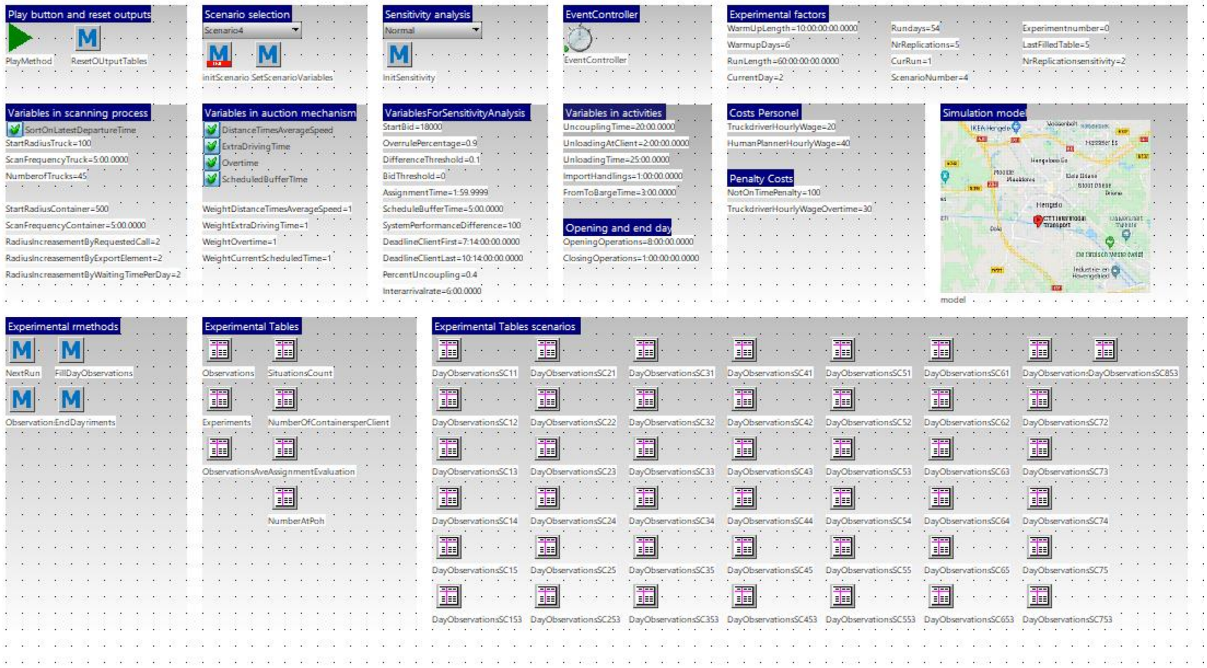


Figure 70: Dashboard simulation model.

On this dashboard a couple of elements can be found. Each section of this dashboard is descripted in more detail, considering the function:

- *Play button and reset output tables*

The *Playmethod* initializes the scenarios-specific and sensitivity experiment-specific input variables. It calls the *ResetOutputtables* method, which deletes the current values in the experimental tables. Furthermore, it initializes the event controller on the "model-frame" and starts the simulation.

- *Scenario selection and sensitivity analysis*

In the scenario selection and sensitivity analysis two dropdownitems are shown. Each run is initialized with the scenario and type of experiment. Both are linked with a method (*Setscenariovariables* and *InitSensitivity)*, which initialize the necessary input variables of that scenario and experiment, if necessary.

- *Eventcontroller*

The *eventcontroller* coordinates and synchronizes the different events taking place during a simulation run.

- *Experimental factors*

The experimental factors consist of the simulation run characteristics and counter. Using these variables, the *NextRun* method can decide the next necessary run.

- *Variables in scanning process and variables in auction mechanism and variables for sensitivity analysis*

This section represents the input variables per scenario or experiment. These variables are initialized when the dropdownitems are changed.

- *Variables in activities, opening and end day, cost personnel and penalty costs*

These variables indicate some assumed times and costs for the simulation model. These variables could be adapted if desired in further research.

- *Experimental methods*

NextRun is called after each run. It calls the *filldayobservation,* that fills the experimental tables. Furthermore, *NextRun* stops the simulation, resets the simulation, the increases the run counter or experiment and start the new run.

- *Experimental tables and experimental tables scenarios*

In the experimental tables section five tables are presented. The table *Assignmentevaluation*, the total number of assignments is kept, specifying on new-, the same-, one option-, multiple option -, forward scheduling assignments. Furthermore, the counters of arriving, driving, returning and containers at client are kept per scenario and per run. The N*umberatPoh* table keeps the number of containers at the port of Rotterdam. This table shows whether the number of barges is sufficient to handle interarrival rate of the source. *SituationsCount* counter the number occurring per situation per scenario and per run of Figure 28. *NumberOfContainersPerClient* keeps track of the number of containers at the end of the day per location, some results are shown in Appendix E. Furthermore, the total number of pick-ups and the average waiting time per location is stored. The experiment tables scenarios store the performance indicators. Each column represents a scenario. Each row represents a run counter. The table name is linked with both attributes, starting with scenario and secondly the run counter. For example, scenario 3, run 2 gets the table name: "*DayobservationsSC32*".

Methods and variables dashboard

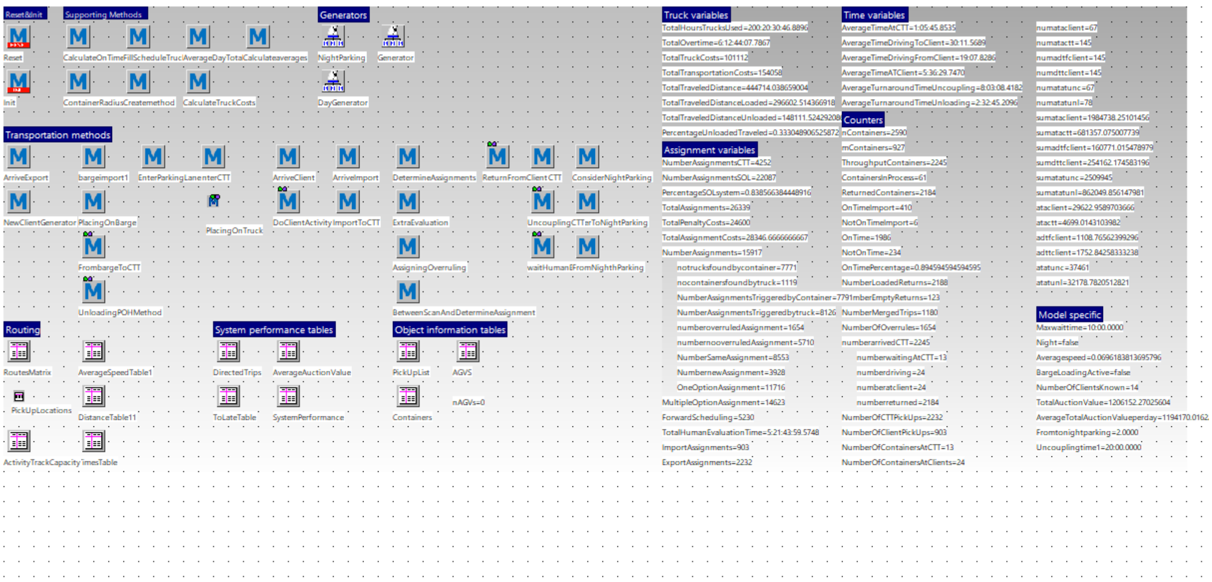


Figure 71: Methods and variables dashboard

In the methods and variables dashboard above, the following section can be found:

- Reset & init

The reset deletes all events, statistics data, and movables. This method is called after the reset-button is pressed or called in the simulation model. The init initialized the settings at the start of a simulation run.

- Supporting methods

These methods help the transportation methods or calculate the important performances.

- Generators

These generators help to indicate specific times or working days in a simulation run.

- Transportation methods

These methods are called after each an event in the transportation of the containers to clients and back to CTT. Due to the many possibilities in the assignments using the different scenarios, many different methods are created to separate the discrete events with the concerning activities. Besides these methods also the objects (containers and trucks) have user-defined-attribute methods which can be called with a certain time frequency. Furthermore, the variables on the right-hand side, are used very often within these methods.

- Routing

In these tables the routes can be found from and to different locations. Furthermore, the average speed per client is determined using a distance and desired driving timetables.

- System performance

In these tables, the location-specific performances, to-late times, and auction value performances are measured and kept.

- Object information tables

In these tables, all relevant information from containers and trucks are kept.

- Truck variables

These variables indicate the truck performances during the simulation.

- Assignment variables

These variables indicate the assignment performances during the simulation.

- Time variables

These variables indicate the turnaround time performances during the simulation.

- Counters

These variables indicate the counters during the simulation. These counters are used for performances measurement and for the verification of the model within different environments.

- Model-specific

These variables indicate some important model-specific variables.

Appendix G

3D-representation of simulation model

In this study, the transportation process of CTT is simulated. Using Siemens Tecnomatix Plant Simulation, a 3D model is created. Figure 72gives a representation of this model.

[CONFIDENTAL INFORMATION]

Figure 72: 3D representation of simulation model

Appendix H

This appendix shows the result tables of both experiments with the initial settings as the experiments in the sensitivity analysis.

Initial results

Two screenshots are made of the results from the scenarios with the initial settings.

Output		ThroughputContainers	ContainersInProcess	Ontime	Notontime	OnTimePercentage	NumberLoadedReturns	NumberEmptyReturns	NumberMergedTrips	NumberOfContainersAtCTT	NumberOfContainersAtClients	NumberOfCTTPickUps	NumberOfClientPickUps	NumberAssignmentsCTT	NumberAssignmentsSOL	PercentageSOLSystem	TotalAssignments
Scenario1		235.5166667	24.91111111				233.9	13.07	116.626667	60.9259259	14.9111111	234	92.9266667	1035.60333	0	0	1035.60333
Scenario2		235.5166667	29.44074074				233.896667	13.2433333	125.806667	60.7962963	19.2407407	234	93.6466667	1564.23667	1270.23	0.44749274	2834.46667
Scenario3		235.5166667	28.85185185		[CONFIDENTAL INFORMATION]		233.853333	15.0866667	125.273333	60.5	18.7925926	234	93.4366667	393.546667	2108.79	0.84468791	2502.33667
Scenario4		235.5166667	28.76666667				233.83	15.6033333	125.25	60.5962963	18.7666667	234	93.3733333	438.293333	2133.32667	0.82809247	2571.62
Scenario5		235.5166667	28.47407407				233.886667	18.4266667	125.013333	60.4481481	18.3185185	234	92.5566667	38.8466667	2304.54667	0.98376179	2343.39333
Scenario6		235.5166667	28.44814815				233.856667	18.58	126.343333	60.4518519	18.4481481	234	94.0666667	0	2362.59	1	2362.59
Scenario7		235.5166667	24.85555556				233.946667	17.26	118.173333	60.737037	14.8555556	234	92.8766667	0	1020.99667	1	1020.99667
Main output graphs		235.5166667	28.7962963				233.864667	16.188	125.537333	60.5585185	18.7133333	234	93.416	486.984667	2035.89667	0.82080698	2522.88133

TotalHoursTrucksUsed	TotalOvertime	NumberOfOverrules	TotalPenaltyCosts	TotalAssignmentCosts	Average Truck Costs per day	Average transportation costs	Total transportation costs	AverageTimeAtCTT	AverageTimeDrivingToClient	AverageTimeDrivingFromClient	AverageTimeAtclient	AverageTurnaroundTimeUncoupling	AverageturnaroundTimeUnloading	AverageAuctionValue	TotalTraveledDistance	TotalTraveledDistanceLoaded	TotalTraveledDistanceunLoaded
2425375.31	64469.1732	0	2405.33333	6904.02222	563070.5	23320.89	1399253.4	1.15026429	0.54811643	0.32030207	4.28686051	6.75369499	2.69285573	1023488.16	2924054.62	1902771.14	1021283.48
1946405.89	65162.9604	188.06	2562.33333	10428.2444	457087.019	24346.96	1460817.4	1.09783368	0.57066449	0.32978996	5.80036017	8.28114974	2.64866643	1138680.78	2809016.41	1902614.81	906401.602
1853478.2	59756.8092	161.66	2503.33333	2623.64444	434426.52	15922.04	955322.4	1.09227376	0.51624176	0.32296416	5.55105396	7.98815521	2.56680812	1099458.71	2810474.91	1904867.68	905607.222
1856017.07	59009.8415	158.206667	2466	2921.95556	434520.651	16190.90	971453.8	1.09261969	0.50706044	0.32079986	5.49049303	7.91853399	2.5544511	1093621.53	2807774.98	1903088.61	904686.376
1772368.24	56013.6036	142.256667	2484.33333	258.977778	414660.337	13056.57	783394.4	1.08987652	0.48278252	0.29700512	5.32646528	7.72366794	2.4924001	1052027.11	2809235.03	1897603.07	911631.963
1782312.47	55223.9068	142.706667	2521.33333	0	417100.197	12883.26	772995.4	1.08818939	0.48237719	0.29513636	5.27718948	7.66842992	2.48615507	1051366.35	2818110.75	1900207.07	937565.986
2315157.48	60802.1677	0	2462	0	538109.382	15830.67	949840	1.15252053	0.4813797	0.29178352	4.112134	6.53192462	2.5696618	1006815.2	2950966.34	1901678.36	1049287.98
1842116.38	59033.4243	158.578	2507.46667	3246.56444	431558.945	16479.9447	988796.68	1.09215861	0.51182528	0.31313909	5.48911238	7.91598736	2.54969616	1087030.9	2810922.42	1901676.25	913178.63

Figure 73: Initial settings output

Sensitivity analysis results

Two screenshots are made of the results from the sensitivity analyses. The outcomes are compared with the initial outcomes. Only the relevant scenarios are considered to evaluate the changes in the concerned performance indicators.

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experiment	handled scenarios	ThroughputContainers	ContainersInProcess	Ontime	Notontime	OnTimePercentage	NumberLoadedReturns	NumberEmptyReturns	NumberMergedTrips	NumberOfContainersAtCTT	NumberOfContainersAtClients	NumberOfCTTPickUps	NumberOfClientPickUps	NumberAssignmentsCTT	NumberAssignmentsSOL	PercentageSOLSystem	TotalAssignments	TotalHoursTrucksUsed	TotalOvertime
initial	234567	**235.5166667**	**28.7962963**				**233.8646667**	**16.188**	**125.5373333**	**60.55851852**	**18.71333333**	**234**	**93.416**	**486.9846667**	**2035.896667**	**0.820806984**	**2522.881333**	**1842116.377**	**59033.42428**
1	234567	235.5166667	29.5333333				233.84	16.34833333	126.06	60.55	19.53333333	234	93.9	486.1966667	1967.221667	0.812673522	2453.418333	1919003.435	59023.09747
2	234567	235.5166667	29.1037037				233.84	15.94166667	125.3633333	60.5537037	19.1037037	234	93.22666667	485.6666667	2038.473333	0.822497966	2524.14	1831588.522	59739.88391
initial	2356	**235.5166667**	**28.8037037**				**233.8733333**	**16.33416667**	**125.6091667**	**60.54907407**	**18.7**	**234**	**93.42666667**	**499.1575**	**2011.539167**	**0.818985611**	**2510.696667**	**1838641.203**	**59039.31997**
3	2356	235.5166667	27.87731481				233.8916667	16.89375	124.6583333	60.57407407	17.87731481	234	94.01875	175.70625	1939.589583	0.931228167	2115.295833	1958790.593	58866.52785
4	2356	235.5166667	28.03935185				233.8875	16.56041667	124.4645833	60.65046296	18.03935185	234	93.9	234.1625	1899.9	0.908936994	2134.0625	1966201.601	59089.34884
initial	3567	**235.5166667**	**27.65740741**				**233.8858333**	**17.33833333**	**123.7008333**	**60.53425926**	**17.6037037**	**234**	**93.23416667**	**108.0983333**	**1949.230833**	**0.957112425**	**2057.329167**	**1930829.1**	**57949.12179**
5	3567	235.5166667	27.77314815				233.8958333	17.5375	124.0354167	60.52546296	17.77314815	234	93.575	106.5270833	1953.160417	0.955057723	2059.6875	1943577.735	58702.41117
6	3567	235.5166667	27.73611111				233.8875	17.3125	123.9916667	60.59259259	17.73611111	234	93.33958333	129.6583333	1957.1625	0.948267952	2086.820833	1945857.686	58536.77362
initial	23456	**235.5166667**	**28.7962963**				**233.8646667**	**16.188**	**125.5373333**	**60.55851852**	**18.71333333**	**234**	**93.416**	**486.9846667**	**2035.896667**	**0.820806984**	**2522.881333**	**1842116.377**	**59033.42428**
7	23456	235.5166667	29.0537037				233.8633333	16.52166667	126.405	60.53333333	19.0537037	234	93.82166667	481.4083333	2016.043333	0.822039613	2497.451667	1840722.997	58472.69231
8	23456	235.5166667	28.78148148				233.8566667	15.70166667	125.575	60.54814815	18.78148148	234	93.54833333	500.105	2089.845	0.821240148	2589.95	1853687.7	59275.11076
initial	23456	**235.5166667**	**28.7962963**				**233.8646667**	**16.188**	**125.5373333**	**60.55851852**	**18.71333333**	**234**	**93.416**	**486.9846667**	**2035.896667**	**0.820806984**	**2522.881333**	**1842116.377**	**59033.42428**
9	23456	235.5166667	36.09074074				233.6866667	17.74666667	126.67	60.49259259	26.09074074	234	93.22	414.3716667	1847.893333	0.828223636	2262.265	1775055.009	57874.54545
10	23456	235.5166667	27.79814815				233.8783333	15.17166667	124.71	60.51481481	17.79814815	234	93.06166667	510.6466667	2112.903333	0.819616005	2623.55	1858816.181	59989.36235
initial	1234567	235.5166667	**27.67830688**				**233.8814286**	**15.89571429**	**123.212381**	**60.63650794**	**17.61904762**	**234**	**93.26904762**	**495.7895238**	**1600.068571**	**0.729147845**	**2095.858095**	**1993016.383**	**60062.63748**
11	1234567	235.5166667	27.35714286				233.8964286	15.99047619	123.3119048	60.54761905	17.35714286	234	93.66785714	517.8630952	1748.308333	0.731574427	2266.171429	2002642.109	59958.32897
12	1234567	235.5166667	30.13624339				233.822619	15.4952381	123.4321429	62.87698413	20.13624339	234	93.40238095	492.5797619	1574.65119	0.7313149	2067.230952	2054319.347	66487.23334
initial	1234567	235.5166667	**27.67830688**				**233.8814286**	**15.89571429**	**123.212381**	**60.63650794**	**17.61904762**	**234**	**93.26904762**	**495.7895238**	**1600.068571**	**0.729147845**	**2095.858095**	**1993016.383**	**60062.63748**
13	1234567	235.5166667	27.83994709				233.8761905	15.99285714	123.4702381	60.67724868	17.83994709	234	93.4047619	501.9345238	1600.736905	0.726655531	2102.671429	1994389.523	59950.00421
14	1234567	235.5166667	27.92724868				233.8916667	15.69642857	123.5952381	60.6547619	17.92724868	234	93.51428571	493.672619	1625.20119	0.729998802	2118.87381	1996057.265	60361.31513
initial	1234567	**235.5166667**	**27.67830688**				**233.8814286**	**15.89571429**	**123.212381**	**60.63650794**	**17.61904762**	**234**	**93.26904762**	**495.7895238**	**1600.068571**	**0.729147845**	**2095.858095**	**1993016.383**	**60062.63748**
15	1234567	235.5166667	41.91005291				224.8107143	11.80595238	120.9690476	355.2433862	31.91005291	225.2797619	89.6797619	610.8130952	2471.280952	0.749166	3082.094048	1857116.697	61328.82438
16	1234567	235.5166667	28.03835979				233.8761905	13.25952381	124.397619	61.22751323	18.03835979	234	93.5297619	529.7464286	1758.832143	0.737455741	2288.578571	1935722.819	59433.07548
initial	1234567	**235.5166667**	**27.67830688**				**233.8814286**	**15.89571429**	**123.212381**	**60.63650794**	**17.61904762**	**234**	**93.26904762**	**495.7895238**	**1600.068571**	**0.729147845**	**2095.858095**	**1993016.383**	**60062.63748**
17	1234567	218.2916667	25.89285714				217.275	15.81071429	113.5083333	52.90740741	16.68386243	217.5309524	86.77261905	447.2130952	1458.622619	0.727531019	1905.835714	1892774.505	53428.38333
18	1234567	259.025	35.22089947				249.6666667	14.89761905	134.3261905	314.3267196	25.22089947	249.997619	100.2190476	580.0404762	2080.552381	0.739202753	2660.592857	2118302.466	89508.79977

experiment	handled scenarios	NumberOfOverrules	TotalPenaltyCosts	TotalAssignmentCosts	Average Truck Costs per day	Average transportation costs	Total transportation costs	AverageTimeAtCTT	AverageTimeDrivingToClient	AverageTimeDrivingFromClient	AverageTimeAtclient	AverageTurnaroundTimeUncoupling	AverageturnaroundTimeUnloading	AverageAuctionValue	TotalTravelledDistance	TotalTravelledDistanceLoaded	TotalTravelledDistanceunLoaded
initial	234567	**158.578**	**2507.466667**	**3246.564444**	**431558.9447**	**16479.94467**	**988796.68**	**1.09215861**	**0.51182528**	**0.313139092**	**5.489112383**	**7.915987359**	**2.549696164**	**1087030.895**	**2810922.416**	**1901676.247**	**913178.6299**
1	234567	96.49166667	2550	3241.311111	448405.7422	16944.28667	1016657.2	1.098265607	0.512418493	0.315115455	5.518819377	7.93650329	2.569366173	1069607.186	2778583.205	1902609.086	875974.1198
2	234567	140.87	2512	3237.777778	429389.9025	16423.08833	985385.3	1.090891007	0.510996042	0.313339987	5.604592955	8.029076459	2.548354623	1083386.996	2794472.26	1903774.229	890698.0314
initial	2356	**158.6708333**	**2517.833333**	**3327.716667**	**430818.5183**	**16552.20667**	**993132.4**	**1.09204334**	**0.513016491**	**0.3112239**	**5.488767222**	**7.915350701**	**2.548507429**	**1085383.237**	**2811709.274**	**1901323.157**	**915301.6933**
3	2356	116.1395833	2525.833333	1171.375	457658.4886	15069.92292	904195.375	1.106931612	0.497709825	0.306324065	5.108896176	7.529758593	2.542197572	1061748.136	2849709.146	1901880.455	947828.6913
4	2356	117.975	2515.208333	1561.083333	459120.4408	15492.03333	929522	1.107822222	0.502449043	0.308647746	5.148734762	7.580392337	2.548632425	1066393.358	2847337.915	1901673.687	945664.2288
initial	3567	**111.6558333**	**2492.75**	**720.6555556**	**451074.1091**	**14423.13417**	**865388.05**	**1.10571505**	**0.490695293**	**0.30172229**	**5.06671068**	**7.478044421**	**2.528756272**	**1052416.843**	**2847196.758**	**1901089.046**	**951023.2888**
5	3567	110.425	2475.416667	710.1805556	453988.0233	14472.42708	868345.625	1.105807508	0.491915383	0.302329087	5.065731624	7.48471522	2.52609345	1052382.765	2851129.644	1905396.287	945733.3569
6	3567	113.99375	2455.833333	864.3888889	454579.8462	14618.3375	877100.25	1.106875333	0.496113514	0.303927704	5.078568681	7.491014349	2.542250176	1056481.579	2851271.809	1905793.869	945477.9391
initial	23456	**158.578**	**2507.466667**	**3246.564444**	**431558.9447**	**16479.94467**	**988796.68**	**1.09215861**	**0.51182528**	**0.313139092**	**5.489112383**	**7.915987359**	**2.549696164**	**1087030.895**	**2810922.416**	**1901676.247**	**913178.6299**
7	23456	152.88	2538.5	3209.388889	430633.5609	16461.385	987683.1	1.090519988	0.513311545	0.313573225	5.534260516	7.956927469	2.55215191	1085515.954	2803523.335	1903978.629	899544.7058
8	23456	164.68	2504.5	3334.033333	433780.5367	16630.74667	997844.8	1.092217662	0.517122359	0.313269652	5.502900971	7.94052548	2.551528428	1091972.383	2819016.427	1904311.493	914704.9338
initial	23456	**158.578**	**2507.466667**	**3246.564444**	**431558.9447**	**16479.94467**	**988796.68**	**1.09215861**	**0.51182528**	**0.313139092**	**5.489112383**	**7.915987359**	**2.549696164**	**1087030.895**	**2810922.416**	**1901676.247**	**913178.6299**
9	23456	131.7766667	2642.5	2762.477778	416110.8687	15748.66833	944920.1	1.090568082	0.505418901	0.314549469	7.12678159	9.534613239	2.551343743	1067094.349	2734272.667	1905725.732	828546.935
10	23456	166.585	2487.166667	3404.311111	435112.0738	16718.13167	1003087.9	1.092217362	0.510670812	0.313080123	5.339606784	7.763433044	2.55033059	1091768.427	2831229.598	1906258.849	924970.7492
initial	1234567	**113.27**	**2486.380952**	**3305.263492**	**465567.8009**	**17364.46857**	**1041868.114**	**1.109082552**	**0.512660362**	**0.311111578**	**5.120650918**	**7.552222344**	**2.572999763**	**1066493.978**	**2847090.435**	**1901832.962**	**948066.3737**
11	1234567	115.9678571	2490.357143	3452.420635	467989.7034	17568.20714	1054092.429	1.093839145	0.515194178	0.311761913	5.032553366	7.458255829	2.55608827	1071658.73	2856287.971	1905500.075	950787.8953
12	1234567	116.6714286	2574.642857	3283.865079	481633.263	17825.44167	1069526.5	1.163757149	0.511389609	0.310017498	5.42872125	7.903087511	2.631483219	1071079.63	2849074.735	1905269.719	943805.016
initial	1234567	**113.27**	**2486.380952**	**3305.263492**	**465567.8009**	**17364.46857**	**1041868.114**	**1.109082552**	**0.512660362**	**0.311111578**	**5.120650918**	**7.552222344**	**2.572999763**	**1066493.978**	**2847090.435**	**1901832.962**	**948066.3737**
13	1234567	125.9035714	2479.166667	3346.230159	465681.1736	17404.90714	1044294.429	1.108603411	0.513135153	0.313243604	5.176258839	7.612825047	2.572871419	943250.7142	2849263.89	1905321.699	943942.1908
14	1234567	110.5630952	2489.047619	3291.150794	466444.8733	17372.40714	1042344.429	1.108319696	0.51382491	0.31135813	5.192881028	7.628397173	2.571009219	1193298.142	2844322.109	1904963.268	939358.8411
initial	1234567	**113.27**	**2486.380952**	**3305.263492**	**465567.8009**	**17364.46857**	**1041868.114**	**1.109082552**	**0.512660362**	**0.311111578**	**5.120650918**	**7.552222344**	**2.572999763**	**1066493.978**	**2847090.435**	**1901832.962**	**948066.3737**
15	1234567	260.6285714	2275.952381	4072.087302	436577.4132	17176.41548	1030584.929	1.258451519	0.500247477	0.299499152	8.160168167	10.67445436	2.726141598	983424.0179	2773788.436	1832510.336	941278.1002
16	1234567	142.3857143	2533.928571	3531.642857	452748.0578	17314.85	1038891	1.117569932	0.514732786	0.306435623	5.308128825	7.740539035	2.581830265	1051246.488	2835106.069	1904409.86	930696.2086
initial	1234567	**113.27**	**2486.380952**	**3305.263492**	**465567.8009**	**17364.46857**	**1041868.114**	**1.109082552**	**0.512660362**	**0.311111578**	**5.120650918**	**7.552222344**	**2.572999763**	**1066493.978**	**2847090.435**	**1901832.962**	**948066.3737**
17	1234567	100.652381	2297.261905	2981.420635	441047.1119	16239.31786	974359.0714	1.089388344	0.510373243	0.311144701	5.116164579	7.525518124	2.551063367	985132.5226	2671568.289	1771873.552	899694.7367
18	1234567	188.5047619	2470.952381	3866.936508	503466.0181	18852.12857	1131127.714	1.159434341	0.520766038	0.30772938	5.823739752	8.297033149	2.635706637	1156478.968	3047317.251	2033601.272	1013715.979