Dimitrios Karampelas

Evaluating cooperation policies for rail utilization in the port to hinterland freight transport system

A combined method approach

Thesis report
M.Sc. Transport, Infrastructure and Logistics
Delft, September 2018.

Evaluating cooperation policies for rail utilization in the port to hinterland freight transport system

A combined method approach

By

Dimitrios Karampelas

in partial fulfilment of the requirements for the degree of

Master of Science

in Transport, Infrastructure and Logistics

at the Delft University of Technology,

to be defended publicly on Thursday October 11, 2018 at 4:00 PM.

Student number: 4595092

Project duration: March 2017 – September 2018

Thesis committee: Prof. dr. ir. L. A. Tavasszy

Delft University of Technology

Faculty of Technology, Policy and Management (TPM)

Dr. M. Y. Maknoon

Delft University of Technology

Faculty of Technology, Policy and Management (TPM)

Ir. M. B. Duinkerken

Delft University of Technology

Faculty of Mechanical, Maritime and Materials Engineering (3mE)

Daily Supervisor: Dr. ir. I.K. Kourounioti

An electronic version of this thesis is available at http://repository.tudelft.nl/.

Front page image: Train transporting containers from port to hinterland.
source: https://www.naftemporiki.gr by EUROKINISSI/PANAGOPOULOU GEORGIA

Preface and Acknowledgements

The thesis project that is presented in this report is the final part to obtain the Master of Science in Transport, Infrastructure and Logistics of TU Delft. This project aims to perform a scientific research by applying the knowledge acquired by the Master's courses. The present work initiated on March 2017 in TU Delft, as part of the synchro-gaming project of the faculty Technology, Policy and Management. The study conducted to fulfill this thesis required a wide range of methods and knowledge to be applied that helped me improve my skills in different levels: from the use of methods to programming (coding) and time management.

At this point, I would like to express my gratitude to the people that assisted me on completing this Master thesis project. Especially, I would like to acknowledge and extend my gratitude to Dr. ir. I.K. (Ioanna) Kourounioti for providing the topic and for her essential guidance. Additionally, I would like to thank the committee of my thesis. The comments of the chairman Prof. dr. ir. L. A. (Lóránt) Tavasszy and the discussions with my supervisors Dr. M. Y. (Yousef) Maknoon and Ir. M. B. (Mark) Duinkerken were of great help.

Furthermore, I would like to acknowledge the support provided by Nikiforos, Dionysia, Giorgos Ch., Afroditi, Sotiris, Giorgos Tz., Konstantinos, Eleni and Vasilis and their help on organizing and participating in the gaming sessions of this thesis, as well.

Finally, I would like to thank my family Nikos, Giota, Nicole and Dimitra for their efforts and support all these years and Chris for being an inspiration and guide for my engineering path.

D. N. Karampelas

Delft, 27th September 2018.

Contents

List of Tables

List of Figures

Executive summary

Every company and organization is trying to achieve the highest possible profits while catching up with government regulations. After the COP21 agreement on the environment and the aim of European Union to reduce climate gas emissions by 80-95% until 2050, and specifically in transport related emissions by 54-67% comparing to 1990 (European Commission, 2011), current solutions proved to be inadequate for the companies and transportation firms. For this reason, several concepts have been proposed for freight transportation to promote sustainability. Researchers have introduced synchomodality concept as a development of "traditional" intermodal and multimodal concepts.

In order to achieve the optimal level of synchronized services, collaboration between all stakeholders is required (Tavasszy and De Jong, 2013) and cooperation is one of the prerequisites of synchromodality (Singh et al., 2016). However, in reality every actor operates for his individual profits and benefits and as a result, the relationship between them is competitive rather than cooperative. Thus, currently, system's performance assumed to be closer to the non-cooperative point. By the intervention of different policies in the negotiations and information sharing, the aim is to move closer to the optimal solution.

This work intended to find, test and evaluate the right interventions to move towards collaboration of the actors in order to have an efficient freight transportation system. The general framework that was followed in this thesis is based on the combination of gaming and simulation as used by Kurapati et al. (2017) and Kourounioti et al. (2018) enhanced by an optimization model. This framework was used iteratively in order to test and evaluate different policies and their level of performance.

This study combined the three methods of gaming, simulation and optimization in order to extract the advantages of each method while avoiding their disadvantages in the highest possible level.

At first, the game sessions were useful to observe and record the current performance of the players and used to define the simulation model of the game, based on real data. The decisions of the actors in simulation were modeled using utility function and Discrete Choice Modelling (DCM). Subsequently, a number of policies were proposed using literature review and expert interviews and tested using the simulation model. Their performance was then compared with a possible coordinated system that included stochasticity and with the upper bound that was set by the optimization model.

The outcomes led to the conclusions that fine and subsidy policies do not have a significant effect on utilization rate of the trains and the reduction of used trucks and thus they found to be inadequate measures. Furthermore, the cooperation between the train operators to co-decide which terminals-destination to service is the policy with the highest performance, between the policies that included one kind of actors (only horizontal collaboration). Simple vertical collaboration (alliance of freight forwarder and one operator) has even negative impact on the performance, as it reduces the transport options of the alliance members. Subsequently, the results of the policy testing show that the higher the level of collaboration the more the performance improved. The alliance between freight forwarders to consolidate their freight and the trade of containers between operators apart do not have high impact on the performance, but the combination of these two interventions achieves much better results. The highest level of cooperation, that is simultaneous collaboration in vertical and horizontal dimension, lead to the highest performance among the policy alternatives. However, this performance could not reach coordinator's performance as there was still competition for the unconsolidated containers.

1. Introduction

This introduction chapter describes the aim of this thesis, addresses the research intentions and the identified problems and presents the approach to be followed in order to contribute in the research topic of freight transportation and more specifically in port to hinterland freight transportation.

1.1. Port to Hinterland freight transportation

1.1.1. General Introduction

Every company and organization is trying to achieve the highest possible profits while catching up with government regulations. After the COP21 agreement on the environment and the aim of European Union to reduce climate gas emissions by 80-95% until 2050, and specifically in transport related emissions by 54-67% comparing to 1990 (European Commission, 2011), current solutions proved to be inadequate for the companies and transportation firms. Focusing on the ports and the freight transport to hinterland terminals, there is an ongoing necessity for modal shift towards more environmentally friendly modes in transport. Many European Port authorities are aiming to reduce truck-use and have cargo transported by rail or barge. Largest Europe's ports as port of Rotterdam and Antwerp have set truck reduction targets of 15-20% until 2035 and 2020 respectively, while port of Hamburg has set a target of 5% shift from truck to rail until 2025 (Van den Berg and De Langen, 2014). For this reason, several concepts have been proposed for freight transportation to promote sustainability. Researchers have introduced synchomodality concept as a development of "traditional" intermodal and multimodal concepts.

1.1.2. Synchromodality

Synchromodality is "*a concept of optimising all network transportation in an integrally operated network, making of all transportation options in the most flexible way*." (Van Riessen et al., 2015). Furthermore, synchromodal concept is described as a freight transport system that provides a service independent of the mode, but as a range of customized services and requirements (figure 1) (Tavasszy et al., 2015). As described by Behdani et al. (2014) synchromodal transportation promotes an integrated view of freight transport in two dimensions, vertical and horizontal, as illustrated in figure 2. "Vertical" dimension describes the integration of the logistic services (e.g. same shipping bill) while the "horizontal" dimension refers to the integration of the modes that are used for transport. As there are several papers that focus on the vertical integration of logistic services, the main distinctive feature of synchromodality is the horizontal dimension (Behdani et al., 2014), that integrates the transport service on different modalities as one transport mode.

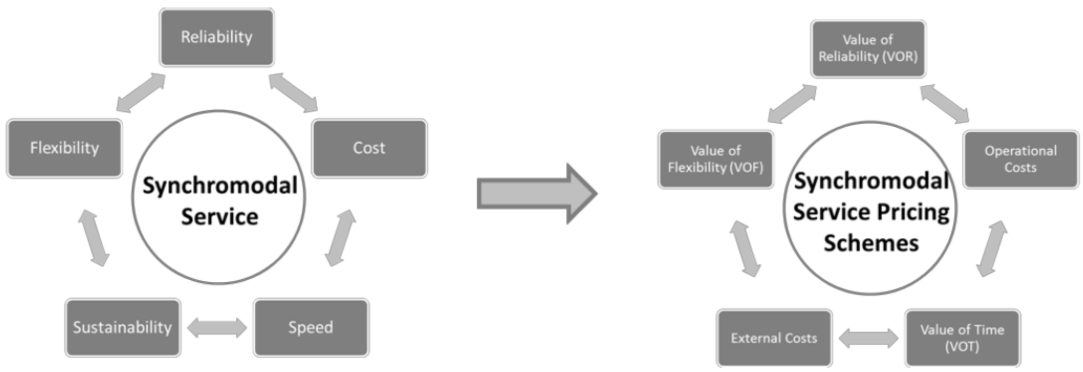


Figure 1 Synchomodality as a set of services and requirements (Tavasszy et al., 2015)

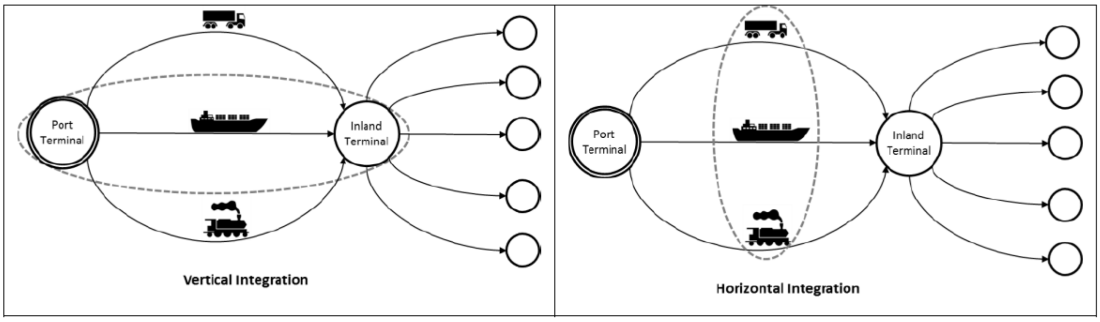


Figure 2 Integrated freight transportation view (Behdani et al., 2014).

A key factor to make synchromodal concept feasible and successful is the cooperation of the involved actors (Pfoser et al., 2016). However, these actors have much different businesses and involved in different aspects of freight transportation, as can be seen in the "TRAIL layer model" in figure 3 (Kurapati et al., 2018). This diversity of the actors makes their coordination a difficult task but can lead to potentially high benefits for all of them (Pfoser et al., 2016).

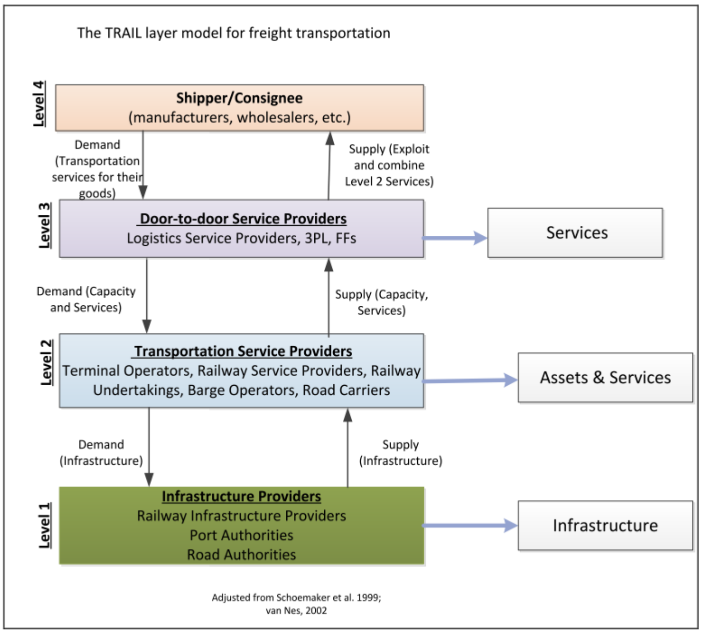


Figure 3 The TRAIL layer model (Kurapati et al., 2018)

1.2. Problem definition and research questions

After the presentation of the general context, the problem definition and the research gaps follow.

1.2.1. Problem statement

As stated in chapter 1.1.2. cooperation is one of the key success factors of new transport systems as synchromodality. In order to achieve the optimal level of synchronized services, collaboration between all stakeholders is required (Tavasszy and De Jong, 2013) and cooperation is one of the prerequisites of synchromodality (Singh et al., 2016). However, in reality every actor operates for his individual profits and benefits and as a result, the relationship between them is competitive rather than cooperative. Pfoser et al. (2016) mentions that many companies are not willing to cooperate with their competitors and a mind shift towards collaboration is needed, as it is a critical success factor of synchromodality.

The need for cooperation is also addressed by Kourounioti et al. (2018), focusing on the in-game behavior of the Rail Cargo Challenge Rotterdam (RCCR) board game, who states "*Game playing results show that the inability of stakeholders to cooperate results in lower profits and lower reputation rates.*" (Kourounioti et al., 2018). There are several studies to record the preferences of the actors in synchromodalilty using games (see Kurapati et al. (2018); Kourounioti et al. (2018); Buiel et al. (2015)). However, there are not many papers that extent the gaming tool to test and evaluate different policies in freight transportation. This is proposed as future research by Kurapati et al. (2017) by changing parameters of the game and capture the effects on the performance indicators. This could give deep insight of different policy interventions (Kurapati et al., 2017). This is also an aim of this thesis: to investigate gaming as a policy validation tool.

As can be conducted, the identified gap is the in-game implementation of the right interventions to move towards collaboration of the actors in order to have an efficient freight transportation system.

Combining the aforementioned aspects, this thesis will try to find and implement cooperative policies that will move players' performance in the game RCCR as close to optimality as possible. The aim of these policies is to align the individual benefits of actors with the overall goals of the port to hinterland freight transport system.

1.2.2. Research questions

The research questions and sub-questions that arise after the description of the relative topics and problem statement are related to a transport system that promotes actors' collaboration and services' coordination, aiming to the efficient system operation on port to hinterland transportation. In addition, the use of innovative methodology of the combination of gaming, simulation and optimization is examined. In that way there are two main aspects of the thesis. The first tries to fill a more theoretical gap in literature, related with the impact of different policies on performance, and the second is associated with a more practical issue of using gaming as a policy validation tool. The research is based on the Rail Cargo Challenge Rotterdam, which was initiated by Port of Rotterdam to identify the causes of low utilization of rail alternative, which is assumed as a sustainable mode comparing to truck.

Summarizing, the research questions and the sub-questions are related to the identified gap and the innovative methodological approach that are:

- Policies towards collaboration that will lead to an efficient freight transport system in port to hinterland.
- Apply an innovative methodological approach in a hybrid framework that combines gaming, simulation and optimization to test and evaluate policies.

The objective of this thesis that is relevant to the problem statement and the identified gaps is set as:

The research objective is to examine cooperation policies between the involved actors that can lead to a higher level of performance in port to hinterland freight transport system, using a mixed method based on gaming to test and evaluate these policies.

The main research questions connected to the research gaps is:

RQ1. "How can we achieve a higher level of performance through cooperation in the port to hinterland freight transport system?"

RQ2. "To what extent can we combine gaming with simulation and optimization to test and evaluate these policies and strengthen game application?"

And the sub-questions are:

SQ1. Which are the most relevant policies for cooperation?
SQ2. What is the highest achievable in-game performance under full information and no stochasticity?
SQ3. What can be the in-game performance of a coordinated system including stochasticity?
SQ4. How the selected policies influence the overall in-game performance relative to the highest achievable performance?
SQ5. Can the configuration of game rules, according to specific policy plans, affect players' performance in the expected way?

1.3. Methodological Approach

1.3.1. Methodological framework

Gaming gives the opportunity to be used for testing and evaluation of new operating procedures that are required for the cooperation of the actors, as stated in the recommendation for future research in the work of Buiel et al. (2015). As mentioned in subsection 1.2.1., this potential extension of the gaming tool is also addressed by Kurapati et al. (2017).

The general framework that will be followed in this thesis is based on the combination of gaming and simulation as used by Kurapati et al. (2017) and Kourounioti et al. (2018) for capturing the behavior and decision making of the stakeholders in gaming sessions for synchromodality. At first the games are used to let participants express their attitudes and preferences and then the simulation metamodel is developed using the same design of the game and the observed choices of the players (Kourounioti et al., 2018).

In this thesis the aforementioned framework will be enhanced with an optimization model in order to set a base for comparison and it will be used iteratively in order to test, evaluate and validate different policies and their level of performance. The optimized performance will set the upper limit and will be used as a reference point for comparison. The general framework can be seen in figure 4.

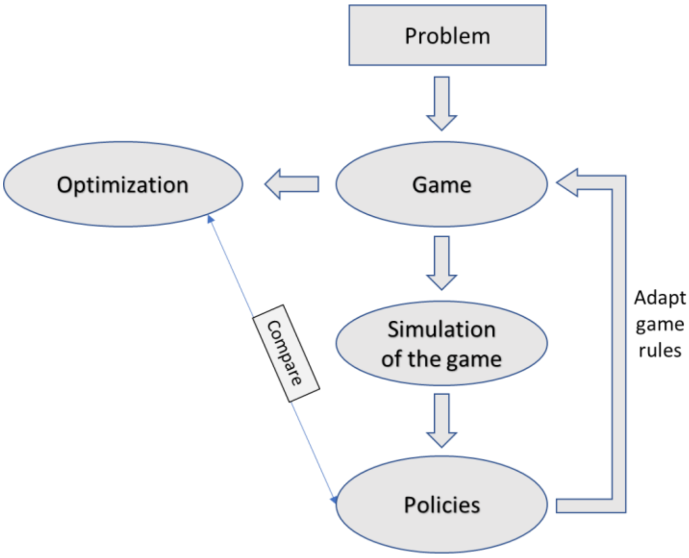


Figure 4 General framework

Based on the general framework a more detailed description of the methodological framework that will be followed is shown step by step in figure 5 and is described in this paragraph. The first step is the development of the game. The Rail Cargo Challenge Rotterdam board game is already developed and some game sessions have already been done (see Kouronioti et al., 2018 ; Kurapati et al., 2017). After the development of the game, two independent branches follow. The first branch is associated with the creation of a reference point of the highest possible performance aiming in a system optimum state while the second branch includes observation and simulation of actors' behavior, behavioral policy implementation and evaluation. The "highest", reference point is needed to compare the policy alternatives. The planning to achieve this highest performance could be done by a coordinator that would have access to all the available information and could bypass the negotiations of actors, that lead to an inefficient system. The decisions of the coordinator are only based on the efficient planning to achieve system optimality and not to maximize individuals' profit. Subsequently, the steps on the second branch aim to find policies and incentives that will move actors towards more cooperative behavior and through cooperation and information exchange could approach the "optimal" system performance that was mentioned above. In order to achieve this, several steps will be applied. First, game sessions are organized to observe players' behavior and performance. Observations captured in these sessions are used to develop a simulation model of the behavior of the players in the game (representation of in-game behavior) (step 2). For these two steps there is already some data available, as mentioned previously, from the research of Kurapati et al. (2017) and Kourounioti et al. (2018). The first simulation approach of RCCR, found in the work of Kurapati et al. (2017), uses probabilistic distributions of negotiated prices accepted by the train operators in-real games. In that way the negotiations are expressed by randomly drawing prices from these distributions and compare them with the respective prices of the freight forwarders. In this thesis, the simulation model will be approached much differently, using modeled behavior and not by comparing probabilistic values. The third step of this branch is to find policies that can influence players' behavior towards collaboration. Subsequently, depending on the policies that will be chosen, the simulation model will be changed to identify the respective changes in performance (step 4). Simulation is used here as it is relatively easier and faster to change parameters and identify the results comparing to gaming. Then, a comparison of this performance with the reference performance (in coordinated system) is done (step 5). This simulation modification and performance comparison will be done for all the selected policies. After this iterative process, an evaluation of the results follows (step 6). The best of the above policies will be selected to be used in game sessions with changed player behavioral rules (step 7-9). Their new performance will be then measured and compared to the highest achievable score found by the optimizer of the game. In this way, it will be examined if the policies have the desired outcomes on actors' choices and if this performance was in accordance with the simulation model.

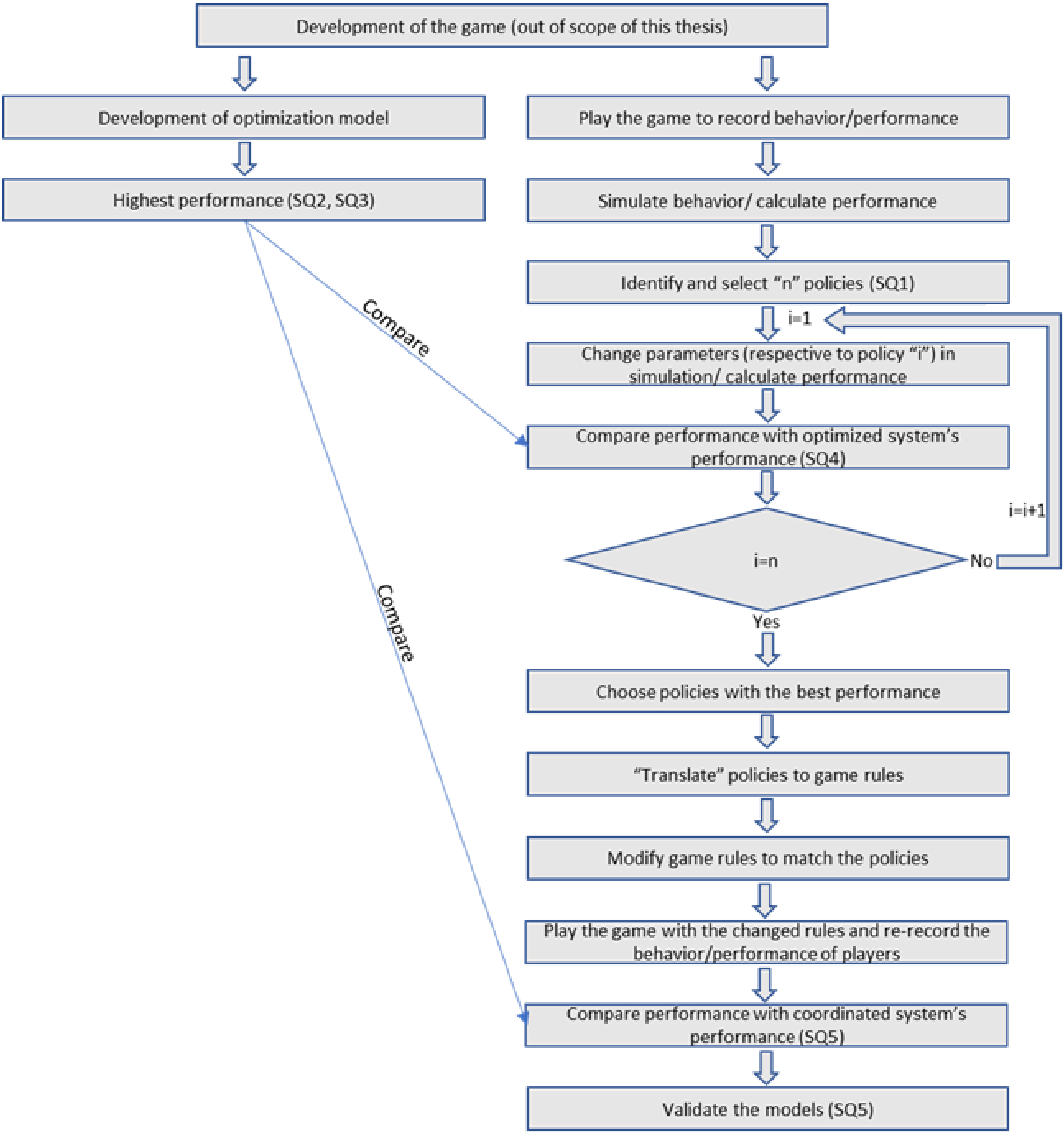


Figure 5 Methodological Framework

In addition to the main methodological framework, in order to simulate the behavior of the players, Discrete Choice models (see Ben-Akiva et al., 1985; Bierlaire, 1998) in dynamic environment (e.g. negotiation rounds between the players) will be used to describe the decision making of the actors. According to Ben-Akiva and Lerman (1985) Discrete Choice analysis is the most used methodology for travel decisions and mode choice.

Furthermore, the optimization model will be based on the Service Network Design models (SND) (see Andersen et al., 2007; Crainic, 2000) when using full information, while a Model Predictive Control (see Camacho & Alba, 2013; Kouvaritakis & Cannon, 2016) combined with SND will be used to describe a possible coordinated system that includes stochasticity and decision making under partial information.

In figure 6 the comparison framework can be seen, which is the insight for the methodological framework. At the top point is the system optimum achieved by using full information. At the bottom position is the performance in a non-cooperative system. The system performance lays in the line between these two points, depending on players' decisions and stochasticity. Currently, system's performance assumed to be closer to the non-cooperative point. By the intervention of different policies in the negotiations and information sharing the aim is to move closer to the optimal solution.

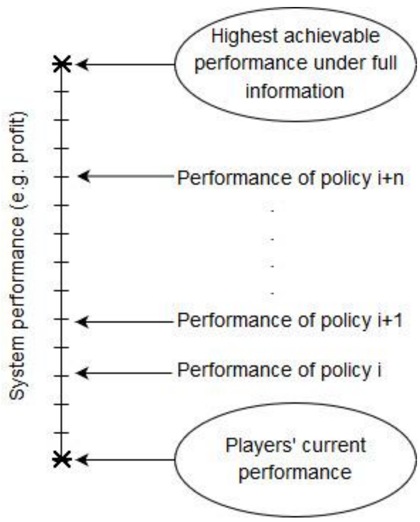


Figure 6 Comparison framework representation

In order to have a stable base of comparison, it should be ensured that the policies are only associated with the behavioral rules that affecting the negotiations of the players. In that way, the service options in the network and the resources that can be inputted on the system (e.g. shippers' prices) do not change. Thus, the optimal level of system performance achieved by the coordinator is not changing as the collaboration policies are implemented.

1.3.2. Research Methods

This section includes the description and approach of the used methods of this study, the reason why each method is used and what are the desirable outcomes that each method can contribute over the others.

The three main methods for the analysis that are used in this study are gaming, simulation and optimization. Literature review is also used to support the choices and the content of the methods. In the next subsections each of the gaming, simulation and optimization methods are described and after this a summary of the pros and cons of each method follows.

Input and output of the models

In order to have a connection and a valid comparison between the results of the models the units of inputs and outputs are the same for gaming, simulation and optimization model. However, the different decision process in the models on how the inputs will be handled lead to different values of outputs, but in same units.

The main input of the models is a number of container orders that have to be transported from their origin port terminal to their destination. The orders have stochastic characteristics, as day of release, day of expire, origin-terminal and destination.

The outputs of the models are the decisions on when and by which mode each container will be transported. The efficiency of these decisions is quantified in two performance indicators: profit and truck-use.

The inputs, outputs and the KPI's of the models are further described in the next chapters that the models are presented in detail.

Gaming

The base method that is used to represent the port to hinterland freight transport system and actor's behavior in this study is gaming.

Games are used from practitioners to better understand the value of flexibility in freight transport and by educational institutes to teach intermodal container logistics (Van Riessen, 2018). Furthermore, gaming is used as a way to raise actor's awareness towards new transport systems as synchromodality that is expected to increase efficiency in freight transportation (Kourounioti, 2018). This tool (gaming) has three objectives for synchromodality according to Buiel et al. (2015):

1) Let the actors experience synchromodal planning,

2) Show to the actors the benefits and

3) Achieve the mind shift towards cooperation between actors.

The game that is used is Rail Cargo Challenge Rotterdam. Rail Cargo Challenge Rotterdam is a game developed by TU Delft gamelab, The Barn, ProRail and TNO within the "Synchro-gaming" project (TU Delft gamelab site, 2018) and in collaboration with stakeholders of port of Rotterdam.

Acoording to Kourounioti et al. (2018), *"The key research objective of the Rail Cargo Challenge Rotterdam (RCCR) is to assess the attitudes and behavior of stakeholders in the freight transport domain with respect to the efficient bundling of containers to be transported to their final destination using rail".*

For the purposes of this study, three gaming sessions were organized. The first two sessions were useful to understand actors' behavior and collect data. The third gaming session was used to validate the results of the implementation of a chosen policy and identify if the players responded on the expected way on the changed rules.

Gaming has the advantage that can give an actual – and not modeled- human behavior, while can also provide a discussion with the actors on the results and their individual reflection on the system operation. The main disadvantages of gaming, is that it has a high simplification level compared to the "real" world and it is difficult to take many samples, due to the availability of players and the gameplay time itself. As an indication a gaming session of RCCR game requires at least 5 players and 1 game master and has a duration of about 3 hours.

Due to the low availability of the stakeholders, the gaming sessions were not organized with relevant industry players, but with TU Delft's students.

More information about the RCCR game follow in chapter 2.2. and in Appendix A.

Simulation

The simulation model is used as a representation of the game. The simulation model gives the opportunity, by changing simulation structure or parameters, to model different game scenarios according to new policies, without the need of organizing multiple gaming sessions. Of course, ideally all the scenarios would be more realistic to be tested in gaming sessions, but due to time restrictions, the simulation alternative is preferred. A sample of 100 simulation runs lasts a few minutes, while only one game session needs 2.30-3 hours.

A first approach of a simulation meta-model of RCCR game was done by Kurapati et al. (2017). In their study, the simulation is based on a probabilistic comparison of the proposed prices in the negotiation phase between the players.

In the current study, the simulation model is approached differently than the aforementioned work. First, the flowchart of the game was structured and the simulation model was made according to the game steps. A very important element lays on the decision making of the players on what mode to choose, during the negotiation phase of the game. These decisions are modeled using Discrete Choice Modeling and specifically the Multinomial Logit model (MNL). According to Ben-Akiva and Lerman (1985) Discrete Choice analysis is the most used methodology for travel decisions and mode choice. In addition, the proposed negotiation prices were drawn from a distribution, using observed prices from gaming sessions.

The disadvantage of the simulation is the fact that it is a model of the game, that is already an abstraction of reality. However, this method is used due to the convenience of testing different alternatives in a very short time, compared to gaming.

The simulation model was coded in python 2.7. The parameters used for the Discrete Choice model were based on observed data from gaming sessions and were estimated using the software BIOGEME 1.8 (see Bierlaire, 2008). BIOGEME package is distributed free in order to develop the research area of Discrete Choice Models (Bierlaire, 2003).

More detailed description of the simulation model, the flowchart, utility functions, parameter results and player decision rules can be found in chapter 3.3. and Appendix B.

Optimization

Optimization model is used in order to find the upper bound of performance and identify the potential benefits of a coordinated or fully-cooperative system.

Two approaches of optimized performance are used in this study. The first model uses full information, excludes stochasticity and sets the upper bound, while the second uses only the exact information that players have and gives a coordinated system perspective. The second model can be also assumed as a policy measure of a central coordinator and is closer to the simulation of the game, as the coordinator takes the decisions per round. However, as the coordinated model is based on optimization and does not include human behavior, it is described with the optimization part.

The first model, referred as optimization model, assesses all information of the system and excluding stochasticity by taking the results of the stochastic elements as input. This optimization model has no physical meaning, as excludes stochasticity, which is not realistic. However, the practical usefulness of the model is that sets the theoretical upper bounds of the game performance in each case, in order to quantify the potential for system improvements and set a basic element for comparison between the different policy scenario. In a way the optimization model can give a quantification of how “worse” is the planning of the players compared to the highest performance that they could have achieved, with the specific demand and resources.

The second model, referred as coordinator's model, is a combination of the aforementioned optimization model and a Model Predictive Control (MPC). This model has a "physical" translation and represents a version of a coordinated system that assesses only the available information each time. The information of the coordinator is exactly the same as players' information and released at the same time that become available to the players, as well. As a result, coordinator's performance falls under stochasticity, too. The difference of the coordinated system and the current system is that the coordinator takes decisions to maximize system's KPIs and bypasses players' negotiations that lead to inefficient decisions for the system.

The main difference of the two models is that the optimization model guarantees the highest performance, given the same input, as makes the planning under full information and no stochasticity. On the other hand, MPC coordinator takes and performs the decisions on each round separately under stochasticity. This makes coordinator's performance lower compared to the optimized performance. However, this difference can give an insight of the impact of the stochastic elements on performance and, consequently, separate this difference with the impact of players' negotiations.

In order to compare the simulated results with the performance of the optimization model that assess full information, first the simulation model was executed for one sample, the information for the stochastic elements were saved and then the optimization model was executed with all the information as input. This was used to find the highest possible performance for this sample, with the specific number of orders, order characteristics and stochastic element outcomes. It becomes obvious, that the performance of the optimization model does not take one single value, but depends on the input that differs for each sample.

On the other hand, the coordinated system's model (MPC) was executed after each simulation step (game round) and not at the end of the sample. In this way the coordinator had as input exactly the same information at each round as the simulation model -and the players at each round- and not full information, as the optimization model. In this way the coordinator included the uncertainty of the stochastic elements and can be assumed as a special case of policy of centralized control center, that bypasses players' negotiations.

The optimization approach is based on the arc-based Service network design or "capacitated multicommodity network design" (CMND) as described by several articles (Andersen et al., 2007; Crainic, 2000) with some adaption.

Coordinator's decisions on the coordinated system's model are based on the aforementioned optimization model combined with Model Predictive Control (see Camacho & Alba, 2013; Kouvaritakis & Cannon, 2016). The main elements that are used from the MPC is that the coordinator makes the planning for a planning horizon (e.g. four rounds) by assessing all the currently-available information, but applies only the decision for the current round. Every new round that new information become available to the system, a new planning is done for the planning horizon. In this way, stochasticity is handled as the disturbances on the MPC concept (see Kouvaritakis & Cannon, 2016).

The optimization model and coordinator's model were first formulated as Linear Programming problems using mathematical terms and then solved in python 2.7 using the external library and application programming interface (API) of IBM CPLEX.

Optimization model and the coordinated system model, their approach and mathematical models are presented in Chapter 4.

Pros and Cons of each method

The different methods have several advantages and disadvantages that are summarized in this subsection.

First, gaming is used to enable the stakeholders identify their problems and observe operational complications that lead to inefficiency. Also, it helps researchers to observe human behavior and decision making of all actors and their interactions from multiple sides on the same time, something that it is difficult to capture in real operations. In addition, it allows for different scenarios testing (e.g. policies interpreted into game rules) in a controlled environment and low cost, compared to real operations testing. As Bradley et al. (1977) notes, gaming has lower implementation costs, which allows for the test of performance of different alternatives with the participation of the actors and decision makers. Furthermore, it is a more entertaining and "relaxed" method that engage stakeholders to express their preferences easier comparing to more traditional data collection methods, as surveys. On the other hand, it is a time-consuming method for the participants and combined with the low availability of the stakeholders, leads to limited possibilities for high number of samples. Another disadvantage of gaming as research method is the high level of abstraction compared to the "real" world. However, as all models are a simplification of the system that they represent, the games should also be handled as a model that serve specific purposes (e.g. behavior observation) and not as an exact representation of the system.

The second used method, simulation, allows for a high number of samples in lower time than game sessions. This is the main reason that is used as a supplementary method in this study. Simulation can also be adapted easily to new scenarios in order to quantify their performance. However, it is a model of the game, which is already a simplification of reality. Another disadvantage is that the behavior of the players is modeled with Discrete choice model and is not a "real" behavior, as in gaming.

Optimization model gives the highest achievable performance and can act as a guide to the players for the best allocation of the resources (e.g. train capacities) and the decisions that lead to a more efficient system. The main disadvantage of the optimization model is that it does not include any human behavior.

On tables 1-3 the advantages and disadvantages of each method are summarized. As can be seen on these tables, most of the disadvantages of one method are covered by the other methods. This is the reason why all of these methods were chosen to be combined: To extract the advantages of each method while avoiding their disadvantages in the highest possible level.

Table 1 Gaming pros and cons

Gaming	
+	-
Stakeholders can identify their problems and observe operational complications	Time consuming (compared to simulation)
Observe behavior, test policies and raise awareness	Limited sample
More fun and relaxed way to engage stakeholders	Higher level of abstraction

Table 2 Simulation pros and cons

Simulation	
+	-
Allows for high sampling in low time	Models the game which is already an abstraction of the “real” world
Allows for different scenarios modeling	Behavior is modeled and not “real”

Table 3 Optimization pros and cons

Optimization	
+	-
Sets the upper bound for performance	Does not include behavior
Gives insight on the optimal decisions for the system	

1.3.3. Approach for each research (sub)question

In this chapter the approach to answer each of the sub questions that will lead to the answer of the main research questions is given.

SQ1. Which are the most relevant policies for cooperation?
In order to find the relevant policies for collaboration in port to hinterland transportation literature review was used. Additionally, some expert consultation relevant to the topic was required to answer this sub question. In that way different policy scenarios can be structured. This sub-question is answered by using literature of Chapter 2 and presented in Chapter 5.

SQ2. What is the highest achievable in-game performance under full information and no stochasticity?
In order to find the highest possible performance, the RCCR game is used and an optimization model for this game is developed, assessing full information at the end of each game and including the results of the stochastic elements, thus excluding stochasticity. In this way, the specific performance gives the upper bound of the comparison framework, that cannot be exceeded, given the same input. The answer of this sub-question is in Chapter 4.

SQ3. What can be the in-game performance of a coordinated system including stochasticity?
This performance can be calculated by using the optimization model combined with a Model Predictive Control. The outcome of this model compared with the performance of the previous sub question can give an insight of the negative impact of stochasticity in the system. This sub-question is answered in Chapter 4.

SQ4. How the selected policies influence the overall in-game performance relative to the highest achievable performance?
As described in chapter 1.3.1 both simulation and gaming is used to test and evaluate each of the policies and compare their performance with optimization model's. First in simulation runs the respective parameters for the policies are tested to check their performance and compare it with the performance of the optimization model. At this point it is worth noting that it would be more straightforward and realistic if all the parameter changes would be tested directly to the gameplay of the actors. However, the time and effort needed for this is obviously prohibitive and that is the reason that simulation is preferred for the selection of parameter that need to be changed. As a comparison, a couple of rounds of gameplay with human players can last for 2-3 hours while several runs of the simulation model can be fulfilled in one minute. After the final selection of the parameters that should be changed (choice of a policy), these parameters are also changed in the gaming sections with real players to measure the performance of the actors. The performance of the actors was then measured from the game runs and was compared to game optimizer's high score. This sub-question is answered by the analysis' results in Chapter 6.

SQ5. Can the configuration of game rules, according to specific policy plans, affect players' performance in the expected way?
In order to answer this sub-question, the simulation and gaming outcomes, before and after the implementation of the policies was assessed to identify if players' behavior changed in the expected way. Thus, it was examined if the configuration of game parameters or rules, according to specific policy plans could affect player's performance. This sub question requires the combination of both theoretical and practical part of the thesis. On the one hand there are the theoretical expected outcomes of each policy. On the other hand, there are the data captured

from the practical game runs. These data included the performance of the actors when playing the game. By comparing the initial performance and preferences of the actors in the gameplay, before and after the implementation of each policy in the game (through parameter changing), the practical outcomes of the policies on the actors can be found. These outcomes then can be compared to evaluate the theoretical expected outcomes of each policy.

2. Literature review and description of RCCR game

This chapter presents the relevant literature for port to hinterland and choice behavior of the actors and the required background information in order to understand the Rail Cargo Challenge Rotterdam game.

2.1. Literature review

2.1.1. Collaboration and Coordination mechanisms

Business integration may be used as a practice to increase revenue, achieve economies of scales, enhance market share and distribute the risks among the participants (Sudarsanam, 2003). According to Mason, Lalwani & Boughton (2007), business collaboration in transport management is not only important for reduction in costs, but generally for "value optimization", such as improvement of service level and customer satisfaction.

Saeedi et al. (2017) mention that business integrations range from light to heavy forms. A light form of business integration is subcontracting, while heavy forms are the strategic alliances and business acquisitions (Saeedi et al., 2017). Van Der Horst & De Langen (2008) note that "*interfirm alliances are a more effective arrangement than complete vertical integration*".

Brandenburger and Nalebuff (1996) propose the term coopetition for ports, which is the cooperation with the competitors in order to reach in a win-win state for all competitive actors. Saeedi et al. (2017) argue that competition in the intermodal freight transport system could be decreased by business integrations in both horizontal and vertical dimensions.

Van Der Horst & De Langen (2008) mention that in order to establish an alliance, the capabilities of the companies should be "complementary" and the transaction costs should be low.

According to Saeedi et al. (2017) there are two types of vertical collaboration, the "restricted" and the "flexible". In the restricted situation the two parts are obliged to work together until the one part fulfills its capacity and if the other part still has remaining capacity, then can sell it to other operators (Saeedi et al., 2017).

Brooks et al. (2009) write that "*Port authorities can deliberately enable competition and set conditions in concession agreements. They can develop access rules to enhance efficient use of infrastructure, and they can develop supporting facilities like port community systems*".

According to Van Der Horst & De Langen (2008) there are "*four key mechanisms to enhance coordination: the introduction of incentives, the creation of interfirm alliances, changing the scope, and the creation of collective action*". These coordination mechanisms with their possible arrangements can be seen in figure 7.

Coordination mechanism	Possible coordination arrangements
Introduction of incentives	Bonus, penalty, tariff differentiation, warranty, auction of capacity, deposit arrangement, tariff linked with cost drivers
Creation of an interfirm alliance	Subcontracting, project-specific contract, standardised procedures, standards for quality and service, formalised procedures, offering a joint product, joint capacity pool
Changing scope	Risk-bearing commitment, vertical integration, introduction of an agent, introduction of a chain manager, introduction of an auctioneer, introduction of a new market
Creating collective action	Public governance by a government or port authority, public–private cooperation, branch association, ICT system for a sector of industry

Figure 7 Typology with examples of coordinating mechanisms (Brooks et al. 2009)

In the work of Van Der Horst & De Langen (2008) it is noted that cargo exchange can resolve the problem of long-stay of the barges in the ports. Cargo exchange can be done by collective action or by interfirm alliances, with the incentive for the involved parties to achieve economies of scale (Van Der Horst & De Langen, 2008). Van Der Horst & De Langen (2008) also notice that especially in Port of Rotterdam can be found 34 collective actions and 31 interfirm alliances in different forms of cooperation (e.g. capacity pools, exchange websites), while monetary adjustment incentives (e.g. penalties) identified in six cases.

Brooks et al. (2009) listed real port examples that used some of the above arrangements for coordination mechanisms. This can be seen in figure 8.

Type	Practical examples of coordinating mechanisms
Scope	Port authority (PA) investments in inland intermodal terminals. Examples: Barcelona's PA in terminals in Zaragoza and Toulouse (France); and Melbourne.
	PA investments in hinterland rail freight connections (Rotterdam, Amsterdam, Melbourne, Barcelona)
Alliances	Joint investment by Port of Tacoma, rail carriers, terminal operators to establish a rail command center in the port.
	Transformation of Port of Rotterdam's port community system in joint venture with Port of Amsterdam.
Incentives and rules	Agreed rules for decreasing the dwell time of containers at the deep-sea terminals in Los Angeles and Long Beach.
	Joint action of an association of inland barge terminals, the port authority in Rotterdam and in-port barge terminals, to agree on transhipment conditions for barges.
Collective action	Investment in port community systems, by the Port of Rotterdam and the Port of Barcelona.

Figure 8 Typology with examples of coordinating mechanisms (Brooks et al. 2009)

2.1.2. Intermodal competition (train-truck)

Crozet (2017) exploring the competition between the truck and train in freight transportation and a potential opening in rail freight transport market, mentions as a major difference of road and rail the level of network access. The rail to road network ratios are very small (e.g. 10/100 for Germany, 3/100 in France), which makes extensive massification necessary for rail, in order to be competitive (Crozet, 2017).

Furthermore, according to Crozet (2017) more than eight train operators left the market between 2000 and 2004 in Sweden. An important factor for these "exits" was the intermodal competition of road transport where mega-trucks of 60 tons were allowed (Crozet, 2017).

2.1.3. Mode choice in freight transportation

Floden et al. (2017) in their literature review on choice of transport service, found that "a number of key factors reoccur in most of the articles: cost, transport quality, reliability and transport time", while the environmental factors are being researched more and more but they are still found to have insignificant effect on mode choice (Floden et al., 2017). The above attributes and their level of importance are illustrated in figure 9, as found in Floden et al. (2017). Cost, damage (transport quality), reliability and speed (transport time) are also addressed as the top four important factors in the work of Cullinane & Toy (2000).

Maier et al. (2002) found reliability as the most important factor on choosing between transport alternatives and underpin that rail is not preferred by the logistic managers even if all the other attributes are equal.

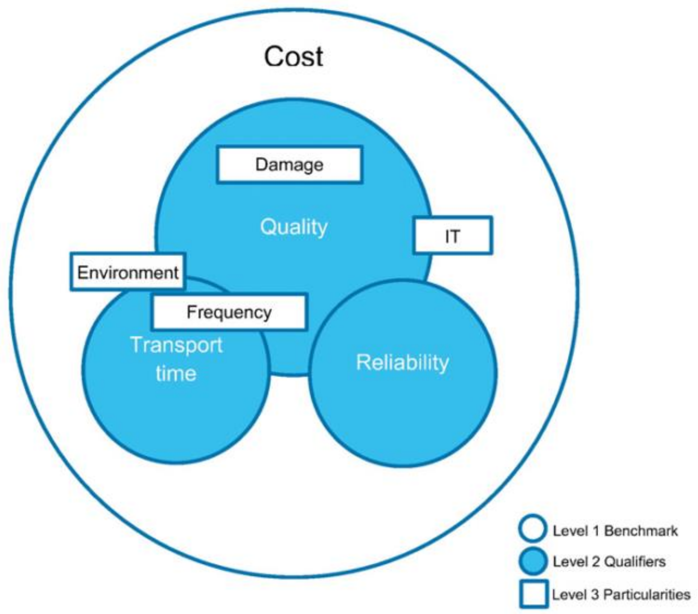


Figure 9 A graphical representation of the important factors selecting transport service (Floden et al, 2017)

Holguín-Veras, Xu, de Jong, and Maurer (2011) conclude that the interaction between shippers and carriers can explain freight mode choice decisions and that this decision greatly depends on shipment size.

Reis (2014) investigated whether the variables used in medium to long-distance transport mode choice can also be used in intermodal short-distance choices and concluded that these variables, except price, are not significant for the explanation of freight forwarders choice and that road transport is generally preferred over intermodal option.

Feo- Valero, García-Menéndez & Sáez-Carramolino, et al. (2011) found that in inland freight transport frequency of service has an important role and regulators should focus on this in order to make rail a competitive alternative over road transport option.

Beuthe and Bouffioux (2008) analyzing the important attributes of freight transport for different types of goods, note that cost is the dominant attribute for the mode choice for all categories while especially for container transport the most important factor is cost with a weight of 71%, followed by transport time, reliability and frequency of service.

2.2. Gaming applications and RCCR

An innovative approach to evaluate the impact of different policy scenarios on actors' preferences by using a combination of gaming (also called simulation gaming), simulation and optimization will be used on this thesis, as an extension of the already developed games of Synchro-Gaming project that department of Engineering Systems and Services (TPM) of TU Delft is involved.

2.2.1. Introduction to gaming

The games that are used for purposes are also called simulation games (Harteveld, 2011). As an abstraction of the real-world games can also be considered as models. In figure 10, the different types of modelling, including gaming, can be seen as found in the work of Bradley et al. (1977). These are Operational exercises, gaming, simulation and analytical models. In the first two types the actors have an active role and can interact with the model. In the other two types the actors have only an external role. Although operational exercises take place in actual world environment and are closer to the real operations, usually the cost of implementation is prohibitively high (Bradley et. al, 1977). On the other hand, gaming is a simplification and abstraction of reality, leading to lower implementation costs, which allows for the test of performance of different alternatives with the participation of the actors and decision makers. (Bradley et. al, 1977).

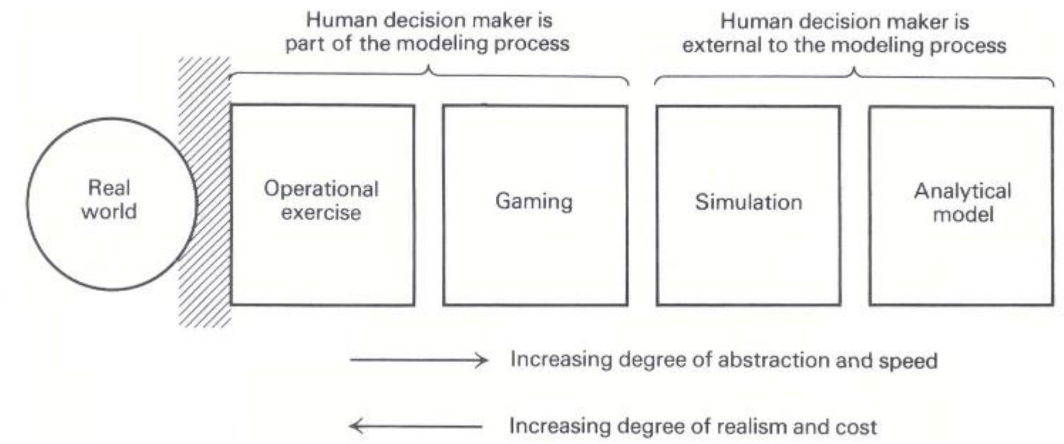


Figure 10 Types of models (Bradley et al., 1977)

2.2.2. Applications of games

Serious or simulation games are used for centuries by military to analyze tactics, develop strategies and prepare missions (Smith, 2010). However, the modern development of the games started by the evolution and combination of war games, computer science, operational research in 1950's. (Wolfe and Crokall, 1998). After the war games, also business used games for training, analysis, policy and decision making (Duke, 1974).

In transport sector, gaming has been applied in several cases. Meijer et al. (2012) developed and used a game to support ProRail analyze capacity management problems and develop strategic behavior. Subsequently, Meijer (2012) in a different paper describes six more games for Dutch rail infrastructure management, with different scopes, including policy related topics, utilization of technical aspects, process management, handling of major disruptions, rolling stock management and test of resilience and robustness. Also, games are used from practitioners to better understand the value of flexibility in freight transport and by educational institutes to teach intermodal container logistics (Van Riessen, 2018). Furthermore, gaming is used as a way to raise actor's awareness towards new transport systems as synchromodality that is expected to increase efficiency in freight transportation (Kourounioti, 2018). This tool (gaming) has three objectives for synchromodality according to Buiel et al. (2015):

1) Let the actors experience synchromodal planning,

2) Show to the actors the benefits and

3) Achieve the mind shift towards cooperation between actors.

The first results of synchromodal games seem promising. After playing a synchromodal game, 72% of the participants raised their awareness of the importance of flexibility in freight transportation and 48% understood the importance of synchromodality (Kourounioti et al., 2018). This shows a trend for common acceptance by all actors.

2.2.3. Rail Cargo Challenge Rotterdam game (RCCR)

Rail Cargo Challenge Rotterdam is a game developed by TU Delft gamelab, The Barn, ProRail and TNO within the "Synchro-gaming" project (TU Delft gamelab site, 2018). In this chapter a brief description of the context and the rules of the game are described, as found in the game manual and discussed by Kurapati et al. (2017) and Kourounioti et al. (2018). A more extensive description of the game and its rules can be found in appendix A.

Figure 11 Rail Cargo Challenge Rotterdam Board (http://www.seriousgaming.tudelft.nl/games/rail-cargo-challenge)

"The key research objective of the Rail Cargo Challenge Rotterdam (RCCR) is to assess the attitudes and behavior of stakeholders in the freight transport domain with respect to the efficient bundling of containers to be transported to their final destination using rail." (Kourounioti et al., 2018).

RCCR has two main categories of players: rail operators and freight forwarders. These two categories are on the second and third layer of TRAIL model (see figure 3), respectively.

The game is played in rounds. On each round, new containers arrive at the port of Rotterdam in one of the terminals and each container has a specific destination and an expiration date of delivery. Each container is represented by one order card, including the above information (storing terminal, destination, latest day of delivery). The order cards are distributed to the freight forwarders that are responsible for the on-time delivery of the respective containers.

Rail operators: There are two train operators in the game that compete to satisfy forwarders' demand. Each operator is in charge of one train. It is the decision of rail operator which terminals the train visits and at which destination it arrives and this decision can defer per game round. In the case that the schedule of the train operator has more terminals than the maximum possible terminals that can be serviced then rescheduling is required or even transportation by truck.

Freight forwarders: There are three forwarders in the game that are responsible for the on-time delivery of the cargo. Each container is assigned to one forwarder. The forwarder can choose to send the container either by train or by truck. The role of Freight forwarders is to negotiate the price of train transport with train operators and finally decide which mode to choose.

Shippers (Not an active actor in the game): Freight forwarders are paid by shippers that have a preference to train and thus they pay more to have their containers transported by rail. If the containers are not delivered on time no yield is payed to the forwarders. A container is assumed to be delayed if the latest day of release it is transported by truck. Note that shippers do not have an active role in the game and does not need a person to play this role.

Dice in the game: A stochastic element (dice) is included in RCCR. The role of the dice is to determine the maximum number of terminals that each train is allowed to visit. The stochasticity of the dice represents possible last-minute delays or, on the other hand, low traffic in the terminals.

Each player is assumed to have his own company and tries to achieve the highest possible profits.

The reputation of the port is also important as the lower the reputation the less the container orders that are given to freight forwarders. Thus, as the reputation of the port increases, more customers (shippers) prefer Port of Rotterdam, new containers reach to PoR terminals and new resources are inputted on the system. The reputation is lowered with the use of truck.

The aim of the game is to promote horizontal and vertical collaboration between the actors, as the merging of orders and the appropriate selection of terminals and destination is required to utilize the train and lead to highest profits for players.

2.2.4. Key Performance Indicators (KPIs)

The Key Performance indicators that are set in the game are two. The first is the monetary profitability and the second is the reputation of the Port.

The profitability is measured on the game currency (tokens), while the reputation is closely connected with the sustainability aspect and is reduced with the use of each truck, which is assumed a non-environmental friendly solution.

Key Performance Indicators (KPIs):

$$Profit = total\_train\_revenue - total\_train\_cost + total\_truck\_on\_time\_revenue + total\_truck\_delayed\_revenue - total\_truck\_cost$$

$$Port\_Reputation = -total\_\#trucks\_used$$

(*Port reputation is increased by one point if no trucks are used in one round)

3. Game and simulation model

3.1. Important aspects of the game and players' decisions

In this section an analysis of the important game aspects is done. In this analysis, as "system" is referred the group of Port, train operators and freight forwarders. Shippers are assumed to be an external passive actor (none of the players has this role), that create the demand and pay freight forwarders for the successful delivery of their freight. Truck operators are also assumed to be out of the system, as they do not have an active role in the game.

Next the decisions of each player are summarized:

Freight forwarders: Each of these players are responsible for the transportation of specific containers. The actions and decisions that they have to take are:

- Negotiate the price for each container transport with train operators.
- Choose between train and truck. This decision is not only depended on the price but can also include the reliability perception for each train operator.
- Decide to send each container the specific day or wait for one of the next available days before container expiry date.

Train operators are scheduling the train service. The decisions that each train operator have to take during the game are:

- Negotiate the price for each container transport with freight forwarders.
- Choose the number of terminals to service. This decision includes the risk of servicing less terminals than the decided, depending on the dice described in the previous chapter.
- Choose which terminals to service.
- Choose the destination of the train.
- Decide to undertake the responsibility to transport a container. By the time that the train operator takes this decision, he is responsible for the successful transport of the container and his further decision can affect the yield of the freight forwarder. This means that if the train operator cannot successfully send the container by train and has to fulfil the order by truck, the train operator will pay for the truck fee and the freight forwarder will get yield as using truck, although he has chosen train.
- Decide to send each container the specific day or wait for one of the next available days before container expiry date.

Except the decisions of the players there are also some other aspects that need to be addressed.

Firstly, the resources of the system are the exchange currency (tokens) and the port reputation. Reputation linearly decreases by the use of each truck and it is straightforward that it is maximized by the minimization of truck use. As for the currency, except the starting budget of each player, new tokens are only inputted in the system by shippers.

Secondly, after the preliminary analysis of the game that can be found in appendix A.2., and as can be seen in figure 12, it is observed that as the agreed price to transport a container by train increases, the income of freight forwarder (per container) decreases, while the income of train operator increases. This happens as the tokens are transferred from the one player to the other. At the same time, system income (per container) stays on the same level. As can be conducted, the system profit is independent of the negotiated price between the train operators and the freight forwarders.

However, there is an undergoing risk that these negotiations could fail and result in the use of truck alternative instead, which greatly reduces system's profit (see Figure 12).

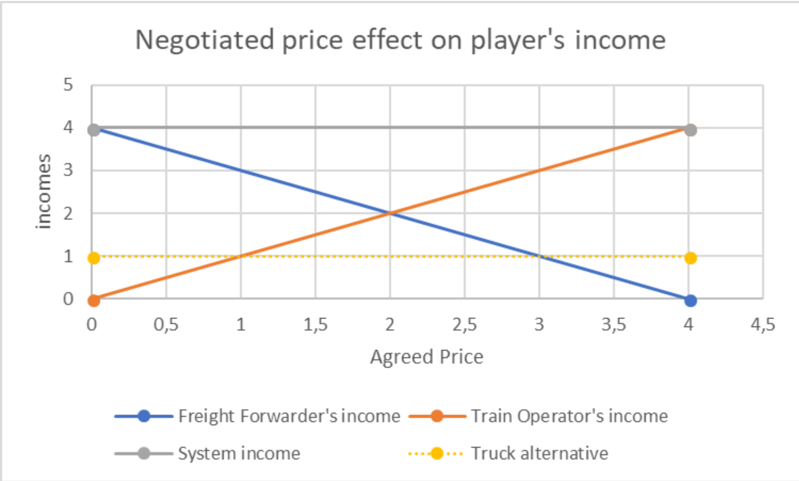


Figure 12 Each player's income per container as function of agreed price (train use)

Another important element of the game is the reputation of the port, which is directly connected with the truck use. As more trucks are used, port reputation reduces and less container orders come to the port terminals. This results in less customers in the port system and lower profitability.

It can be seen that the lower profitability and efficiency of the non-coordinated system, mostly come from the negotiation part of the game, the lack of information and the low cooperation between the actors. Cooperation could be used in order to utilize the trains (e.g. consolidate freight with same origin-destination) and take decisions to increase the profit for the whole system through information sharing. The use of train instead of truck in the highest possible level would most probably lead to higher individuals' profits as well, as more new (monetary) resources are inputted on the system and can be split between individuals.

3.2. Current in-game performance

The game sessions are used to collect data and observe players' behavior. These observations are important as they are used to set the decision rules for the simulation model as well.

Note that the costs and revenues in the game sessions for this thesis are multiplied by 5 compared to the basic game rules, in order to achieve a better variation in negotiation prices.

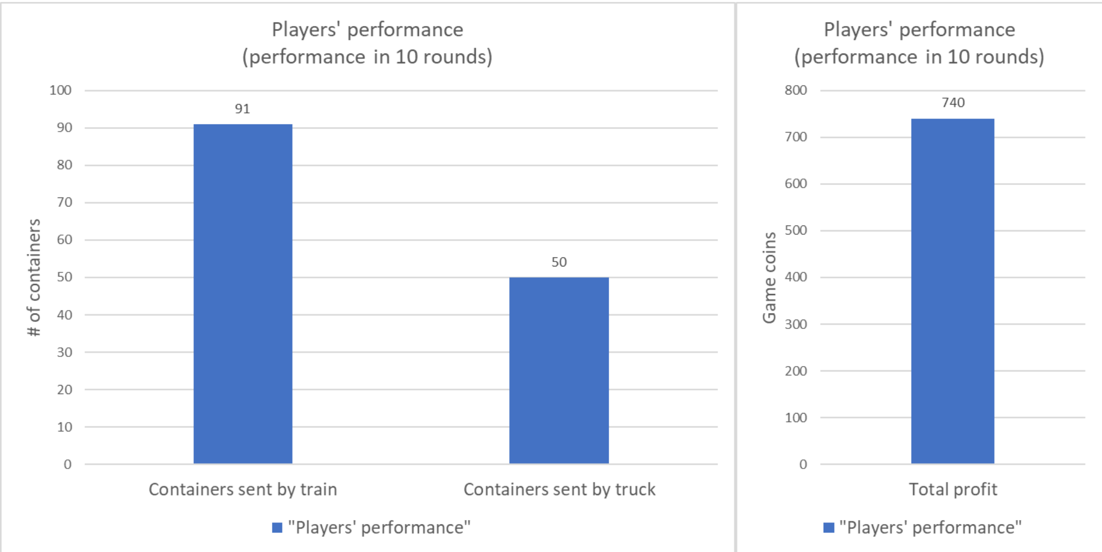


Figure 13 Players' performance, game 1 (19/5/2018)

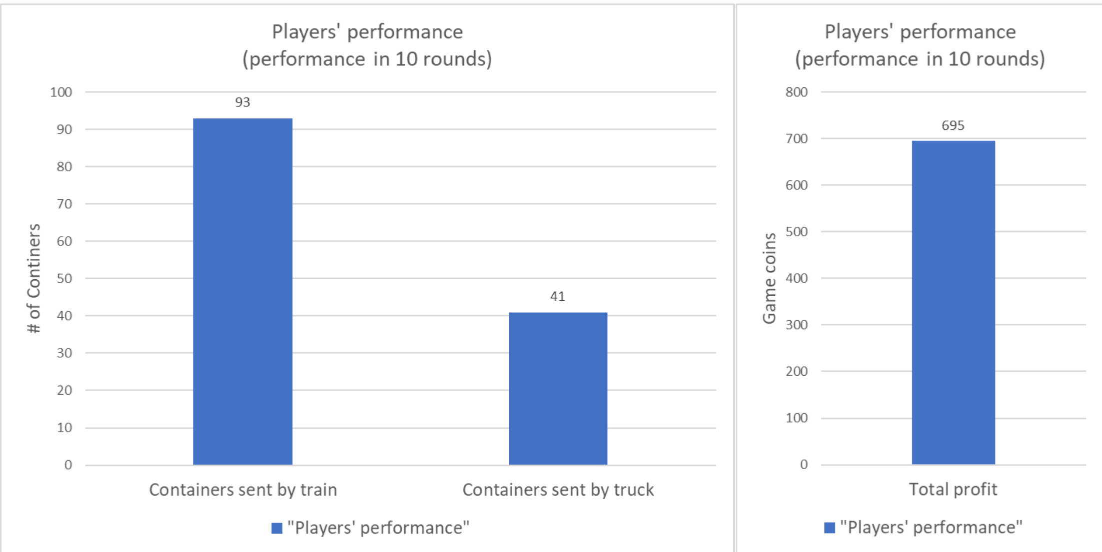


Figure 14 Players' performance, game 2 (29/6/2018)

As can be seen in figures 13, in the first game players achieved a profit of 740 currency units, by transporting 91 containers by train and 50 containers by truck (on-time and delayed). Players' performance in the second game, as illustrated in figure 14, reached 695 game currency units in profit, by transporting 93 containers by train and 41 by truck.

It should be noted that the total containers transported by truck and by train are not the same. As mentioned in the description of the game, the amount of the containers depends on the reputation of the port (use of truck in each round). Thus, in the first game the reputation on the first rounds was higher and more containers reached on the terminals. Although the players did not manage to send more containers with the train at the end comparing to the second game, the more containers that became available to the system led to higher profits, but to lower end reputation.

3.3. Game simulation

3.3.1. Simulation steps

The simulation model is based on the RCCR game process and rules. The simulation model is presented step by step in the next flow chart in figure 15. A more extensive description of the model and the sub-steps for operators' decisions (step 3, step 7) and the freight forwarders' decisions (step 4) can be found in Appendix B.

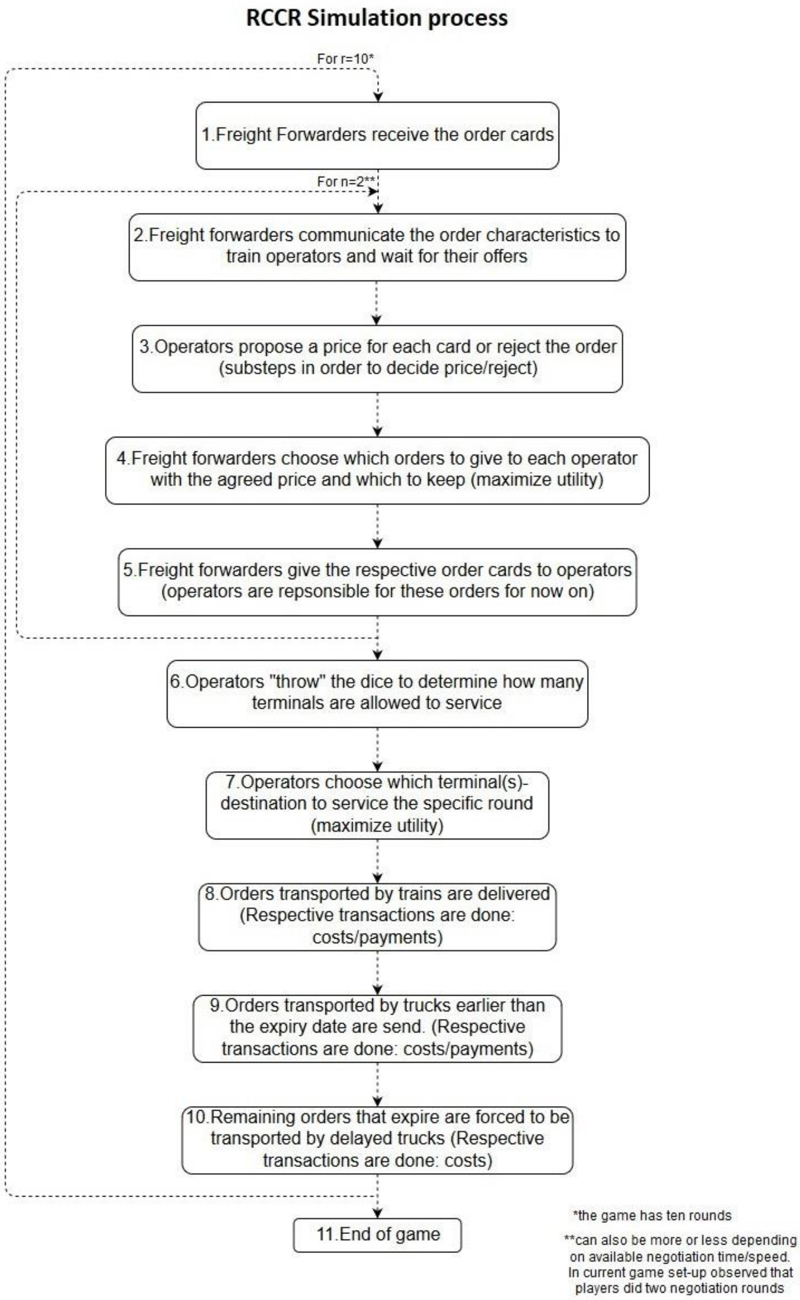


Figure 15 Simulation model steps

3.3.2. Discrete Choice Model in simulation

An important aspect of the simulation model is the way freight forwarders and train operators take their decisions. In this simulation, simple utility maximization is used for the decision of train operators in steps 3 and 7 (see figure 15). Also, a Discrete Choice Model (DCM) and specifically a Multinomial Logit model is used in step 4 (see figure 15) to model the decisions of freight forwarders for the mode of transport to be used. According to Ben-Akiva and Bierlaire (1999) the most important assumptions of the DCM are the decision maker, the alternatives, the attributes and the decision rule.

In order to choose the most important factors to include in the utility functions of the decision model, literature is used. In literature review (see chapter 2.1.), the most important factors for mode choice in port to hinterland freight transportation found to be cost, transport time, reliability, transport quality and in some cases frequency of the service. As in the game RCCR transport time, transport quality and frequency of service are not included, the factors that are finally chosen in the utility functions are cost and reliability.

Freight forwarders' utility functions

Freight forwarders' decisions appear on step 5 of simulation (see figure 15). Freight forwarders make their decision for each order card separately. The important assumptions of the Discrete Choice Model (see Ben-Akiva & Bierlaire, 2009) in this case are:

- The decision maker: Freight forwarder
- The alternatives: depend on the expire date (see next)
- The attributes: cost, reliability (transport time and quality are not included in RCCR game)
- The decision rule: utility maximization, MNL model

The alternatives for freight forwarders depend on the expiry round of the order card.

➢ If it is the last round (day) before the order expires, the discrete choices for each freight forwarder are:

1) train operator 1,

2) train operator 2 or

3) delayed truck.

And the respective utility functions are:

$$U_{Train_1} = \beta_{price} * (revenue - operator1price) + \beta_{reliability} * reliability1 + \\ +(\beta_{train})$$

$$U_{Train_2} = \beta_{price} * (revenue - operator2price) + \beta_{reliability} * reliability2 + \\ + (\beta_{train})$$

$$U_{truck\_delayed} = \beta_{price} * (revenue\_delay - cost\_delay) + \beta_{truck\_delayed}$$

➢ If it is not the last day before the order expires, the discrete choices for each freight forwarder are:

1) train operator 1,

2) train operator 2,

3) early truck or

4) keep the order to decide next day.

And the respective utilities are:

$$U_{Train_1} = \beta_{price} * (revenue - operator1price) + \beta_{reliability} * reliability1 + \\ +(\beta_{train})$$

$$U_{Train_2} = \beta_{price} * (revenue - operator2price) + \beta_{reliability} * reliability2 + \\ +(\beta_{train})$$

$$U_{truck\_early} = \beta_{price} * (revenue\_early - cost\_early) + \beta_{truck\_early}$$

$$U_{keep\_order} = +\beta_{keep\_order}$$

The parameters for each utility function were estimated using observed data from the game sessions. The values of the parameters can be seen in Table 4.

Table 4 Estimated parameters in Utility functions

β_{price}	0.108
$\beta_{reliability}$	0.146
β_{train}	0 (train set as base case)
$\beta_{truck\_delayed}$	-1.45
β_{truck_early}	-2.44
β_{keep_order}	-1.06

Note that as the truck cost and revenue are constant, these prices were incorporated in the alternative specific parameter. Thus, $U_{truck\_delayed} = +\beta_{truck\_delayed}$ and $U_{truck\_early} = +\beta_{truck\_early}$. Furthermore, it is worth noting that the parameter for the early trucks ($\beta_{truck_{early}}$) found to be less than the parameter for delayed truck. This is justified from the game sessions, as the early truck alternative found to be the most rarely used, as the players prefer to keep the order cards for the next rounds most of the times.

The software used for estimation is BIOGEME 1.8 (see Bierlaire, 2008). BIOGEME package is distributed free in order to develop the research area of Discrete Choice Models (Bierlaire, 2003). More information for the decisions of freight forwarders, the used Discrete Choice Models and the estimated parameters can be found in Appendix B.2.

Train operators' utility functions

Train operators' decisions appear on step 3 and step 7 of the game simulation. On these steps, simple utility maximization is used as the decision rule, as the operators do not choose among a set of mode alternatives, but decide which origin-destination pair will service to achieve the highest benefits. The weights in the utilities (paramters) for the price and for the delayed orders are assumed to be the same as estimated for freight forwarders in the previous subsection.

First, on step 3, train operators negotiate with freight forwarders and decide which containers to agree to transport (so they have to make an informal plan-strategy on which terminal(s)-destination to service this round) and on step 7 decide and announce formally which terminal(s)-destination will actually service.

On step 3 of simulation, during negotiation phase, the outcome of the dice, that defines the maximum number terminals that operators are allowed to service, is not yet known. Thus, in this step, train operators negotiate with freight forwarders and agree to transport orders with the aim to maximize their expected profits. This includes some risk in the decision process on this step, as if the operators decide to agree on orders for more terminals than the maximum number of terminal that the dice will determine, then the expiring orders will have to be transported by a delayed truck.

On the other hand, on step 7, the outcome of the dice is known and the operators decide which terminal(s)-destination to choose in order to maximize their "real" profits.

It was observed from the real game sessions that the decision of the operators on which cards to buy from the freight forwards depends on highest demand and on the cards that had already bought from previous rounds. More detailed information about the decision process of train operators are given in Appendix B.3.

3.3.3. Simulation results

For the simulation model, the utility functions with the estimated parameters as described in chapter 3.3.2. were used.

As can be seen in figure 16, the simulated profit has a high variation. This can be explained due to the different outcomes of the stochasticity of the dice and by the different "paths" of decisions that the players can take and, as a result, lead to different profit outcomes in the end.

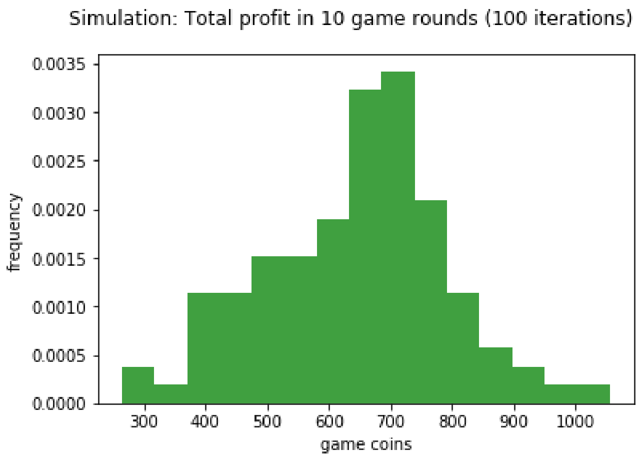


Figure 16 Total system profit in 10 game rounds. (100 simulation runs)

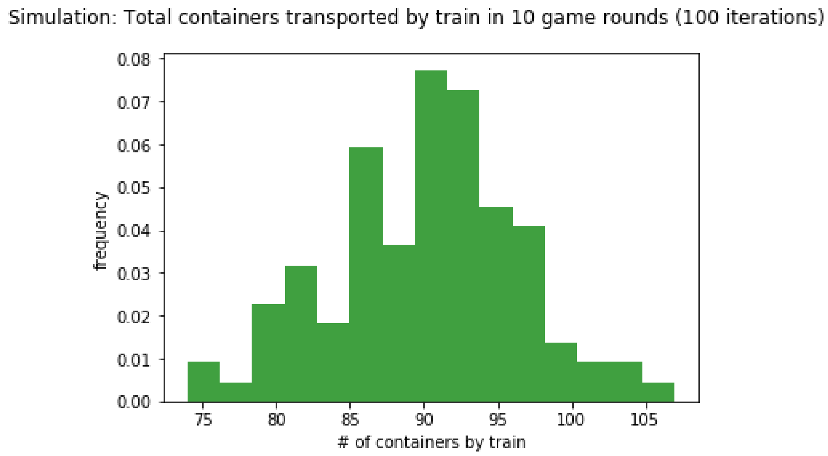


Figure 17 Total number of containers transported by train in 10 game rounds. (100 simulation runs)

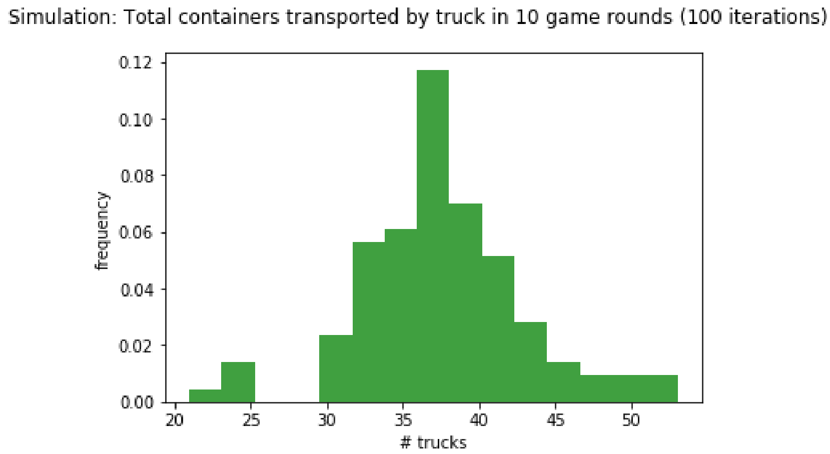


Figure 18 Total number of containers transported by trucks (on-time and delayed) in 10 game rounds. (100 simulation runs)

4. Optimization Model and a Coordinated Perspective

As shown in preliminary analysis of the game (chapter 3.1., Appendix A.2.), in order to maximize system's profit, players should utilize the trains, as much as possible, and have truck option as an alternative for the containers that cannot be delivered by the train services. It was also deducted that the lower profitability and efficiency of the non-coordinated system, mostly come from the negotiation part of the game, the lack of information and the low cooperation between the actors. In the game sessions, freight forwarders also aim to send most of their containers by train as their individual income per container is more. However, negotiation on prices or choices of terminals-destination by train operators that are not optimal for the system, due to lack of information, lead to inefficiency. All these complications could be bypassed by a coordinated or a fully cooperative system. This chapter describes two models that will move towards this way.

The use of each model and their differences were described in the methodological part in section 1.3.2.

The difference of the coordinated system and the current system is that the coordinator takes decisions to maximize system's KPIs, as defined in chapter 2.2.4, and not individual's profits.

4.1. Optimization Model of the RCCR game

In the next subsections the inputs, outputs, objectives, assumptions and mathematical model of the optimization model are presented.

4.1.1. Input of the model

The inputs of the optimization model are:

- New containers that are released in each round (day).
- Each container has a specific terminal of arrival, destination and latest round (day) to depart from the terminal (after this round the order expires). The information for each container order (terminal, destination, expire) become known only at round (day) of its arrival.
- The maximum number of terminals that each train can service in the current round is given (it is determined by a dice). This information is not available for next rounds.

4.1.2. Output of the model

The output of the model is to find:

- Which terminal(s) and which destination to service each train in the current round.
- Which containers to send by train, which to keep for next rounds (if the order is not expiring the current round), which to send by trucks (on-time or delayed).

4.1.3. Objective of the model

Maximize the KPIs for the system: Profit and Reputation of "Port of Rotterdam" in game. (see also chapter 2.2.4.)

4.1.4. Assumptions of the model

The assumptions are set by the rules of the game.

1. All containers have to be delivered before expire date.
2. The transport options are: two trains, on-time truck and delayed truck.
3. If the last day before a container order expires, the container cannot be transported by train, it should leave with a truck that is assumed to be delayed (delayed truck).

4. If a truck is used, to transport a container, two days before expiry round it is assumed to be an on-time truck. (In last round before expiry, only a delayed truck can be used).
5. Costs are not dependent on distance, terminal choice, destination choice.
6. Fixed cost to operate each train each round.
7. Trains have to pay the fixed operational cost per round independently of utilization rate (even if the train is empty), distance, terminal choice, destination choice.
8. Fixed revenue per container transported by train.
9. Fixed cost per container for truck-use.
10. Trucks pay their fixed cost per container only if they are used.
11. Fixed revenue per container transported by on-time truck.
12. Fixed revenue per container transported by delayed truck.
13. Only two trains are available.
14. Each train has a capacity of 10 containers.
15. Each train can service only one destination per round.
16. Each train can service up to one, two or three terminals per round depending on a stochastic element of game (dice) that its outcome is determined in each round. Thus, the outcome of the stochastic element (dice) is not known for the future rounds and each case has a specific chance to happen.
17. Reputation of "Port of Rotterdam" is reduced by one point for each truck that is used (on-time and delayed trucks).
18. Reputation is increased by one point if no trucks are used in a round.

4.1.5. Optimization approach and mathematical model

The optimization approach is based on the arc-based Service network design or "capacitated multicommodity network design" (CMND) as described by several articles (Andersen et al., 2007; Crainic, 2000), with some adaption. The aforementioned model is changed to better fit the specific problem. Firstly, a profit maximization formulation is considered, instead of cost minimization, as the train services have a fixed cost, independent of the arc that is used. Secondly, to reduce the decision variables and as the arcs have no cost of use (fixed cost per train), each train service is not described with design arcs but with design nodes ($xter_{in}^{tr}$, $xdest_{j}^{tr}$) that represent the terminals/destination that each train can visit each round. In the case of flow arcs the decision variables of rail service could be represented as r_{iklj}^{tpr} as each train t∈T can service up to three terminals (e.g. i,k,l∈O) to transport the containers p∈P in round r∈R to destination j∈D. However, this would require about T*P*R*O*O*O*D=2*18*4*5*5*5*2=36000 decision variables, only for the rail flows. As there are no cost for using each arc and in order to reduce the required decision variables, the flow arcs of rail service (r_{inj}^{tpr}) are represented as binary variables that train t∈T transports container p∈P in round r∈R from terminal i∈O, which is the n^{th} terminal choice of the operator (n∈N), to destination j∈D. In this case, the decision variables for rail flows are reduced to T*P*R*O*N*D=2*18*4*5*3*2=4320 instead of 36000. The flow decision variables are binary as each commodity p∈P represents only one container; thus, flow is either zero or one.

The Integer programming optimization is presented next.

Sets:	
T	Set of trains that are operating (t∈T).
P	Set of containers (IDs) (p∈P).
O	Set of origin terminals (i∈O).
D	Set of destination (j∈D).
R	Set of planning horizon rounds (days) (r∈R)
N	Set of possible choices in priority order for terminals (n∈N). (e.g. 1st choice, 2nd choice, 3rd choice for a maximum of 3 out of 5 Terminals) (Equals to the dice alternatives)
Parameters:	
$dest_j^p$	Binary parameter: 1 if container p∈P has j∈D as destination, 0 otherwise.
$term_i^p$	Binary parameter: 1 if container p∈P has i∈O as destination, 0 otherwise.
$train\_term^{tr}$	Non-negative integer: maximum number of terminals that train t∈T is allowed to service on planning round r∈R.
$profit\_rail$	Revenue for a successful container transport by train (as train has constant cost for operating, cost not included)
$profit\_truck\_early$	Profit for each container transported by an on-time truck (revenue -cost)
$profit\_truck\_delay$	Profit for each container transported by a delayed truck (revenue -cost)
$expire^{pr}$	Binary parameter: 1 if container order p∈P has expired on round r∈R, 0 otherwise. (The indicated round shown in the order cards is the last round that the container can be transported, thus expire=0 at the specific and previous rounds and expire=1 the following days).
$release^{pr}$	Binary parameter: 1 if container order p∈P has released on round r∈R, 0 otherwise. (The round that the container reaches the origin terminal and the following rounds, release=1. Before this round release=0)
Variables:	
r_{inj}^{tpr}	Binary variable: 1 if train t∈T transports container p∈P from origin terminal i∈O, which is the nth (n∈N) terminal choice, to destination j∈D in round r∈R, 0 otherwise.
$xter_{in}^{tr}$	Binary variable: 1 if train t∈T services terminal i∈O as nth choice (n∈N) in round r∈R, 0 otherwise.
$xdest_j^{tr}$	Binary variable: 1 if train t∈T has as destination j∈D in round r∈R, 0 otherwise.
te^{pr}	Binary variable: 1 if on-time (early) truck transports container p∈P in round r∈R, 0 otherwise. (trucks can service all terminals and destinations at all rounds)
td^{pr}	Binary variable: 1 if delayed truck transports container p∈P in round r∈R, 0 otherwise.

Objective Function (maximize profit):

$$max \sum_{t\in T}\sum_{p\in P}\sum_{r\in R}\sum_{i\in O}\sum_{n\in N}\sum_{j\in D} r_{inj}^{tpr} * profit\_rail + \sum_{p\in P}\sum_{r\in R} te^{pr} * profit\_truck\_early + \sum_{p\in P}\sum_{r\in R} td^{pr} * profit\_truck\_delay \quad (1)$$

Subject to:

$$\sum_{t\in T}\sum_{r\in R}\sum_{i\in O}\sum_{n\in N}\sum_{j\in D} r_{inj}^{tpr} + \sum_{r\in R} te^{pr} + \sum_{r\in R} td^{pr} = 1, \qquad \forall\, p \in P \quad (2)$$

$$\sum_{p\in P}\sum_{i\in O}\sum_{n\in N}\sum_{j\in D} r_{inj}^{tpr} \le 10, \qquad \forall\, t \in T, r \in R \quad (3)$$

$$r_{inj}^{tpr} \le dest_j^p, \qquad \forall t \in T, p \in P, r \in R, i \in O, n \in N, j \in D \quad (4)$$

$$r_{inj}^{tpr} \le term_i^p, \qquad \forall t \in T, p \in P, r \in R, i \in O,, n \in N\; j \in D \quad (5)$$

$$r_{inj}^{tpr} \le xter_{in}^{tr}, \qquad \forall t \in T, p \in P, r \in R, i \in O, n \in N, j \in D \quad (6)$$

$$r_{inj}^{tpr} \le xdest_j^{tr}, \qquad \forall t \in T, p \in P, r \in R, i \in O, n \in N, j \in D \quad (7)$$

$$r_{inj}^{tpr} \le (1 - expire^{pr}), \qquad \forall t \in T, p \in P, r \in R, i \in O, n \in N, j \in D \quad (8)$$

$$te^{pr} \le \left(1 - expire^{p(r+1)}\right), \qquad \forall p \in P, r \in R \quad (9)$$

$$td^{pr} \le (1 - expire^{pr}), \qquad \forall\, p \in P, r \in R \quad (10)$$

$$r_{inj}^{tpr} \le release^{pr}, \qquad \forall t \in T, p \in P, r \in R, i \in O, n \in N, j \in D \quad (11)$$

$$te^{pr} \le release^{pr}, \qquad \forall p \in P, r \in R \quad (12)$$

$$td^{pr} \le release^{pr}, \qquad \forall\, p \in P, r \in R \quad (13)$$

$$\sum_{i\in O}\sum_{n\in N} xter_{in}^{tr} \le train\_term^{tr}, \qquad \forall t \in T, r \in R \quad (14)$$

$$\sum_{n\in N} xter_{in}^{tr} \le 1, \qquad \forall t \in T, r \in R, i \in O \quad (15)$$

$$\sum_{i\in O} xter_{in}^{tr} \le 1, \qquad \forall t \in T, r \in R, n \in N \quad (16)$$

$$\sum_{j\in D} xdest_j^{tr} \le 1, \qquad \forall t \in T, r \in R \quad (17)$$

$$r_{inj}^{tpr}, xter_{in}^{tr}, xdest_j^{tr}, te^{pr}, td^{pr} \in \{0,1\}, \qquad \forall t \in T, p \in P, r \in R, i \in O, n \in N, j \in D \quad (18)$$

Objective function (1), maximizes the profit. The first term represents the profit obtained by the successful transport of containers by train, the second term includes the profit by on-time (early) trucks and the third term the profit by delayed trucks.

Constraint (2) ensures that each container is transported only once and only by one of the available modes/services: train “t”, on-time truck or delayed truck.

(3) is the container capacity constraint for each train t∈T and for each round r∈R.

Constraint (4) ensures that each container p∈P can only reach the destination that is assigned to.

Constraint (5) ensures that each container p∈P can only be picked up by the terminal that is assigned.

Constraints (6)-(7) ensure that each container p∈P can only be transported by train t∈T on the round r∈R, if the specific train is servicing the respective terminals/destinations on the specific round.

Constraints (8)-(10) ensure that each container p∈P will reach destination before expire. Also, constraint (9), by using r+1 in $expire^{p(r+1)}$ ensure that an on-time (early) truck cannot be used on the last day that the order is released. In this case only a delayed truck can be used by the rules of the game.

Constraints (11)-(13) ensures that each container p∈P cannot be delivered before the day of release.

Constraint (14) limits the number of terminals that each train can service. A different limit for each train applies per round, depending on the conditions (dice value) in each round.

Constraint (15) restricts each train t∈T to choose each terminal i∈O on each round r∈R no more than one time.

Constraint (16) ensures that each train t∈T on each round r∈R has as n^{th} choice (n∈N) no more than one terminal i∈O.

Constraint (17) restricts the train to have at most one destination.

(18) is a constraint that sets the type of variables to binary.

4.1.6. Performance of optimization model

In this subsection the performance of the optimization model with full information is compared with the simulated performance of the players. In order to make a valid comparison, due to the stochasticity that is included in the game, for each sample the simulation model was ran first and then the optimization model took as input exactly the same information. Then the comparison was done for the respective pairs. As can be seen in figure 20, the optimized model has about 100-200% better performance in profitability than players’ simulated performance in most cases, while this difference greatly increases in some cases. Also, it can be seen in figure 21 that the reduction in trucks (thus in reputation) fluctuates from 50% to more than 90%.

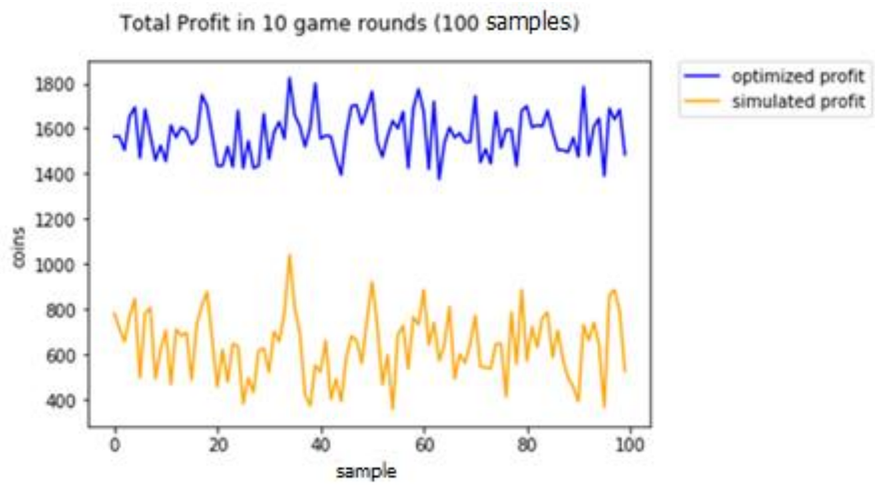


Figure 19 One-by-one comparison of performance in 100 samples in terms of profitability

In figure 19, can be seen that the simulation model profit, as expected, never overcomes optimization model's profit.

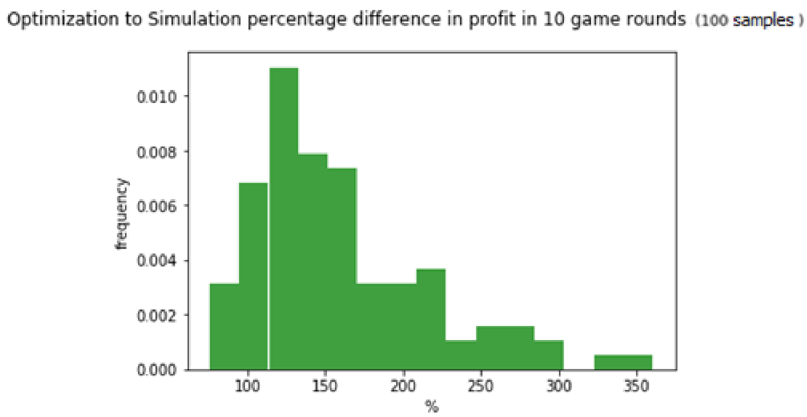


Figure 20 Percentage difference of profit between optimization and simulation

As shown in figure 20, the optimized performance has a better profitability in all cases. The mean percentage difference in 100 iterations is +159,8% and a standard deviation of 57,5.

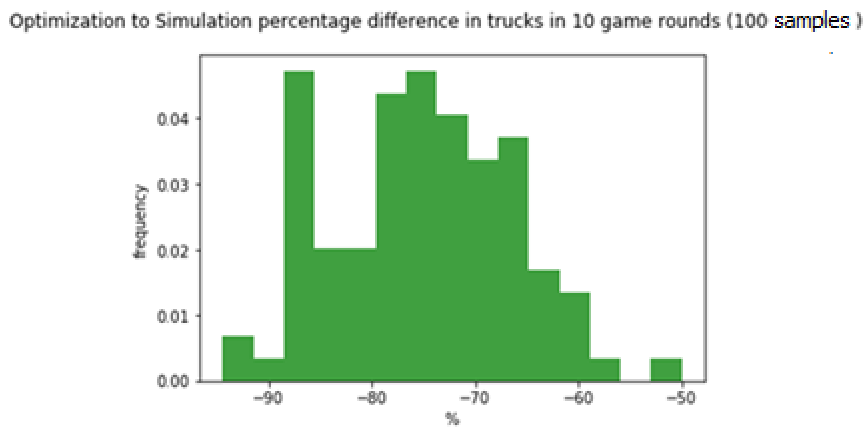


Figure 21 Percentage difference of truck use between optimization and simulation

The mean percentage difference in truck use of figure 21 is -75,1%. Thus, the optimization model achieves about 75% reduction in trucks. The standard deviation is 8,6.

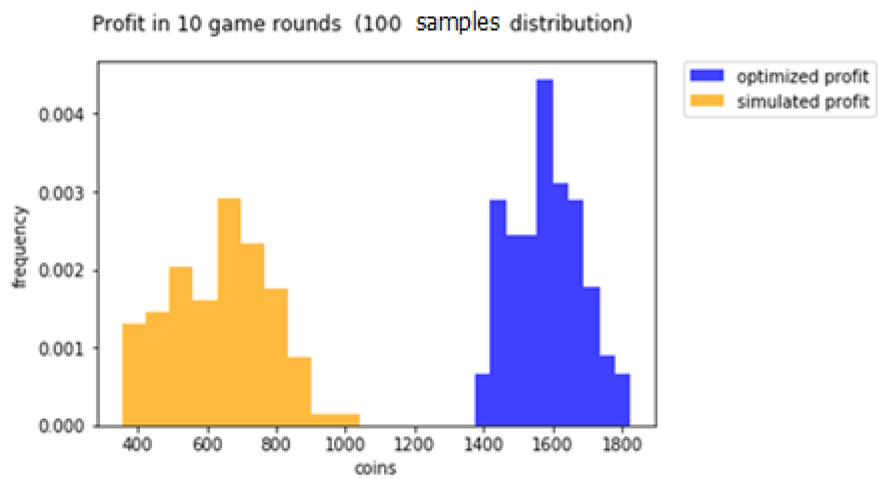


Figure 22 Profit distribution in 100 samples of optimization and simulation model

4.2. Coordinated system

This subsection describes a possible coordinated system that aims to maximize the performance indicators of profit and reputation of the port to hinterland system of RCCR game.

4.2.1. Coordinated system's model

Several coordinator strategies can be defined to control the system. In this thesis, coordinator's decisions are based on the optimization model of the subsection 3.1 combined with Model Predictive Control (see Camacho & Alba, 2013; Kouvaritakis & Cannon, 2016). The main elements that are used from the MPC is that the coordinator makes the planning for a planning horizon (e.g. four rounds) by assessing all the available information, but applies only the decision for the current round. Every new round that new information become available to the system, a new planning is done for the planning horizon. In this way, stochasticity is handled as the disturbances on the MPC concept (see Kouvaritakis & Cannon, 2016).

As the container information become available only in the “current” round and the demand is unknown for the “future” rounds, the optimization model is used in every new round of the game and the planning for a planning horizon is performed with all the available information until this round. Then, according to the model results, only the decisions for the “current” round are taken, the respective containers are transported and the round ends. Subsequently, in the new round, the input information of the model is readapted including information of the new round and the planning is redone, performing only the decisions for the “new” round. The planning horizon is chosen until the round of the latest expiring order.

As the “future” rounds of the game include some stochasticity due to the dice that determines the maximum number of the terminals that each train is allowed to service, the profit calculated from the planning is not “guaranteed”. For this reason, we implement “expected” profit in the optimization model which is the profit multiplied by the probability (expected_profit=chance*profit) of this profit to happen. The objective function of the model is then modified to:

$Objective\ Function$ (maximize <u>expected</u> profit for the planning horizon):

$$
\begin{aligned}
max \sum_{t\in T}\sum_{p\in P}\sum_{r\in R}\sum_{i\in O}\sum_{n\in N}\sum_{j\in D} r_{inj}^{tpr} * chance_n^r * profit\_rail \\
+ \sum_{t\in T}\sum_{p\in P}\sum_{r\in R}\sum_{i\in O}\sum_{n\in N}\sum_{j\in D} r_{inj}^{tpr} * expire^{p(r+1)} * (1 - chance_n^r) \\
* profit\_truck\_delay + \sum_{p\in P}\sum_{r\in R} te^{pr} * profit\_truck\_early \\
+ \sum_{p\in P}\sum_{r\in R} td^{pr} * profit\_truck\_delay
\end{aligned}
$$

,where $chance_n^r$ is the chance (depending on dice) that the train is allowed to service up to n∈N terminals in round r∈R.

The objective function in this case maximizes the expected profit (chance*profit) for the entire planning horizon. The first term represents the profit that can be obtained by the successful transport of containers by train up to the respective probability $chance_n^r$. The second term expresses the risk that the dice can determine less terminals than the number of terminals the coordinator has decided to service. In this case the expiring orders that cannot be transported by train have to be sent by a delayed truck. This probability is (1-$chance_n^r$). The third term calculates the expected profit by on-time (early) trucks and the fourth term the expected profit by delayed trucks.

4.2.2. Coordinated system's performance

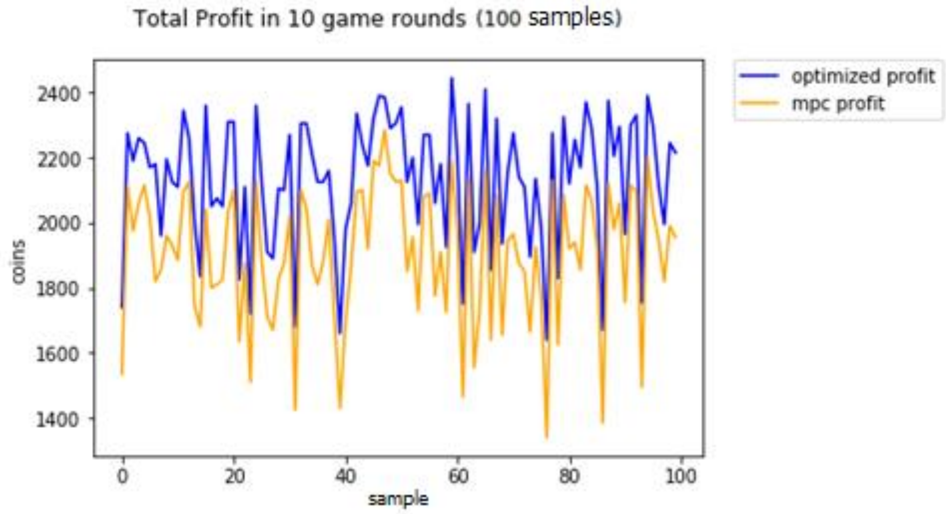


Figure 23 Profit per sample (optimized and coordinated performance)

As expected the optimized system is constantly above coordinator's profit level. This is illustrated in figure 23. The mean profit for the optimized model is 2133 of game currency and for the coordinated system is 1903 of game currency. The difference in performance of the two systems lays on the stochasticity that is included on the coordinated system, when optimized model uses full information. The coordinated system profit approaches the optimized in an average of 12,3% with a standard deviation of 3,5. This is graphically represented in figure 24. It can be assumed that this difference is the clear impact of stochasticity in the profit.

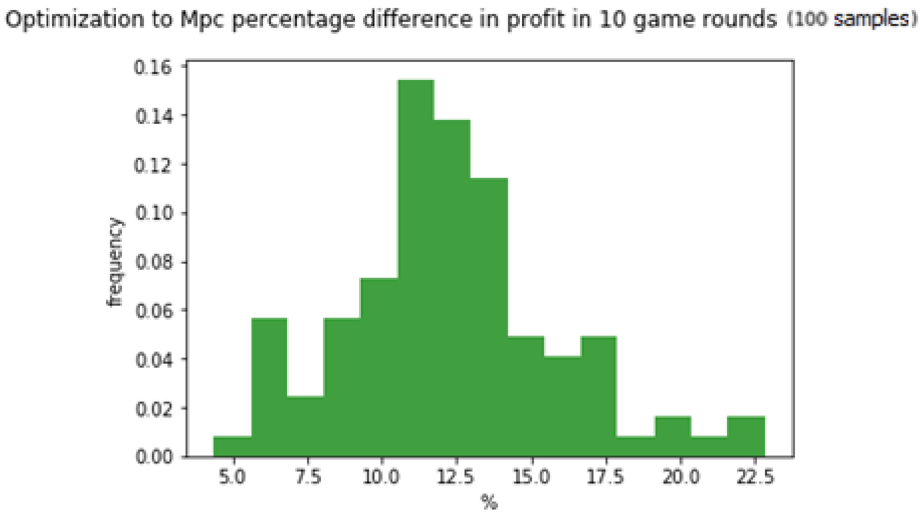


Figure 24 Profit Percentage difference optimized to coordinated performance (Distribution in 100 samples)

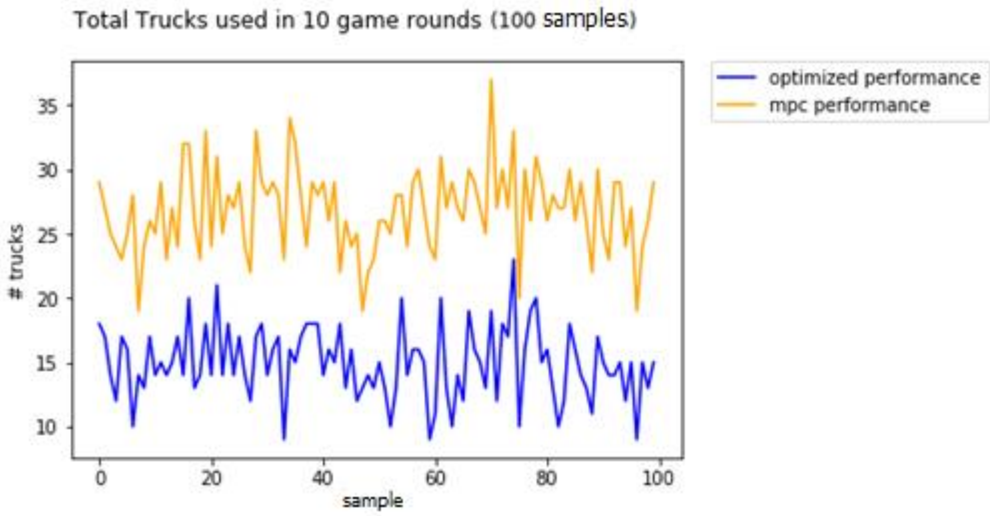


Figure 25 Truck use per sample (optimized and coordinated performance)

The average truck-use for the optimized performance is 15 trucks while coordinator's performance has an average of 27 trucks.

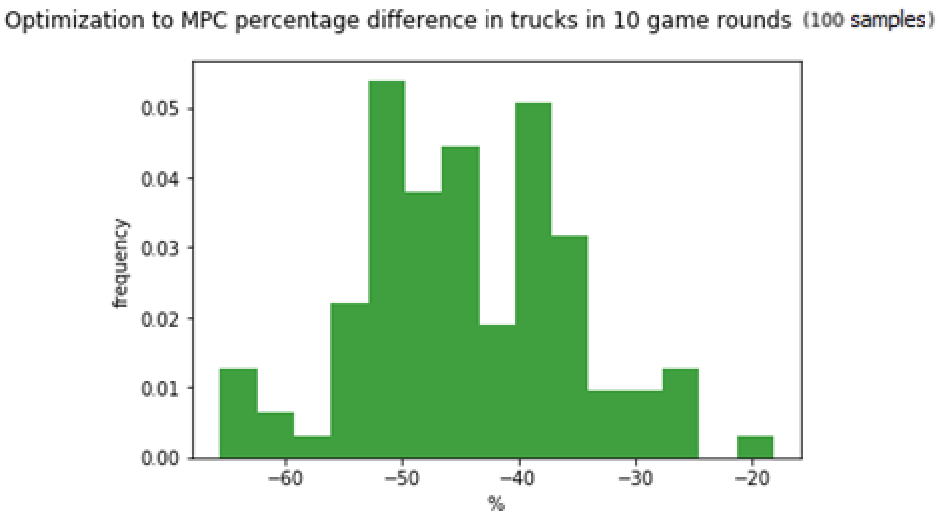


Figure 26 Profit Percentage difference optimized to coordinated performance (Distribution in 100 samples)

As illustrated in figure 26, the optimized performance reduces the truck-use by an average of 44,1% with a standard deviation of 9.

5. Selected Policies

After the literature review in coordination mechanisms and cooperative incentives and in consultancy with experts the policies that will be assessed for their performance are defined in this chapter. The framework of the chosen policies is based on the work of Brooks et al. (2009) that describes these mechanisms especially for port to hinterland transportation. The different chosen policies are divided, according to their kind, to cooperative or information sharing and monetary adjustment policies. The changes on the simulation flowchart due to each policy intervention can be found in Appendix C.

5.1. Information sharing policies

5.1.1. Horizontal collaboration of actors

Alliance between freight forwarders:

> Policy (1). Freight forwarders consolidate their containers to achieve economies of scale and have discount in train transport by train operators. Requires information sharing between alliance forwarders.

Alliance between operators:

> Policy (2). Operators can trade the containers that cannot transport by themselves, if the other operator has chosen the respective terminal-destination.
>
> Policy (3). Operators decide together which terminal(s)-destination to service each train in order to maximize their total benefits, then negotiate with forwarders for the respective orders and at the end of the round share the profits.

Alliance between forwarders and alliance between operators (combinations of 1.1.-1.2.):

> Policy (4). Freight forwarders can consolidate their containers and operators can trade their containers between them.
>
> Policy (5). Freight forwarders can consolidate their containers and operators co-decide trains' terminal(s)-destinations.

5.1.2. Vertical collaboration of actors

Alliance between freight forwarder and operator:

> Policy (6). A freight forwarder deals to transport all his containers with a specific operator for a predefined price, and the operator decides which to send by truck and which by train.
>
> Policy (7). Forwarder gives priority to a specific operator to choose which containers will take in a predefined price and then can negotiate with the other operator for the rest.

5.1.3. Vertical and horizontal collaboration of actors

Alliance between freight forwarders, alliance between operators and alliance between freight forwarders-operator

> Policy (8). Forwarders make alliances to consolidate their freight and give their orders to specific operator in predefined price and operators can trade their containers to the other operator if they cannot fulfil the order.

These policies don't affect the fully coordinated model (optimization), as they concern only the behavior between the players, by which the fully coordinated system is not affected.

5.2. Monetary adjustment policies

Policy (9). Subsidize the utilization of trains above a percentage (e.g. 70%). *Note that this policy may not have a very high effect as the in-game operator profitability is almost proportional with train utilization (if the deviations in negotiated prices are neglected), and thus operators try to utilize their train anyway, even without subsidy.

Policy (10). Fine the use of truck (by operators and freight forwarders). *Note that this would probably raise the fees for train use, as the operators would ask for higher prices, that forwarders could accept in order to avoid fine.

Note that economic policies may affect the performance of the fully coordinated as “new” resources are inserted in the system, if it is assumed that the same policies would apply to both systems (fully coordinated and actor-based).

6. Results and Discussion

6.1. Assumptions, Implementation and verification of the models

6.1.1. Important assumptions of the models

In this subsection the important assumptions for the used models that described in the previous chapters are summarized and listed.

Game model assumptions:

- The game model is an abstraction of the freight transport system between the terminals of Port of Rotterdam and the destinations of Duisburg and Burghausen in Germany.
- Players represent freight forwarders and train operators and is assumed to have behavior that is relevant to real operations' behavior.
- One day is considered as one game round.
- The transport of each container is assumed that can be fulfilled in the same day that is sent.
- Delays are included on the model.
- The game represents typical days under normal operations and without problems.
- Every container order should be fulfilled, either by train or truck.
- There are several rules that the players should follow, as capacity constraints. All the game rules are presented in Appendix A.

Simulation model assumptions:

- Simulation model is a simplification of the game.
- Follows the flow chart of the game design.
- Follows the same rules as the game.
- Does not include human players. Instead decision models (i.e. Discrete Choice Modeling and utility maximization) are used to represent players' decisions.
- Negotiation transport costs are drawn from distributions fitted in observed prices where needed.
- Discounts due to economies of scales is assumed to apply after the consolidation of 4 containers. This is relevant for the alliance policies and not for the current system's simulation model.
- Negotiation time which is set to five minutes according to the game rules is translated into negotiation rounds, as the real time is not relevant for the simulation. One negotiation round is defined as the interval between the proposal of a transport price by the train operator, the acceptance or decline of this price from the freight forwarder and the trade between the accepted orders. In the simulation model, as shown on the simulation flow chart, this number is set as constant to 2 rounds. This number is chosen as it was observed from gaming sessions that they players had time for about two rounds of negotiations in the given five minutes.
- The penalty and subsidy amount that are used in some policies are assumed to be received or given by an actor that is external for the port system (e.g. government).

Optimization model:

- Optimization is a model of the game.
- Does not include human behavior and interactions, neither real nor modelled.
- All the decisions are taken by one decision maker that has access to all the available information and aims for the system's optimal solution.
- Follows all the constraints that are set from the game rules.

- Excludes stochasticity by taking as input the results of the stochastic elements.
- The optimization model is dependent on the performance of the policies that is compared, as it takes the same data as input. For example, as mentioned in the description of the game, lower reputation rate in each round lead to less new orders that are incoming in the system. Thus, if players achieve a reputation that brings 140 containers in the system, the same 140 containers will be taken from the optimization model as input. Thus, as the performance of the players increase and more demand is created, the higher become the profitability of the optimization model, as well. The aim of the optimization model is to quantify the level of possible improvements compared to the planning of the players, when the input is the same.

All the assumptions and constraints of the optimization model can be found in detail in chapter 4.

Coordinator's model:

- Coordinator's model is based on the optimization model, combined with MPC controller approach.
- Does not include human behavior and interactions, neither real nor modelled.
- All the decisions are taken by one decision maker that has access to all the available information and aims for the system's optimal solution.
- Follows all the constraints that are set from the game rules.
- Stochasticity is included.
- It can be assumed as a policy measure that bypasses the negotiation phase and makes a central planning for all the transportation of all the orders.

6.1.2. Implementation and verification

The game sessions were organized using the game boards and decks that were already developed.

The simulation and optimization models were implemented in python 2.7. Specifically, for coordinator's model and the optimization IBM CPLEX API for python was used to solve the Linear Programming formulation of the problems. The hardware of the computer system that was used was an Intel i7-6700HQ 2.60 GHz CPU, 8.00 GB RAM and the operating system was Windows 7 64-bit.

As for the verification of the models, first the simulation model tested if it complies with the game rules and real players' performance. This was verified with multiple runs of simulation model by examining if the container transport routes, player decisions and train origin-destination choices match. In addition, the simulation model had a performance that was close to real players'. However, this was compared with only two game samples, which is a very small sample size. In order to have a more reliable verification more games should be played. Optimization model was verified in the same way and all the constraints were satisfied. An example of the routing with the simulation model and the optimization model can be found in Appendix B.5.

6.2. Performance of policies

In this subsection, the comparison of the policies in terms of the KPIs is presented. A detailed graphical representation for the performance of each policy is given on Appendix C.

For the first eight policies, the base for comparison is the optimization model's performance and thus the comparison between the policies is set as the percentage difference from this reference point.

$$dif = \frac{(policy_{per} - opt_{per})}{opt_{per}} * 100$$

For policies 9 and 10, which are the subsidize of train-use and fine of truck-use respectively, a sensitivity analysis is chosen in order to check the performance in different levels of subsidies and fines.

6.2.1. Policies 1-8

On the next tables the performance of each policy can be seen compared to the optimization model.

Table 5 Profit comparison between policies and optimization model

Profit comparison between each policy and optimization model		
	Mean Dif. (%) (100 samples)	St. Deviation
Current performance	-56,5	7,4
Policy 1	-50,1	8,1
Policy 2	-47	6,2
Policy 3	-44,9	9,2
Policy 4	-44,9	6,9
Policy 5	-46	8
Policy 6	-65,5	7,6
Policy 7	-55,4	8,2
Policy 8	-42,8	7,9
Coordinator's performance	-10,9	2,77

Table 6 Truck-use comparison between policies and optimization model

Truck use comparison between each policy and optimization model		
	Mean Dif. (%) (100 samples)	St. Deviation
Current performance	503,9	293
Policy 1	452,4	235,5
Policy 2	484,1	455,6
Policy 3	418	329
Policy 4	415	203
Policy 5	422	235,9
Policy 6	575	233
Policy 7	535,2	422
Policy 8	390,4	182,2
Coordinator's performance	84	31,6

In figures 27-28, the performance of each policy in terms of profit and truck-use compared to the optimized performance is represented graphically.

As can be seen, all the policies except "policy 6" have a better performance than the current situation. The best performance is achieved by the application of "policy 8", which represents the highest level of cooperation, vertical and horizontal at the same time. Furthermore policies "3" and "4" approach the performance of "policy 8". These two policies concern only horizontal collaboration, that is collaboration between the same kind of actors. At last, it is worth mentioning that only the cooperation between forwarders (policy 1) and only vertical collaboration (policies 6 and 7) are not enough to improve the current system in a high level.

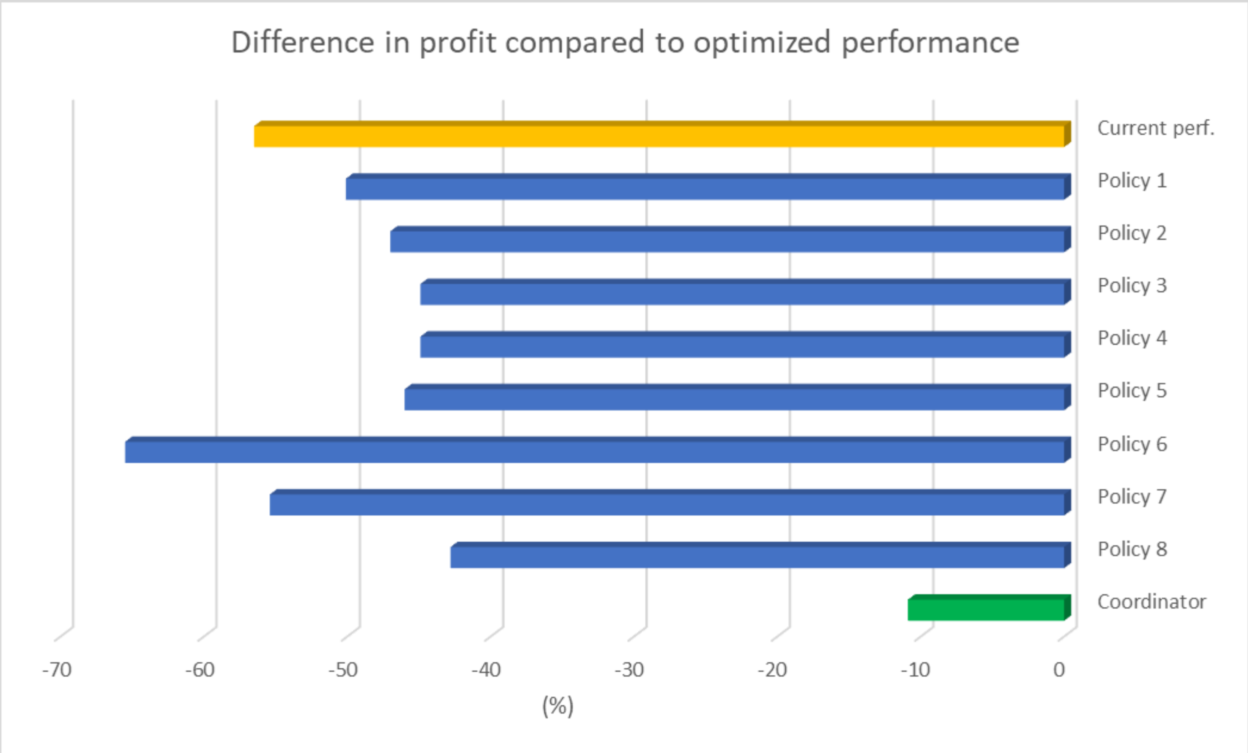


Figure 27 Profit comparison between policies

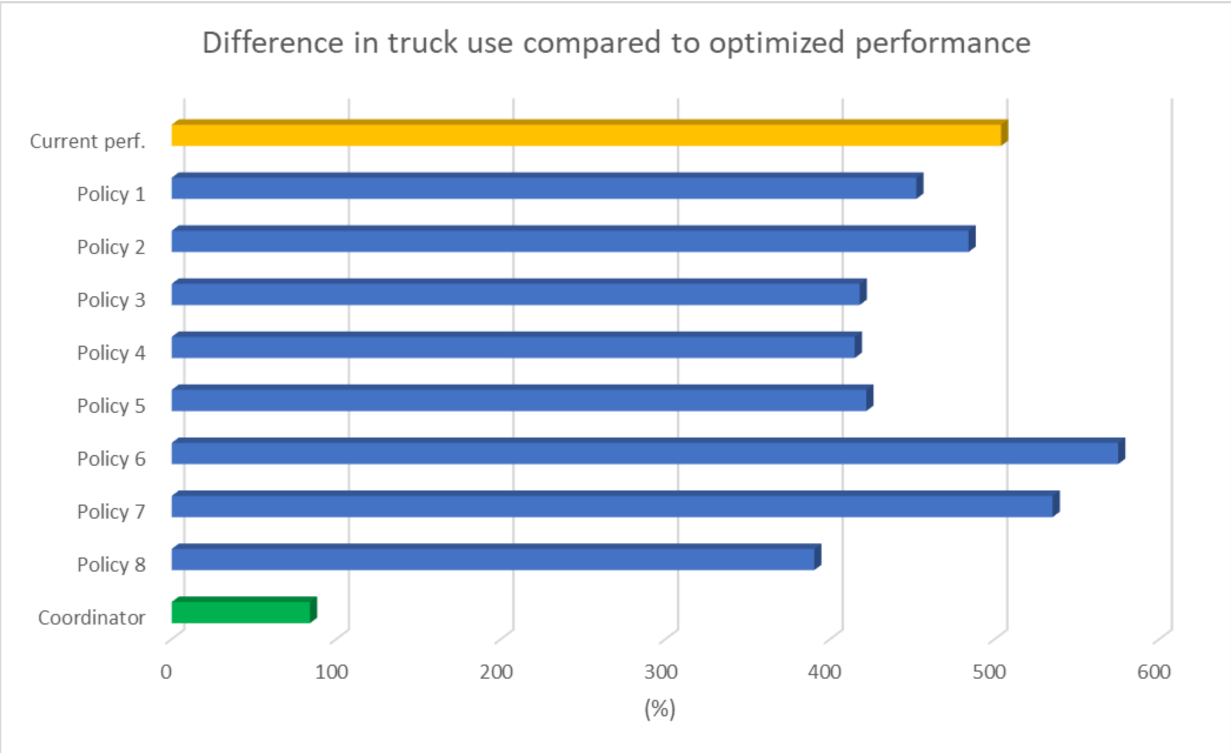


Figure 28 Truck-use comparison between policies

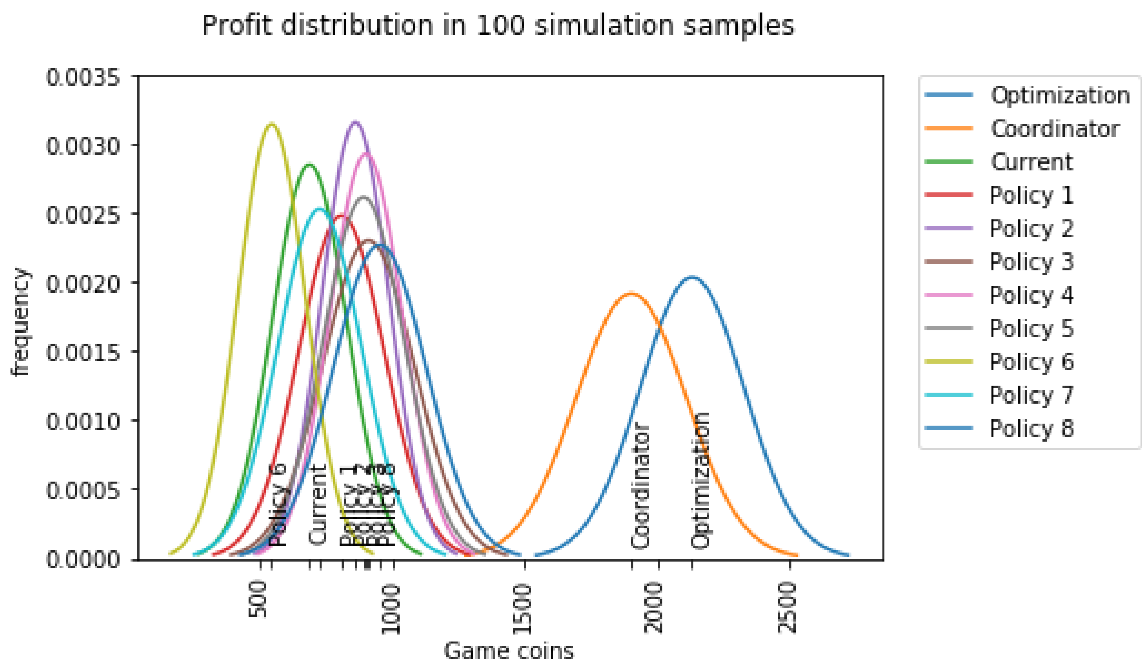


Figure 29 Distribution of profit in 100 samples for the different policy scenarios.

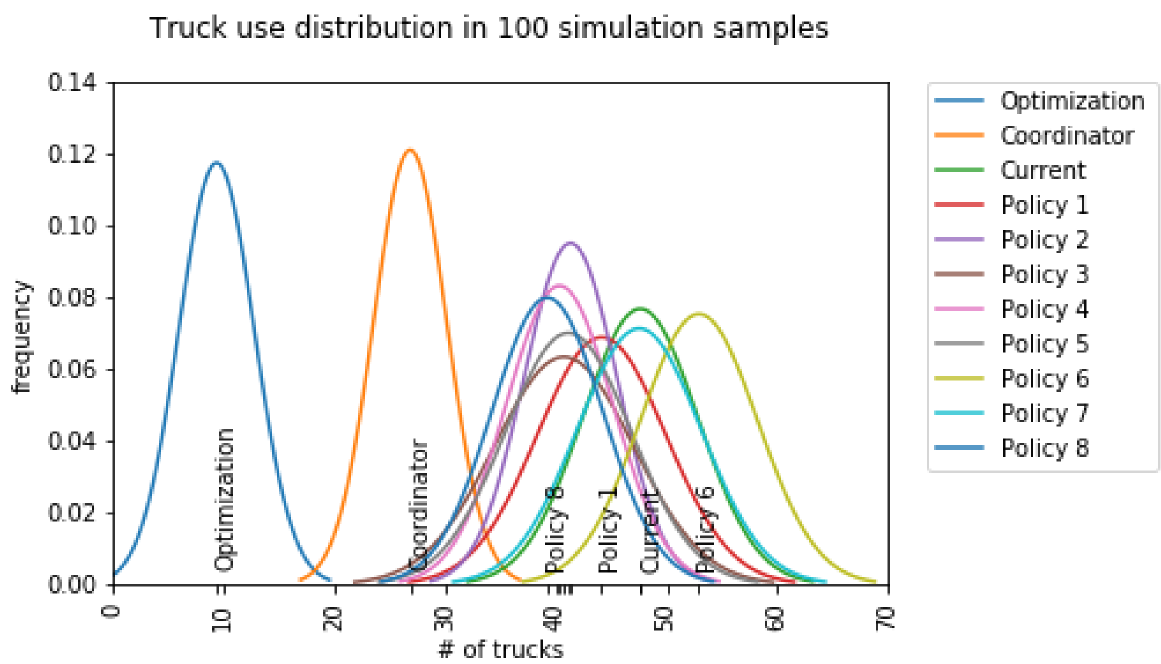


Figure 30 Distribution of truck-use in 100 samples for the different policy scenarios.

Note that the performance of the optimization model in the illustrated distribution of figures 29-30 comes from the comparison between the Coordinator and the optimized system that has the highest performance. The optimization model, when compared with the rest policies has lower performance as the orders that come to the port system are less, due to the lower reputation per round that the players achieve. As mentioned in the methodology part, optimization model has not a direct “physical” interpretation, as the coordinated system. It is only used for comparison, in order to quantify how far from optimal planning are the players, given as input the same number and characteristics of the orders.

6.2.2. Policy 9

Policy 9 is a subsidy policy for the train utilization rate. When the utilization rate overcomes a specific percentage (e.g. 70%), extra benefits are given to train operators. A sensitivity analysis is done for different prices of subsidy, as percentage of the basic train cost. The impact of the subsidies as function of the subsidy amount is illustrated in figures 31-32. The subsidy amount is assumed that comes into the port system from external resources (e.g. government). Also, note that 0% subsidy describes the current system, without any subsidy.

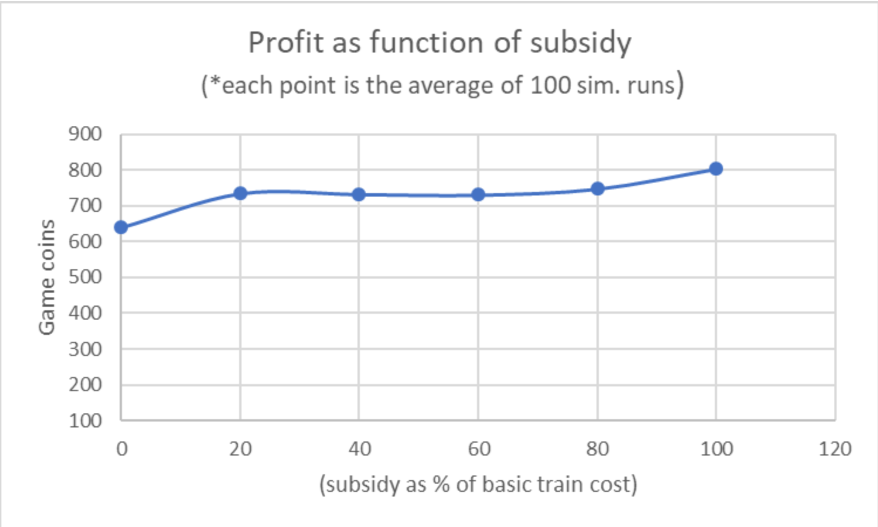


Figure 31 Profit as function of subsidy

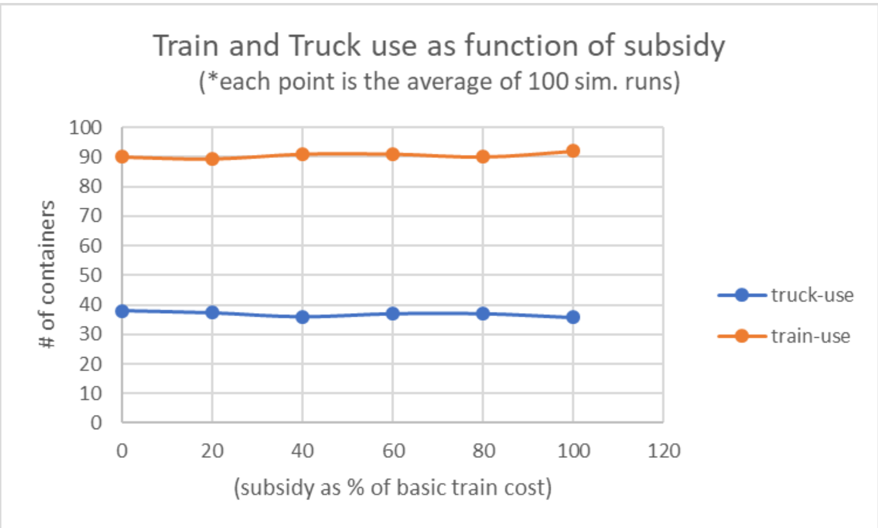


Figure 32 Train and Truck use as function of subsidy

As can be conducted from figures 31-32, the subsidy has not a significant impact on the performance. The profit seems to increase, but this is due to the new resources (subsidy) that come to the system. The "real" performance that is the use of train and truck is in the same level, independently of the subsidy level. This can be explained as the operators already try to utilize, as much as possible, their trains to increase their income. Thus, an increase of the benefits is not critical to achieve a higher utilization rate.

6.2.3. Policy 10

In the same way as the subsidize policy (policy 9), policy 10 penalties the use of truck by freight forwarders. As in the previous policy, in this case as well, the fine is set as a proportion of the basic truck cost and assumed to be paid in an external actor (out of the port system).

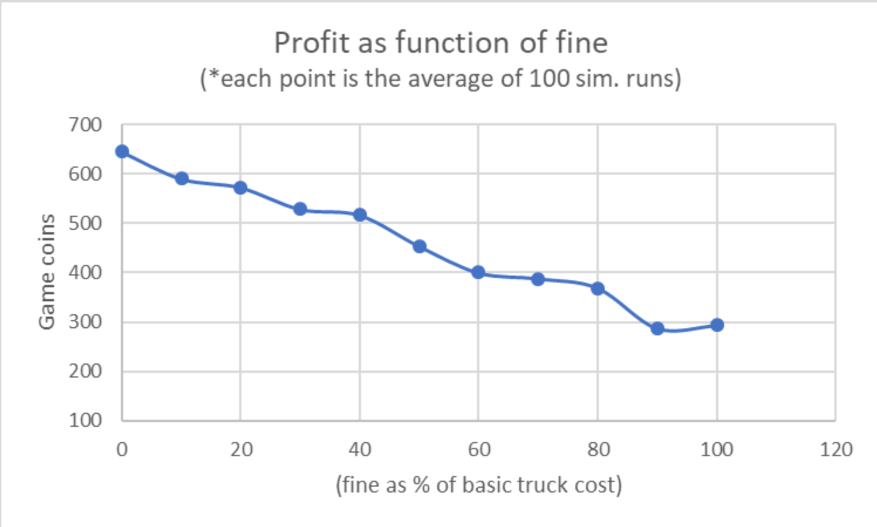


Figure 33 Profit as function of fine

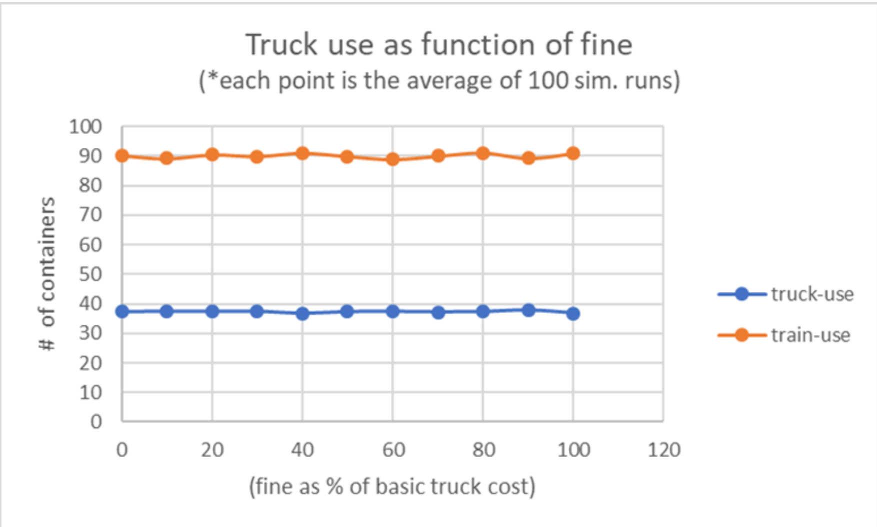


Figure 34 Train and Truck use as function of penalty

As in the subsidy policy case, the fine level is not critical for the reduction of truck-use and increase of train use (see figure 34). This happens because the benefits for the use of truck is already less than trains' and freight forwarders try to send their containers by train when this option is available in a reasonable price. Furthermore, the fine can raise the negotiation prices between forwarders and operators as the operators would know that the truck alternative would be even more expensive than previously. Finally, although the train and truck use is the almost the same the profit line in figure 33 seem to reduce as the fine increases. This happens due to the loss of resources to the external fine receiver.

6.2.4. Remaining challenge to reach coordinator's performance

Due to the big gap between coordinated system's performance and the rest of the policies an explanation of this difference is done in this section.

For this reason, a sensitivity analysis on two parameters that assumed constant on the negotiation phase of simulation model is done, to explore how the change of these parameters could affect system's performance. These are not relevant for the coordinator's model as the negotiation phase of the players is bypassed.

The two parameters are the negotiation time between the players, that is translated in negotiation rounds, and the minimum number of containers that assumed the consolidation effects and economies of scale are achieved.

The negotiation time is set to five minutes, according to the game rules. It was observed from the game sessions that the players had time for about 2 negotiation rounds in five minutes. One negotiation round is defined as the interval between the proposal of a transport price by the train operator, the acceptance or decline of this price from the freight forwarder and the trade between the accepted orders. In the simulation model, as shown on the simulation flow chart, this number was set as constant to 2 rounds.

The number of containers (n) that consolidation effects started for the operators and discount that was given to the freight forwarders due to the economies of scale, assumed also constant in the simulation model. It was observed from the game sessions that above 3 to 4 containers, the operators proposed prices in discount to the freight forwarders. The discount is only relevant in the form of alliances that the players consolidate their containers. The number of containers (n) was chosen as 4 containers for the simulation model.

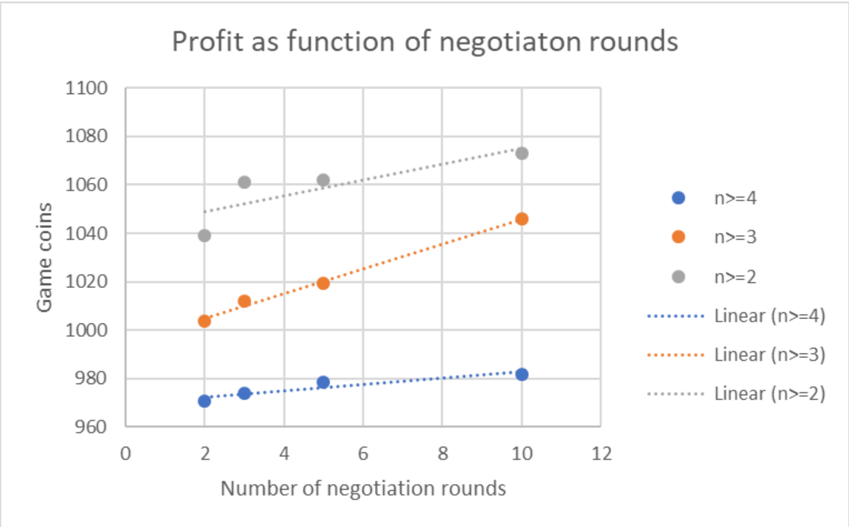


Figure 35 Profit as function of negotiation rounds and number of consolidated containers.

As a base for the sensitivity analysis, policy 8 is chosen.

As can be seen in figure 35, as the negotiation time increases and as the consolidation point drops the profit is increased. By dropping the consolidation point from 4 (current simulation) to 2 containers and by increasing the negotiation rounds from 2 (current simulation) to 5, the performance can be increased about 10%.

However, there is still a remaining gap between policy performance and coordinator. This can be caused by several other reasons. First, there is still competition for the unconsolidated containers. Second, the players do not have a central plan for a planning horizon, but plan individually for their orders. On the other hand, coordinator plans for all the available orders at the same time and for a planning horizon.

At last, the simulation model is based on the current game with the basic rules. The new policies allow for new interactions between the players that may not be incorporated in the most realistic way in the current simulation. This can be a recommendation for future research, to observe players' behavior under the new policy implementation and re-simulate the game.

6.3. Policy 4 implementation in game session

Policy 4 was chosen to play in the last game session to find the result of the policy. This policy was chosen as has a high performance and included the participation of all players. Policy 4 sets parallel horizontal collaboration of freight forwarders and train operators.

As can be seen in figure 36, the profit of the players reached 910 game currency units compared to 717 that achieved in the first to games (average). Also, the truck use dropped to 36 compared to 46 in the previous games and train use increased to 107 from 91 containers.

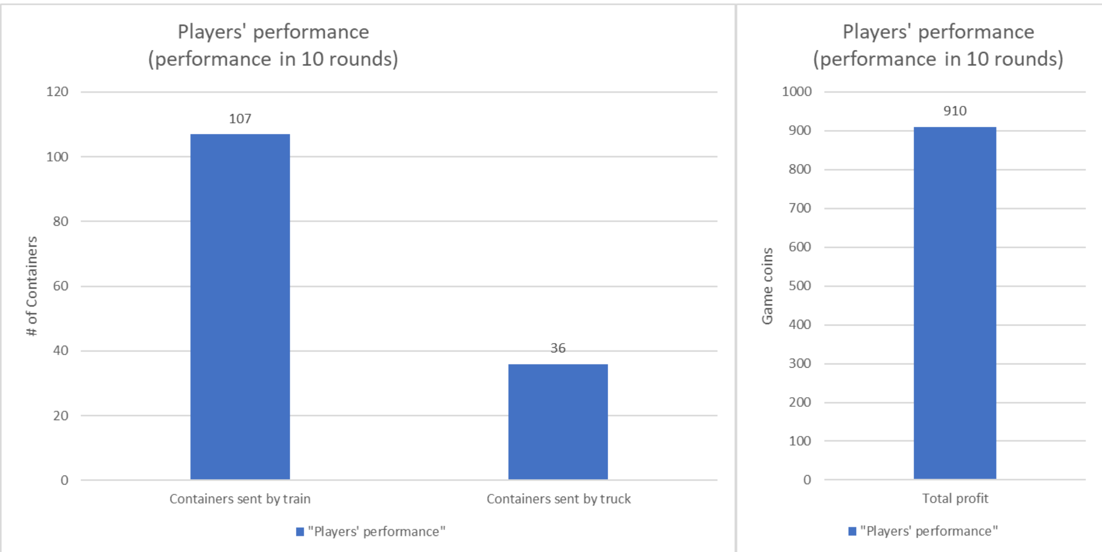


Figure 36 Performance of players in game session with policy 4 applied

6.4. Discussion

In this chapter the results by all models and the comparison between the selected policies were summarized and presented. At the end the results of the in-gage implementation of a cooperation policy were given. These outcomes led to some conclusions that are discussed next.

First, the sensitivity analysis of the fine and subsidy policies show that they do not have a significant effect on utilization rate of the trains and the reduction of used trucks and thus they found to be inadequate measures.

Furthermore, the cooperation between the train operators to co-decide which terminals-destination to service is the policy with the highest performance, between the policies that included one kind of actors (only horizontal collaboration). Simple vertical collaboration (alliance of one freight forwarder and one operator) has even negative impact on the performance, as it reduces the transport options of the alliance members. Subsequently, the results of the policy testing show that the higher the level of collaboration the more the performance improved. The alliance between freight forwarders to consolidate their freight and the trade of containers between operators apart do not have high impact on the performance, but the combination of these two interventions achieves much better results. The highest level of cooperation, that is simultaneous collaboration in vertical and horizontal dimension, led to the highest performance among the policy alternatives.

After assessing the performance of the different policies, one policy was selected and implemented in a game session. The results of the game and the observed behavior showed that the players responded on the expected way on the new rules. The performance of the players was increased compared to the first games and this was mainly achieved by the cooperation of the players on sharing information and consolidating their orders.

However, the performance of the cooperation policies could not reach coordinator’s performance. According to the presented results, coordinator’s performance approaches optimized performance in a very high level. The remaining difference between the optimized performance and coordinator’s performance can be attributed to the stochastic elements, which are assumed known for the optimization model, while for the coordinator are still unknown.

The big gap between highest policy performance and coordinator’s performance can have different sources. For example, high level of cooperation lead to consolidation effects and economies of scale for the participant actors. However, there is still competition for the unconsolidated containers which could lead to inefficient transport for these containers. In addition, the simulated players do not have a central planning for all the orders and do not consider any probabilities for the next rounds, but only assess the current information. Although coordinator assesses the same information, he plans for a planning horizon for the transport of all the available orders.

To conclude, cooperation policies can improve the current system in terms of profitability and sustainability. However, it is worth noting that according to the results, all the stakeholders can benefit more by the implementation of a central system that will have the ability to collect all information and do the planning for the whole system. This of course requires the cooperation and acceptance of all the involved actors.

7. Concluding remarks and further research

Collaboration is necessary for the successful implementation of new freight transport concepts in port to hinterland transportation, as synchromodality. This study tried to fill a research gap of policy testing and evaluation using a combination of gaming, simulation and optimization and evaluate cooperation policies that will move towards system's efficiency. For this reason, an innovative combination of methods was followed.

The combination of the three methods of gaming, simulation and optimization was helpful to explore and understand the behavior of the stakeholders in port to hinterland freight transportation, quantify the impact of different policy interventions on actors' behavior and finally identify how far is this system from a system that have the ability to assess all the information and take the most efficient decisions.

More specifically, the game sessions were useful to observe and record the current behavior of the players. Using the observed data, the simulation model of the game was defined, including a model of the decision-making of the players. Subsequently, a number of policies were proposed using literature review and expert interviews and tested using the simulation model. Their performance was then compared with a possible coordinated system that included stochasticity and with the upper bound that was set by the optimization model.

This methodological combination was innovative as could extract the benefits of each method, while avoiding the disadvantages. The benefits of gaming were the observation of real behavior and a simplified representation of the port to hinterland freight transport system, which allowed for cheap and convenient environment that includes human interaction to test the selected policy scenarios. The disadvantage of gaming was the low sample due to the availability of players. This was by-passed by the simulation that provided high samples and modelling of many different scenarios in a reasonable time, without the need for players. However, as simulation included modeled behavior and not real, gaming was re-used at the end to verify the findings. In addition, optimization was used to understand the potential for the system improvements and set a base for comparison during the policy testing.

By using the above methodology, this study aimed to strengthen and extend the gaming application to test and evaluate different policies in freight transport by intervening on players' in-game behavior and recording their performance in different policy scenarios. This was proposed as future research by Kurapati et al. (2017) and this study tried to filled this gap, as well.

A number of different conclusions and research implications, both practical and theoretical, can be drawn from the outcomes of this study. These are presented in the next subsections.

7.1. Conclusions

This section addresses the most important outcomes of this study, followed by the answer of the research questions and sub-questions as defined on section 1.2.

On the methodological part, this study showed that the combined use of gaming, simulation and optimization allowed to extract each method's benefits, while skipping the main drawbacks. The combined methods were not independent on each other but were chosen in such a way that the advantages of the one method could cover the disadvantages of the others. The proper functioning of the combination appeared on the results, as well. After the analysis that compared different policies, on the last game session for this study, the players responded on the expected way on the in-game policy implementation.

The analysis also indicated that the current system is far from the optimal state and the involved actors achieve much lower profits and port reputation rates. The source of this low performance lays on the lack of information sharing, the inability of the stakeholders to cooperate and the conflicting interests of the stakeholders.

The uncertainty of delays and the stochastic demand themselves only lead to a small proportion of the inefficiency. All the rest difference in performance is due to the ineffective planning. This was shown in the results, as a coordinator that operated under the aforementioned stochastic elements, but by-passed player's negotiations, could achieve a much higher performance that approached the optimal solution in about 10% deviation.

Thus, the near-optimal planning can be done by a coordinator that has access to all available information and is accepted by all the involved actors.

Generally, the higher the level of collaboration between the players the higher the performance that they can achieve. A simultaneous vertical and horizontal collaboration can lead to an improved performance compared to the current system.

However, port managers and stakeholders should be careful on choosing which cooperation policy to implement as not all cooperation policies have a positive effect on performance. Some vertical collaboration interventions that do not include all the involved actors can even have negative outcomes for the system. This happens as the agreements between separate small alliances create more restrictions on the decision-making, that do not guarantee that these are the most effective for the system.

There is still a big difference on coordinator's performance and policies' highest performance. This is mainly because there is still competition for the unconsolidated containers. In addition, most players try to send their orders as soon as possible and do not plan for multiple rounds in cooperation with the other players. This can have short term benefits for the players, but in long-term it can lead to reduction of system profitability and port reputation. However, it should be noted that a coordinated system is much more difficult to apply as it requires the acceptance and the compliance of all the involved actors, which is a much stricter agreement than any cooperation policy.

Finally, the results show that penalty and subsidy policies do not have a significant effect on overall performance, as the companies already try to achieve the highest individual profits by utilizing the transport mean with the highest benefits and avoiding the expensive alternatives. As stated previously, the inefficiency comes from the lack of cooperation and information sharing and not from the price differences of the different transport alternatives.

Considering the analysis, the outcomes and the conclusions the answer to the research questions and sub-questions follow.

RQ1. "How can we achieve a higher level of performance through cooperation in the port to hinterland freight transport system?"

The main research question was answered by considering the results of all parts of methodology. A higher level of performance can be achieved by the simultaneous formulation of interfirm alliances between freight forwarders, between train operators and between freight forwarders-train operators at the same time. This would change the current competitive environment to a more integrated transport system through collaboration that would have the ability to take more efficient and sustainable decisions for the whole port to hinterland system and save more resources that could be distributed to the involved members. However, as shown in chapter 6, this performance cannot yet reach a coordinated system that have access to all available information and decides for system's efficiency and not for individuals' benefits. This difference mainly lays on the competition for the unconsolidated containers and on the difficulty of the actors to achieve a central planning not only for the current orders, but for future time periods as well.

RQ2. "To what extent can we combine gaming with simulation and optimization to test and evaluate these policies and strengthen game application?"

As shown in chapter 6, the simulation model combined with the optimization set a tool for comparison to choose between policy alternatives. As the game is a representation of the port to hinterland freight transport system developed by experts and stakeholder consultation can give a safe and cheap environment for scenario testing, which has the advantage to include human interaction. Simulation model gives the flexibility on testing different policy scenarios, without the need of players. Optimization provides a stable base of comparison between the alternatives and an insight of what is the optimal planning that the players should move. Finally, the outcomes were tested in game sessions and observed that players' behavior responded in the expected way on the changed rules of the game. This showed that the connection between the methods functioned well and that the combination of these methods can be used to avoid the disadvantages of each method. However, it should be noted that as the game is a model, attention is needed on the interpretation of the results to the real-world systems. This greatly depends on the assumptions and simplifications that were done during the development of the game. For example, the assumptions could be valid for Port of Rotterdam, as RCCR developed for this system, but for another port system these assumptions could lead to important omissions.

SQ1. Which are the most relevant policies for cooperation?

The selected policies were described in chapter 5. Different policies and coordination mechanisms for port to hinterland transportation were found by reviewing relevant literature, that presented in chapter 2. Subsequently based on literature and in consultation with experts, ten policies were selected and formulated for the problem of this study. The selected policies were divided into information sharing policies and monetary adjustment policies. The most relevant information sharing policies are based on the form of alliances between forwarders (horizontal collaboration), alliances between forwarders-operators (vertical collaboration) and a combination of these (horizontal and vertical collaboration at the same time). As for monetary adjustment policies, the most relevant measures are subsidy of high train utilization rate and penalty on truck use.

SQ2. What is the highest achievable in-game performance under full information and no stochasticity?

This question was answered in chapter 4. In order to find the highest performance and compare it in different scenarios an optimization model was developed and formulated as a linear programming problem. The optimization model gives the optimal performance for the system by taking as input all the information that the players have and by transporting the same orders in a more efficient way. The optimization model excludes stochasticity by taking as input the outcomes of the stochastic elements, as well. Note that the optimized performance has not a single value, but differs as the input of the stochastic elements, the number and the type of orders that have to be fulfilled differ per game. As an indication, the optimization model achieved an average performance that found to be about 160% higher in profit than the current's system and has a 75% reduction in truck-use.

SQ3. What can be the in-game performance of a coordinated system including stochasticity?

A coordinated system version was defined in chapter 4. The coordinator can be seen as a policy measure of the system. However, as bypasses players' negotiations and does not intervene to players' interactions as policies, it was described separately. Coordinated system's model is based on the optimization model with the difference that operates under stochasticity. Demand is assumed unknown for the coordinator and the outcomes of the stochastic elements as well. In this way coordinator have exactly the same information and at the same time as the players. According to the results, the coordinator achieved 10.9% less profit than the optimized and used 84% more trucks, when the actors of the current system used 5 times more trucks than the optimization model's performance.

SQ4. How the selected policies influence the overall in-game performance relative to the highest achievable performance?

Chapter 6 presents the comparison of the performance between the policies and the optimized system. It is found that the structure of alliances both in horizontal and vertical dimension at the same time can help to achieve a higher performance. On the other hand, small alliances of vertical collaboration (e.g. one freight forwarder with one train operator) found to have even negative effects on the performance of the system. Furthermore, the results showed that penalty and subsidy measures have not a significant effect on utilization rate of trains and on truck-use.

SQ5. Can the configuration of game rules, according to specific policy plans, affect players' performance in the expected way?

After the analysis and comparison of the selected policy scenarios, one policy was chosen to be tested in a game session, in order to validate the outcomes. The results were presented in Chapter 6. The in-game implementation of the policy was done by changing the rules of the game on the last game session. It was observed that the players adapted their behavior by cooperating according to the policy rules and achieving consolidation of their orders which made the planning easier and more efficient for the train operators. Finally, the performance that the players achieved was increased compared to the first game sessions. Of course, the sample of one game is very small to validate the results on the level of performance. However, the observation on the in-game cooperative behavior of the players and the easier planning for the operators compared to the first sessions, showed that the policy itself helped the players to take more efficient decisions for the system.

7.2. Research implications

The outcomes of this study can be used both for practical and theoretical implications.

Practically the results can be used to raise stakeholders' awareness on the importance of collaboration in port to hinterland freight transport. This could be achieved by organizing gaming sessions with the mangers of the port system. At the beginning, the game can be played with the basic rules. This will let stakeholders identify by themselves the problems, the complications in negotiations and the difficulty on taking individual decisions under pressure that lead to the inefficiency of the current system. According to Kourounioti et al. (2018), on a post-game survey after playing RCCR game, 75% of the participants identified the challenges and opportunities of rail bundling. Subsequently, the game rules can be changed with a cooperation policy implementation, as shown in this study. This policy can make players share more information, take more efficient decisions and end up the game with higher profits. This can help stakeholders realize the importance of cooperation and information sharing for the individual profitability and for the whole system efficiency.

Another practical implication is the demonstration of the importance of a central coordinated system that is accepted by all actors. In a similar way as described above, stakeholders can play RCCR game with the basic rules. Parallel, the model of the coordinator as described in chapter 4 can be used, with the same input as the players have. At the end of each round, that the players have taken their decisions, the planning of the coordinator for the specific round can be presented and be compared with players' planning. As shown in the analysis, coordinator's performance is much higher than current performance. Thus, the higher benefits that coordinator's planning can bring to the system can make the stakeholders understand the importance of a central coordinated system both for the companies and for the system.

The theoretical contribution of this study in literature is that showed the importance of cooperation between the actors in port to hinterland transportation, evaluated different cooperation policies and demonstrated the important role of a coordinator that is accepted by all involved members.

A more innovative contribution of this study is the proposed combined methodology of gaming, simulation and optimization to test and evaluate different scenarios. This methodology begins with the understanding of actors' behavior through gaming. Subsequently, using the observed data a simulation model is developed that allows for different scenarios modelling and high sampling in a reasonable time. The optimization model is useful to identify the gap between the optimal performance and the performance of the different scenarios. The explanation of this gap can give an insight of the root causes of this difference and the optimization solution can show ways that can help players increase their performance. Finally, the simulated performance of the chosen scenario can be validated in a game session to observe if the changed rules or parameters have the desirable effects on real players' performance and behavior.

7.3. Recommendations for future research

In this subsection the suggestions for future research are presented, based on this study.

As this study includes a number of different models and due to the low samples provided by the game sessions, the models should be further validated with more observations.

The optimization of the game does not include any human behavior and was developed according the game rules that were clearly stated on the gaming instructions. Thus, the validation of the optimization model for the purpose that was developed is considered sufficient. As a further research it could be proposed an optimization model that would include the decision making of the players.

On the other hand, the simulation model includes a Discrete Choice Model for the decision making of the players. As the parameters for this model were based only in two game session with the same players, in the future, observations from more game sessions and different players could be used for parameter estimation.

In addition, as future research is proposed the more detailed observation on the interaction of the players. The new observations could lead to a more reliable decision model that is included in the simulation model. For example, different decision rules could be tested in the simulation model for the negotiation phase between freight forwarders and operators (e.g. game theory) and be compared with the Discrete Choice Model that is currently used, to find which model fits better to the decision making of the players.

Also, the simulation model is based on the current basic rules. The new policies allow for new interactions between the players that may not be incorporated on the current model in the most realistic way. Thus, using new observations on players' interactions from game sessions, after the in-game policy implementation, a simulation meta-model could be developed, especially to model the behavior of the players under the new policy.

Furthermore, as the costs for information sharing and forming of alliances was not included in the policy performance of this study, in a future study it could be examined how transaction costs can affect the policy performance and implementation.

Finally, as the game sessions were organized with university students due to the low availability of port's stakeholders, it is recommended to validate the results in game sessions with professionals from the field of port to hinterland freight transport.

Bibliography

Behdani, B., Fan, Y., Wiegmans, B., & Zuidwijk, R. (2014). Multimodal schedule design for synchromodal freight transport systems.

Ben-Akiva, M., & Bierlaire, M. (1999). Discrete choice methods and their applications to short term travel decisions. In *Handbook of transportation science* (pp. 5-33). Springer, Boston, MA.

Ben-Akiva, M. E., Lerman, S. R., & Lerman, S. R. (1985). *Discrete choice analysis: theory and application to travel demand* (Vol. 9). MIT press.

Beuthe, M., & Bouffioux, C. (2008). Analysing qualitative attributes of freight transport from stated orders of preference experiment. *Journal of Transport Economics and Policy (JTEP)*, *42*(1), 105-128.

Bierlaire, M. (1998). Discrete choice models. In *Operations research and decision aid methodologies in traffic and transportation management* (pp. 203-227). Springer, Berlin, Heidelberg.

Bierlaire, M. (2003). BIOGEME: a free package for the estimation of discrete choice models. In *Swiss Transport Research Conference* (No. TRANSP-OR-CONF-2006-048).

Bierlaire, M. (2008). Estimation of discrete choice models with BIOGEME 1.7. biogeme. epfl. ch.

Bradley, S., Hax, A., & Magnanti, T. (1977). Applied mathematical programming.

Brandenburger, A. M., & Nalebuff, B. J. (1996). Co-opetition. New York, Bantam Doubleday Dell Publishing Group. *Inc.*

Brooks, M. R., McCalla, R., Pallis, A. A., & van der Lugt, L. M. (2009). Coordination and cooperation in strategic port management: The case of Atlantic Canada's ports. *Atlantic Gateway Initiative Working Paper*

Buiel, E., Visschedijk, G., Lebesque, L. H. E. M., Lucassen, I. M. P. J., Riessen, B. V., Rijn, A. V., & te Brake, G. (2015, January). Synchro mania-design and evaluation of a serious game creating a mind shift in transport planning. In *46th International Simulation and Gaming Association Conference, ISAGA* (pp. 1-12).

Camacho, E. F., & Alba, C. B. (2013). *Model predictive control*. Springer Science & Business Media.

Crozet, Y. (2017). Rail freight development in Europe: how to deal with a doubly-imperfect competition?. *Transportation research procedia*, *25*, 425-442.

Cruijssen, F., Bräysy, O., Dullaert, W., Fleuren, H., & Salomon, M. (2007). Joint route planning under varying market conditions. International Journal of Physical Distribution & Logistics Management, 37(4), 287-304.

Cullinane, K., & Toy, N. (2000). Identifying influential attributes in freight route/mode choice decisions: a content analysis. *Transportation Research Part E: Logistics and Transportation Review*, *36*(1), 41-53.

Dai, B., & Chen, H. X. (2009). A benders decomposition approach for collaborative logistics planning with LTL transportation. In The third international conference on operations and supply chain management, Wuhan, China.

Dai, B., & Chen, H. (2011). A multi-agent and auction-based framework and approach for carrier collaboration. Logistics Research, 3(2-3), 101-120.

Dai, B., & Chen, H. (2012). Mathematical model and solution approach for carriers' collaborative transportation planning in less than truckload transportation. International Journal of Advanced Operations Management, 4(1-2), 62-84.

Duke, R. D. (1974). Gaming: Thefuture's language.

European Commission. (2011). A roadmap for moving to a competitive low carbon economy in 2050. Communication from the commission to the European parliament, the council, the European economic and social committee and the committee of the regions.

Feo-Valero, M., García-Menéndez, L., Sáez-Carramolino, L., & Furió-Pruñonosa, S. (2011). The importance of the inland leg of containerised maritime shipments: An analysis of modal choice determinants in Spain. *Transportation Research Part E: Logistics and Transportation Review*, *47*(4), 446-460.

Flodén, J., Bärthel, F., & Sorkina, E. (2017). Transport buyers choice of transport service–A literature review of empirical results. *Research in Transportation Business & Management*, (23), 35-45.

Harteveld, C. (2011). *Triadic game design: Balancing reality, meaning and play*. Springer Science & Business Media.

Holguín-Veras, J., Xu, N., De Jong, G., & Maurer, H. (2011). An experimental economics investigation of shipper-carrier interactions in the choice of mode and shipment size in freight transport. *Networks and spatial economics*, *11*(3), 509-532.

Kourounioti, I., Kurapati, S., Lukosch, H., Tavasszy, L., Verbraeck, A. (2018). Simulation Games to Study Transportation Issues and Solutions: Studies on synchromodality, *98th Annual Meeting of the Transportation Research Board.*

Kouvaritakis, B., & Cannon, M. (2016). *Model predictive control*. New York: Springer.

Krajewska, M. A., Kopfer, H., Laporte, G., Ropke, S., & Zaccour, G. (2008). Horizontal cooperation among freight carriers: request allocation and profit sharing. Journal of the Operational Research Society, 59(11), 1483-1491.

Kurapati, S., Kourounioti, I., Lukosch, H., Tavasszy, L., & Verbraeck, A. (2018). Fostering Sustainable Transportation Operations through Corridor Management: A Simulation Gaming Approach. *Sustainability*, *10*(2), 455.

Kurapati, S., Kourounioti, I., Lukosch, H., Tavaszzy, L., Verbraeck, A., van Veen, L., & van Nuland, B. (2017, June). Exploring challenges and solutions for container transportation using rail: A modelling and simulation gaming study. In *Models and Technologies for Intelligent Transportation Systems (MT-ITS), 2017 5th IEEE International Conference on* (pp. 158-163). IEEE. Available at: https://ieeexplore.ieee.org/abstract/document/8005657/ [Accessed on 15/03/2018].

Maier, G., Bergman, E.M., & Lehner, P. (2002). Modelling preferences and stability among transport alternatives. *Transportation Research Part E: Logistics and Transportation Review*, 38(5), 319–334.

Mason, R., Lalwani, C., & Boughton, R. (2007). Combining vertical and horizontal collaboration for transport optimisation. *Supply Chain Management: An International Journal*, *12*(3), 187-199.

Meers, D., Macharis, C., Vermeiren, T., & van Lier, T. (2017). Modal choice preferences in short-distance hinterland container transport. *Research in Transportation Business & Management*, *23*, 46-53.

Pfoser, S., Treiblmaier, H., & Schauer, O. (2016). Critical success factors of synchromodality: Results from a case study and literature review. *Transportation Research Procedia*, *14*, 1463-1471.

Reis, V. (2014). Analysis of mode choice variables in short-distance intermodal freight transport using an agent-based model. *Transportation research part A: Policy and practice*, *61*, 100-120.

Saeedi, H., Wiegmans, B., Behdani, B., & Zuidwijk, R. (2017). Analyzing competition in intermodal freight transport networks: The market implication of business consolidation strategies. *Research in Transportation Business & Management*, *23*, 12-20.

Singh, P., van Sinderen, M., & Wieringa, R. (2016). Synchromodal transport: pre-requisites, activities and effects. In *ILS Conference* (pp. 1-4).

Smith, R. (2010). The long history of gaming in military training. *Simulation & Gaming*, *41*(1), 6-19.

Sudarsanam, S. (2003). *Creating value from mergers and acquisitions: The challenges: An integrated and international perspective*. Pearson Education.

Tavasszy, L. A., Behdani, B., & Konings, R. (2015). Intermodality and synchromodality. Available at: https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2592888 [Accessed 10/03/2018].

Tavasszy L. and G. de Jong. Modelling Freight Transport. Elsevier, 2013.

Van den Berg, R., & De Langen, P. W. (2014). An exploratory analysis of the effects of modal split obligations in terminal concession contracts. *International Journal of Shipping and Transport Logistics*, *6*(6), 571-592.

Van Der Horst, M. R., & De Langen, P. W. (2008). Coordination in hinterland transport chains: a major challenge for the seaport community. *Maritime Economics & Logistics*, *10*(1-2), 108-129.

Van Riessen, B., PhD Dissertation (2018), Optimal Transportation Plans and Portfolios for Synchromodal Container Networks.

Van Riessen, B., Negenborn, R. R., & Dekker, R. (2015, September). Synchromodal container transportation: an overview of current topics and research opportunities. In *International Conference on Computational Logistics* (pp. 386-397). Springer, Cham.

Wolfe, J., & Crookall, D. (1998). Developing a scientific knowledge of simulation/gaming. *Simulation & Gaming*, *29*(1), 7-19.

Appendix

Appendix A. Rail Cargo Challenge Rotterdam Game

A.1. Game description and rules

Rail Cargo Challenge Rotterdam is a game developed by TU Delft gamelab, The Barn, ProRail and TNO within the "Synchro-gaming" project (TU Delft gamelab site, 2018). In this chapter the context and the rules of the game are described, as found in the game manual and discussed by Kurapati et al. (2017) and Kourounioti et al. (2018).

"The key research objective of the Rail Cargo Challenge Rotterdam (RCCR) is to assess the attitudes and behavior of stakeholders in the freight transport domain with respect to the efficient bundling of containers to be transported to their final destination using rail." (Kourounioti et al., 2018).

At the early phases, the "world" of the board game consists of three sea terminals in port of Rotterdam (A, B, C) and two hinterland destinations (Duisburg, Burghausen). After some time, two more terminals are added to the game to increase its complexity.

RCCR has two main categories of players: rail operators and freight forwarders. These two categories are on the second and third layer of TRAIL model (see figure 3), respectively.

The game is played in rounds. On each round, new containers arrive at the port of Rotterdam in one of the terminals and each container has a specific destination and an expiration date of delivery. Each container is represented by one order card, including the above information (storing terminal, destination, expire). The order cards are distributed to the freight forwarders that are responsible for the on-time delivery of the respective containers.

Rail operators: There are two train operators in the game that compete to satisfy forwarders' demand. Each operator has one train with maximum capacity of 10 containers and there is a fixed cost (10 tokens) to operate the train for each round. The trains depart from the terminals at the end of each round, regardless the number of containers, and each train can only arrive at one destination. It is the decision of rail operator which terminals the train visits and at which destination it arrives and this decision can defer per round. The maximum number of terminals (1-3) that a train can visit is not constant, though. It is stochastically defined by a dice, which represents possible last-minute delays in the terminals. In the case that the schedule of the train operator has more terminals than the maximum possible terminals that can be serviced then rescheduling is required or even transportation by truck.

Freight forwarders: There are three forwarders in the game that are responsible for the on-time delivery of the cargo. Each container is assigned to one forwarder. The forwarder can choose to send the container either by train or by truck. The train transport fee is negotiable with the train operator while the truck has a fixed cost per container (1 token). Freight forwarders are paid by shippers that have a preference to train and thus they pay more to have their containers transported by rail (fixed 4 tokens per container for rail, 2 tokens per container for truck). If the containers are not delivered on time no yield is payed to the forwarders. A container is assumed to be delayed if the latest day of release it is transported by truck. Note that shippers do not have an active role in the game and does not need a person to play this role.

Each player is assumed to have his own company and tries to achieve the highest possible profits.

The reputation of the port is also important as the lower the reputation the less the container orders that are given to freight forwarders. The reputation is lowered with the use of truck.

The aim of the game is to promote horizontal and vertical collaboration between the actors, as the merging of orders and the appropriate selection of terminals and destination is required to utilize the train and lead to highest profits for players.

Steps/ Algorithm of the game:

1) Reputation of port of Rotterdam is set to zero.
2) Round is set to zero
3) Round is set to Round+1
4) Game master takes the order cards for the specific round. (18 per round)
5) If reputation is between -5 and -9, game master removes three order cards from this round (supposed to be serviced by the competitive port of Hamburg which is out of the system of the game).
6) If reputation is less than -10, game master removes six order cards from this round.
7) Game master give the order cards to Freight forwarders
8) Game master starts the countdown timer for the negotiation phase (5 minutes).

   -Negotiation phase- (start of 5 minutes timer)

9) Freight forwarders communicate the order characteristics to the train operators they want. Usually they ask for an offer by both operators.
10) Freight forwarders and operators negotiate the price to transport the containers by train.
11) Freight forwarders choose to whom they will give the order cards according to their preferences (or keep the orders).
12) Operators take the respective order cards and they are responsible for the transportation of the orders now on. It is expected by the forwarders to transport these orders by train but is the choice of operators from now on what to do with the cards (send by train or truck if they cannot fulfill the order by train).

   -End of negotiation phase- (end of 5 minutes)

13) Operators throw a dice to determine how many terminals they can service (from one to up to three terminals).
14) Each operator announces to game master which terminal(s)- destination will service their train the specific round. (up to three terminals depending on the dice, and only one destination)
15) Operators give the respective cards to game master.
16) Operators pay a fixed price to game master in order to operate the train. (*This fee is paid even if the train is empty) (Fixed price for the operation of the whole train)
17) Game master pays freight forwarders the revenue for successful transport of the container by train. (Game master takes the role of the shipper that pays the forwarders for the transport in this step). (Fixed price)
18) Operators and/or freight forwarders send (if they want) containers with trucks for the orders that expiring in a later round.
19) Operators and/or freight forwarders pay the fee to use the truck. (if they don’t use the service they don’t have to pay anything) (Fixed price per truck used)
20) Game master pays freight forwarders the revenue for transport the container by truck earlier than the expire. (Fixed price)

21) Operators and/or freight forwarders are obliged to send the orders that expire this round by a “delayed” truck.
22) Operators and/or freight forwarders pay the fee for truck use. (Fixed price per truck used)
23) Game master reduces the reputation meter by one point for each truck that was used this round (on-time and delayed)
24) If no truck was used in this round, game master increases the reputation meter by one point.
25) If round is less than 10, go to step 3.

A.2. Preliminary Game Analysis

In this section a general analysis of the game aspect is done. In this analysis, as “system” is referred the group of Port, train operators and freight forwarders. Shippers are assumed to be an external passive actor (none of the players has this role), that create the demand and pay freight forwarders for the successful delivery of their freight. Truck operators are also assumed to be out of the system, as they do not have an active role in the game.

First the decisions of each player are summarized as described previously.

Freight forwarders: Each of these players are responsible for the transportation of specific containers. The actions and decisions that they have to take are:

- Negotiate the price for each container transport with train operators.
- Choose between train and truck. This decision is not only dependend on the price but can also include the reliability perception for each train operator.
- Decide to send each container the specific day or wait for one of the next available days before container expiry date.

Train operators are scheduling the train service. The decisions that each train operator have to take during the game are:

- Negotiate the price for each container transport with freight forwarders.
- Choose the number of terminals to service. This decision includes the risk of servicing less terminals than the decided, depending on the dice described in the previous chapter.
- Choose which terminals to service.
- Choose the destination of the train.
- Decide to undertake the responsibility to transport a container. By the time that the train operator takes this decision, he is responsible for the successful transport of the container and his further decision can affect the yield of the freight forwarder. This means that if the train operator cannot successfully send the container by train and has to fulfil the order by truck, the train operator will pay for the truck fee and the freight forwarder will get yield as using truck, although he has chosen train.
- Decide to send each container the specific day or wait for one of the next available days before container expiry date.

Except the decisions of the players there are also some other aspects that need to be addressed in this preliminary analysis.

To begin with, the resources of the system are the exchange currency (tokens) and the port reputation. Reputation linearly decreases by the use of each truck and it is straightforward that it is maximized by the minimization of truck use. As for the currency, except the starting budget of each player, new tokens are only inputted in the system by shippers.

Shippers pay two (2) tokens for freight delivered by truck and four (4) tokens delivered by rail. Truck cost is one (1) token per container, while the price per container for train transport is defined by the negotiations between each train operator and freight forwarder. Let the average price be av_c_{train}. This is the cost per container (transported by train) for freight forwarders' side and the yield for the train operators' side. The cost to operate the train is 10 tokens per round for each operator. Let also x_{train} be the total containers transported by train and y_{truck} be the total containers transported by truck in one round. Lets assume a situation with one train operator and one freight forwarder in the game, for shake of simplicity. Then the profit equations for each actor type for one round is:

$$Train_{profit} = -10 + av\_c_{train} * x_{train}$$

$$Forwarder_{profit} = -av\_c_{train} * x_{train} - 1 * y_{truck} + 4 * x_{train} + 2 * y_{truck}$$

So, the system new resources are:

$$\begin{aligned} System_{profit} &= Train_{profit} + Forwarder_{profit} \\ &= -10 + av_{c_{train}} * x_{train} - av_{c_{train}} * x_{train} - 1 * y_{truck} + 4 * x_{train} + 2 \\ &\quad * y_{truck} => \end{aligned}$$

$$=> System_{profit} = -10 + 4 * x_{train} + 1 * y_{truck}$$

The equations can easily be deducted to more train operators and forwarders, with the same results.

As can be seen in figure ap1, as the income of freight forwarder (per container) decreases the income of train operator increases, as the tokens are transferred from the one player to the other. At the same time, system income stays the same as it is independent from the negotiated price. The alternative of truck reduces significantly the system income by 3 tokens per container.

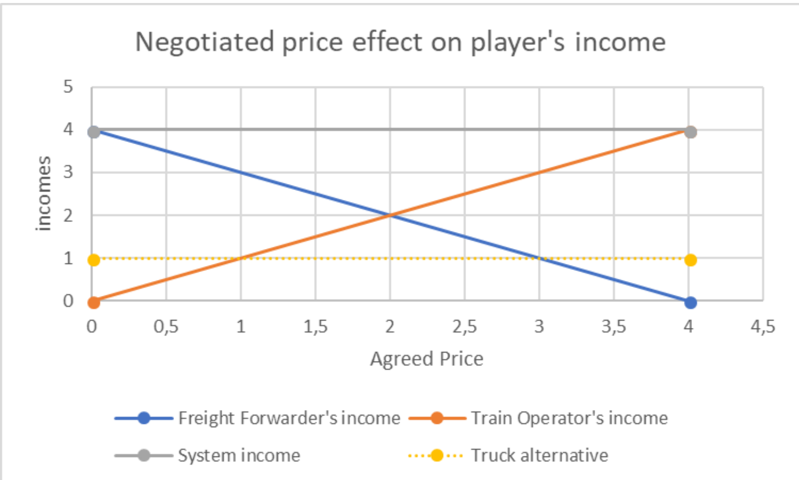


Figure ap1 Each player's income per container as function of agreed price (train use)

As can be conducted by the equations, the system profit is independent of the negotiated price between the train operators and the freight forwarders. In addition, the yield given by the train transportation to the system is quadruplicate of truck's. This means that in order to maximize system's profit, containers should be send by trains, as much as possible, and have truck option as an alternative for the containers that cannot be delivered by train.

Considering the above notes, in a coordinated system, optimality would come from the utilization of the trains and the avoidance of truck use, to the maximum extent.

In the game, freight forwarders are also aiming to send most of their containers by train as their individual income per container is more (4 tokens instead of 1). However, negotiation of prices or choices of terminals/destination by train operators that are not optimal for the system, due to lack of information, lead to inefficiency. All these complications are bypassed by a coordinated or a fully cooperative system.

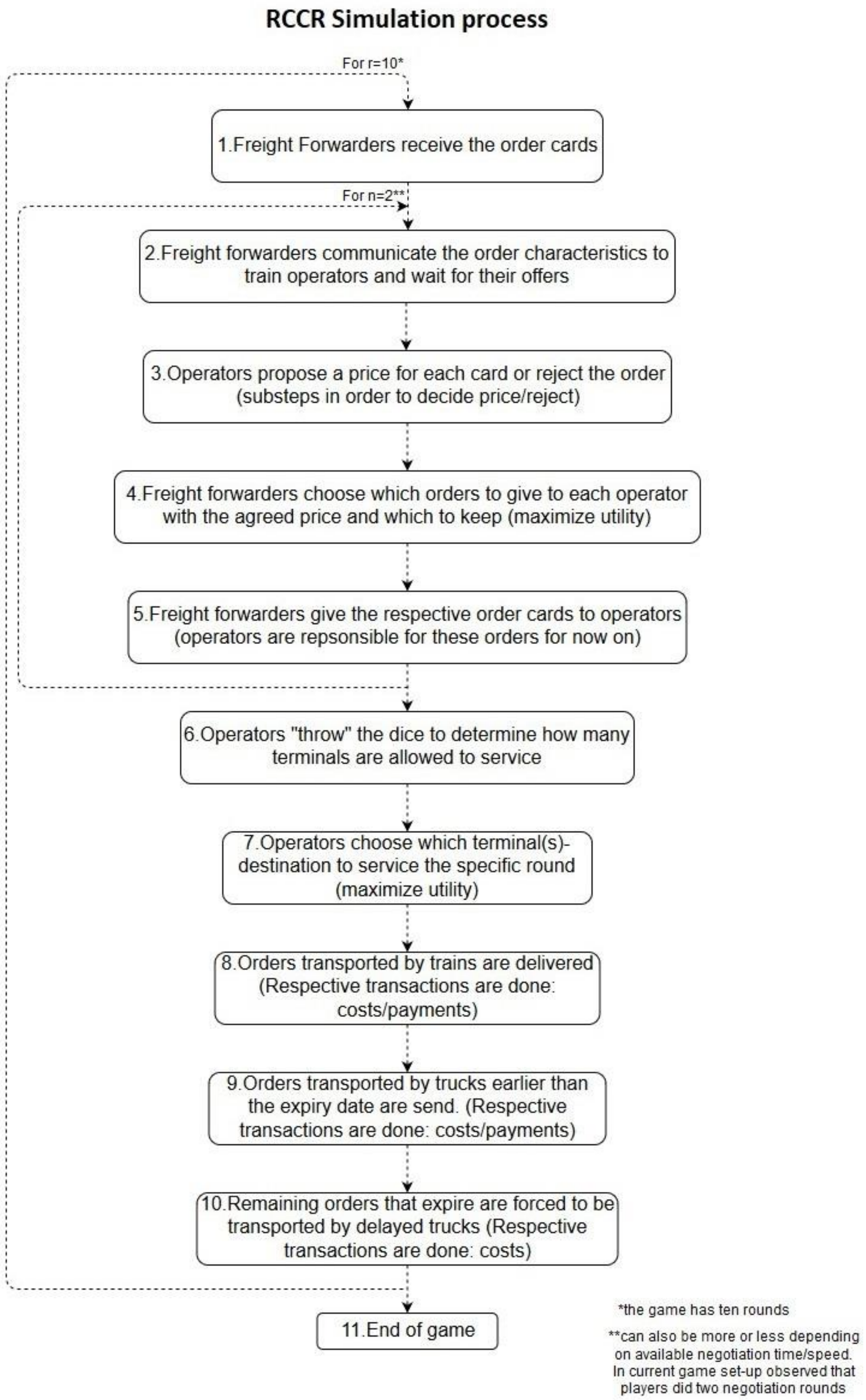
It becomes obvious that the lower profitability and efficiency of the non-coordinated system, come from the negotiation part of the game, the lack of information and the low cooperation between the actors. Cooperation could be used in order to utilize the trains (e.g. consolidate freight with same origin-destination) and take decisions to increase the profit for the whole system through information sharing. The use of train instead of truck in the highest possible level would most probably lead to higher individuals' profits as well, as more new resources (tokens) are inputted on the system and can be split between individuals.

The role of dice in the game is important. After the negotiation phase, train operators use the dice to determine how many terminals are allowed to service. The dice has 1/6 chances to allow only one terminal, 4/6 chances allow two terminals and 1/6 to allow for three terminals. This means that one terminal can always be served (1/6+4/6+1/6=6/6), at least two terminals can be served 5/6 times (4/6+1/6) and three terminals can be served only 1 out of 6 times. If the operator decides in negotiation phase to take orders of more than one terminal, a risk exists that the dice can determine less terminals and thus the orders that are in the additional terminals and expire should be transported by delayed truck. This risk has a probability of 6/6-x for the orders that expire the same day. For example, the probability that at least two terminals can be serviced is 5/6 and thus the probability that the expiring orders will have to be sent by delayed truck is 6/6-5/6=1/6. Orders that are not expiring can be kept for the next round.

Appendix B. Game simulation

B.1. Simulation steps

The simulation model of the game is shown in the next flow chart. The sub-steps for operators' decisions (step 3, step 7) and the freight forwarders' decisions (step 4) are described more precisely in next sections.



B.2. Freight Forwarders' choice modelling

From literature: The review finds that the core factors important for transport service choice are cost, transport time, reliability, and transport quality. After ensuring that basic transport quality requirements are met (e.g., on- time deliveries, transport damages, transport times), most of the decisions are made based on price. But the willingness to pay for lower environmental impact is low. Rail is perceived as more environmentally friendly, although several studies mention a negative attitude towards rail. There is great consistency among the studies in identifying the most important factors. (Floden et al, 2017).

As in the game there is not included transport time and transport quality, the factors that are included are cost and reliability.

The choices are done according to MNL model and the probabilities for each alternative are calculated as:

$$P_i = \frac{e^{U_i}}{\sum_j e^{U_j}}$$

Step 5 of game simulation

Each freight forwarder has a discrete choice for each order card they have (depending also in the expiry date):

-If the order card expires the same day:

Discrete choices-> 1) train operator 1,

2) train operator 2 or

3) delayed truck.

The respective utilities are:

- $U_{Train_1} = \beta_{price} * (revenue - operator1price) + \beta_{reliability} * reliability1 + (\beta_{train})$
- $U_{Train_2} = \beta_{price} * (revenue - operator2price) + \beta_{reliability} * reliability2 \ + (\beta_{train})$
- $U_{truck\_delayed} = \beta_{price} * (revenue\_delay - cost\_delay) + \beta_{truck\_delayed}$

*$\beta_{truck\_delayed}$ probably will be negative.

*If we take as a base case the train, β_{train} can be excluded.

-If the order card expires one of the next days:

Discrete choices-> 1) train operator 1,

2) train operator 2,

3) early truck or

4) keep the order to decide next day.

The respective utilities are:

- $U_{Train_1} = \beta_{price} * (revenue - operator1price) + \beta_{reliability} * reliability1 + (\beta_{train})$
- $U_{Train_2} = \beta_{price} * (revenue - operator2price) + \beta_{reliability} * reliability2 \ + (\beta_{train})$
- $U_{truck\_early} = \beta_{price} * (revenue\_early - cost\_early) + \beta_{truck\_early}$
- $U_{keep\_order} = +\beta_{keep\_order}$

Each freight forwarder takes the decision according to MNL discrete choice model.

The estimated parameters were calculated with BIOGEME 1.8 and can be seen in next figure.

Note that as the cost and revenue of trucks are constant the parameters were integrated in the alternative specific constant. Thus, the used utilities for trucks were $U_{truck\_early} = \beta_{truck\_early}$ and $U_{truck\_delayed} = \beta_{truck\_delayed}$.

```
// This file has automatically been generated.
// 07/14/18 01:47:13
// Michel Bierlaire, EPFL 2001-2008

BIOGEME Version 1.8 [Sat Mar 7 14:36:56 CEST 2009]
Michel Bierlaire, EPFL


                         Model: Multinomial Logit
Number of estimated parameters: 5
        Number of observations: 136
         Number of individuals: 136
           Null log-likelihood: -136.278
           Init log-likelihood: -136.278
          Final log-likelihood: -73.799
         Likelihood ratio test: 124.959
                    Rho-square: 0.458
           Adjusted rho-square: 0.422
           Final gradient norm: +5.871e-005
                    Diagnostic: Convergence reached...
                    Iterations: 7
                      Run time: 00:00
           Variance-covariance: from analytical hessian
                   Sample file: game_sample2.dat

Utility parameters
******************
Name  Value Std err   t-test p-val   Rob. std err Rob. t-test Rob. p-val
----  ----- -------   ------ -----   ------------ ----------- ----------
ASC1  0.00  --fixed--
ASC3  -1.45 0.875     -1.66  0.10  * 0.845        -1.71       0.09       *
ASC4  -2.44 1.04      -2.35  0.02    1.13         -2.17       0.03
ASC5  -1.06 0.839     -1.26  0.21  * 0.879        -1.20       0.23       *
BETA1 0.108 0.0789    1.37   0.17  * 0.0787       1.37        0.17       *
BETA2 0.146 0.243     0.60   0.55  * 0.193        0.75        0.45       *

Utility functions
*****************
1       Alt1    av1     ASC1 * one + BETA1 * xp11 + BETA2 * xp12
2       Alt2    av2     ASC1 * one + BETA1 * xp21 + BETA2 * xp22
3       Alt3    av3     ASC3 * one
4       Alt4    av4     ASC4 * one
5       Alt5    av5     ASC5 * one


Correlation of coefficients
***************************
Coeff1 Coeff2 Covariance Correlation t-test   Rob. covar. Rob. correl. Rob. t-test
------ ------ ---------- ----------- ------   ----------- ------------ -----------
BETA1  BETA2  0.00799    0.417       -0.17  * 0.00490     0.322        -0.21       *
ASC3   ASC5   0.515      0.702       -0.59  * 0.508       0.684        -0.57       *
ASC3   ASC4   0.515      0.567       1.10   * 0.613       0.644        1.14        *
ASC5   BETA1  0.0577     0.872       -1.51  * 0.0601      0.870        -1.43       *
ASC5   BETA2  0.0802     0.394       -1.55  * 0.0715      0.421        -1.47       *
ASC4   ASC5   0.578      0.664       -1.75  * 0.709       0.716        -1.75       *
ASC3   BETA1  0.0555     0.804       -1.91  * 0.0519      0.781        -1.98
```

B.3. Train operators' decisions and utilities (step 3 and step 7)

Train operators' decisions appear on step 3 and step 7 of the game simulation.

First, on step 3, they negotiate with freight forwarders and decide which containers to agree to transport (so they have to make an informal plan-strategy on which terminal(s)-destination to service this round) and on step 7 decide and announce formally which terminal(s)-destination will actually service.

On step 3 of simulation, during negotiation phase, the outcome of the dice, that defines the maximum number terminals that operators are allowed to service, is not yet known. Thus, in this step, train operators negotiate with freight forwarders and agree to transport orders with the aim to maximize their expected utility. This includes some risk in the decision process on this step.

On the other hand, on step 7, the outcome of the dice is known and the operators decide which terminal(s)-destination to choose in order to maximize their "real" utility.

-Train operators try to find the Terminal(s)-Destination combination with the highest utility for them.

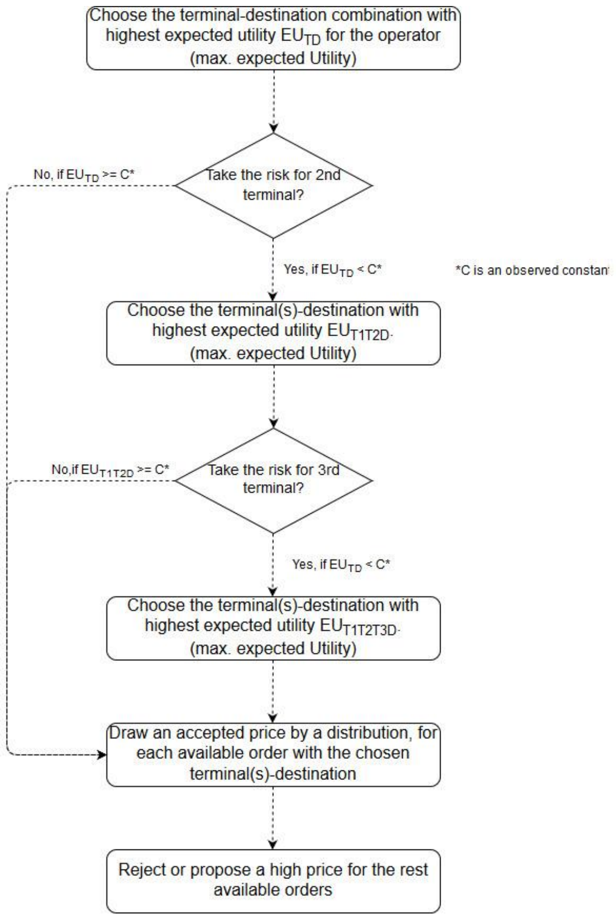
-They collect the order information/characteristics on the negotiation phase by all freight forwarders.

-They aggregate the information to identify highest Terminal(s)- Destination combination demand.

-By assessing the potential utilities, they choose their Terminal(s)-Destination plan and propose a price for the orders with the respective route. Note that this is the plan that the train operators make in their minds in order to agree on which orders to take from the freight forwarders. The actual formal decision on which terminal(s)-destination to service is done in step 7.

The parameters used in the utility functions assumed to be the same as on freight forwarders decisions.

Step 3 of game simulation (negotiation process before the dice has determined how many terminals can be served).



After the negotiation phase, train operators use the dice to determine how many terminals are allowed to service. On step three this outcome is not yet known. So the operators take their decision on the utility that they expect to have.

Parameter C was calculated using observed data from the game sessions. It was observed that the operators would choose to buy cards from different terminal if their revenue was not yet about 40 game coins.

<u>Expected utility for one terminal</u> (dice chance for at least 1 terminal=1):

$$EU_{TD} = \beta_{price} * \sum_{i}(price_i * x_{iTD}) - \beta_{price} * cost_{train} + \beta_{orders_{early}} * orders_{early} + \beta_{orders_{expire}} * orders_{expire} \quad (1)$$

-The first term includes the parameter of price and the number of the available containers (with the specific Terminal-Destination pair) multiplied by their respective offer price. x_{iTD} is a binary variable equal to 1 if container i is on terminal T and goes to destination D, else 0.

-The second term is the cost for operating the train (constant).

-The third and fourth term correspond to the total number of the active orders that operator has already agreed to transport (e.g. from previous rounds) and it is not possible to transport by train this round if he chooses T-D pair. The third term corresponds to the orders that expire in later date while the fourth term shows the orders that expire the specific date and thus they are forced to be sent by a delayed truck. $orders_{early}$,$orders_{expire}$ are integer variables that show the total number of the orders (expiring later/same date respectively) that the operator has already agreed to transport and cannot send by train if choose T-D pair.

<u>Expected utility for two terminals</u> (dice chance 1st terminal=1, dice chance 2nd terminal=5/6):

$$EU_{T_1T_2D} = 1 * EU_{T_1D} + \beta_{price} * \sum_{i}(price_i * x_{iT_2D}) \quad (2)$$

-The first term is calculated by equation (1).

-The second term is the probability multiplied by the benefits.

-The third term is the extra risk: probability of not going to two terminals (6/6-5/6=1/6) multiplied by the impact: how many of the new orders will have to be kept for next round or send by delayed truck. x_{iT_2D} is a binary variable equals 1 if order i is on the second chosen Terminal and goes to destination D, else 0. y_{iearly} is a binary variable equals 1 if order i has an expiry date later that the current day, else 0. $y_{iexpire}$ is a binary variable equal to 1 if order i expiring the current date, 0 else.

*note that utilities for early and delayed orders that are already agreed by the operator are included in EU_{T_1D} and that is the reason that are not visible in (2). In equation (2) only the new risk for early and delayed orders is visible.

*note that $\beta_{orders_{expire}}$ is expected to be negative.

<u>Expected utility for three terminals</u> (dice chance 1st terminal=1, dice chance 2nd terminal=5/6, dice chance 3rd terminal=1/6):

$$EU_{T_1T_2T_3D} = EU_{T_1T_2D} + \beta_{price} * \sum_{i}(price_i * x_{iT_3D}) \quad (3)$$

-The first term is calculated by equation (2)

-The other terms are defined as in equation (2)

Maybe the above model includes a lot of information and probabilities that maybe some players don't have the time to assess and so they decide in simpler way (depending on the player). So, the above equations can be changed without probabilities as: (What do you think?)

U_{TD} remain the same.

$U_{T_1T_2D} = U_{T_1D} + \beta_{price} * \sum_i \left(price_i * x_{iT_2D}\right)$

$$U_{T_1T_2T_3D} = U_{T_1T_2D} + \beta_{price} * \sum_i \left(price_i * x_{iT_3D}\right)$$

*β_{risk} probably negative

In any of the two cases the flow chart for the simulation model of train operators price decision can be:

<u>Step 7 of game simulation (after the negotiation phase and after the dice has determined how many terminals can be served)</u>

-After the dice has dropped, operators know how many terminals can service and also know which orders are obliged to fulfill.

-In step 7, they decide which terminal(s)-destination their train will visit this round in order to maximize their "actual" utility and not the expected.

-The utility functions (and betas) are same as in step three, but without probabilities and risks.

So, depending on the dice and the available cards the operators choose the Terminal(s)-Destination that maximize their own utility:

Case 1, If dice allows for 1 terminal:

- $U_{TD} = \beta_{price} * \sum_i (price_i * x_{iTD}) - \beta_{price} * cost_{train} + \beta_{orders_{early}} * orders_{early} + \beta_{orders_{expire}} * orders_{expire}$ (1)

Case 2, If dice allows for 2 terminals:

- $U_{T_1T_2D} = U_{T_1D} + \beta_{price} * \sum_i \left(price_i * x_{iT_2D}\right)$ (2)

Case 3, If dice allows for 3 terminals:

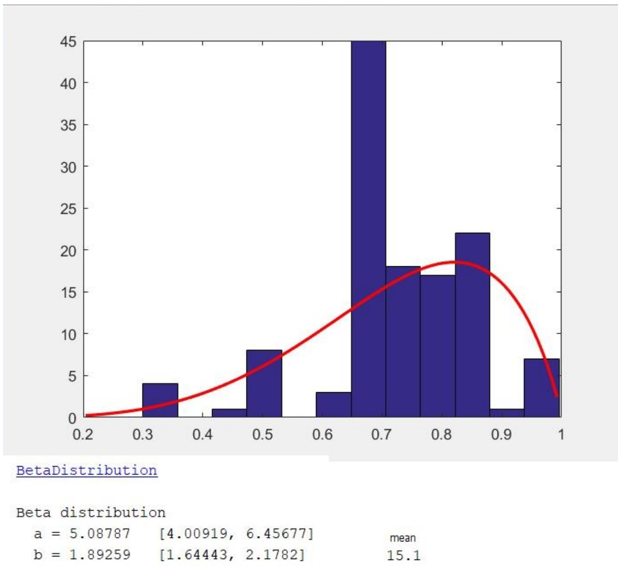
- $U_{T_1T_2T_3D} = U_{T_1T_2D} + \beta_{price} * \sum_i \left(price_i * x_{iT_3D}\right)$ (3)

*All orders that expire and have to leave with delayed trucks and all orders that leave with early trucks are assumed to be included in the term U_{TD} and that is the reason that are not shown as different terms in equation (2)-(3). However, $orders_{early}$, $orders_{expire}$ may have different values in equation

(1),(2) and (3). For example, some orders that were included in e.g. $orders_{expire}$ in case 1 (equation 1) could be sent by train in case 2 and thus $orders_{expire}$ would be reduced.

Proposed negotiated prices from operators

The prices that the train operators propose in the simulation is drawn by a distribution. According to the observation the prices fit to a beta distribution with mean=15.1 , α=5 and b=1.9 .



However, according to Kurapati et al. (2017), the negotiated prices in RCCR game fit to a beta distribution with α=2 and b=5.

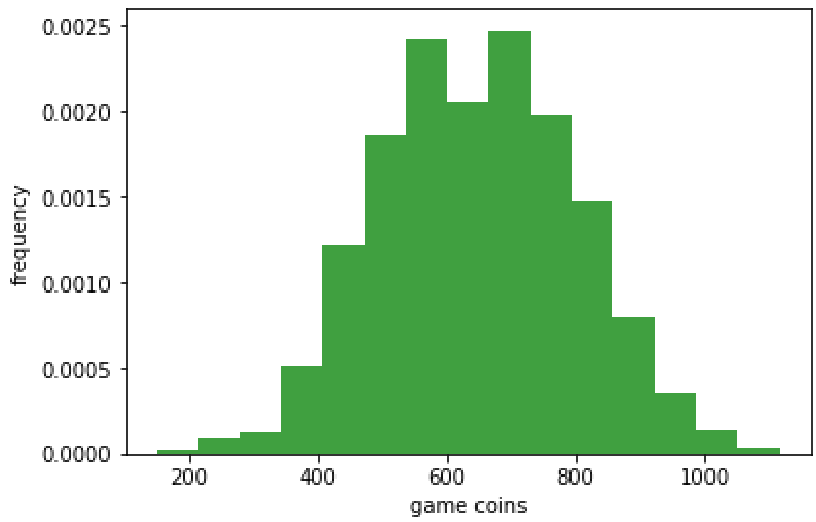
As the observations in this thesis come only from two game sessions, the parameters α,β are corrected taking into account the work of Kurapati et al. (2017).

The final chosen parameters that are included in the simulation model are average=15, α=3.5, β=4.5.

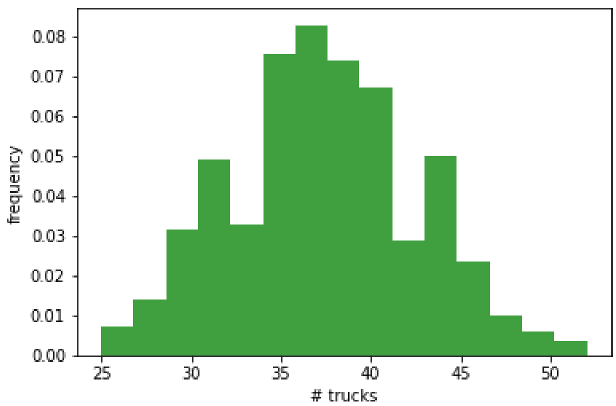
B.4. Simulated performance

Simulation performance

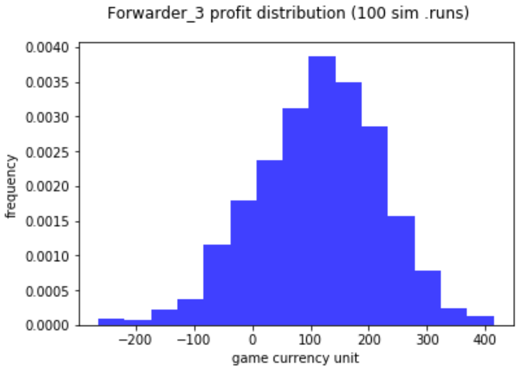
Simulation: Total profit in 10 game rounds (1000 iterations)

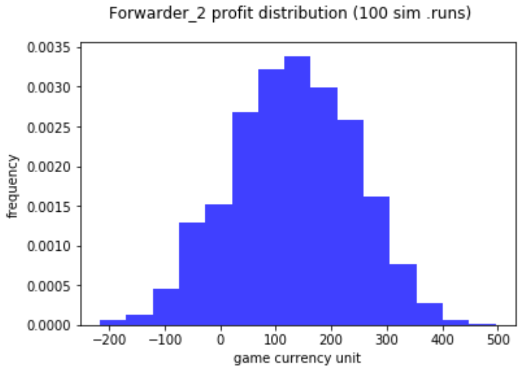


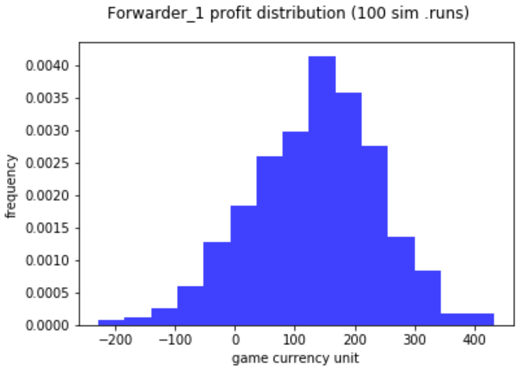
Simulation: Total containers transported by truck in 10 game rounds (1000 iterations)

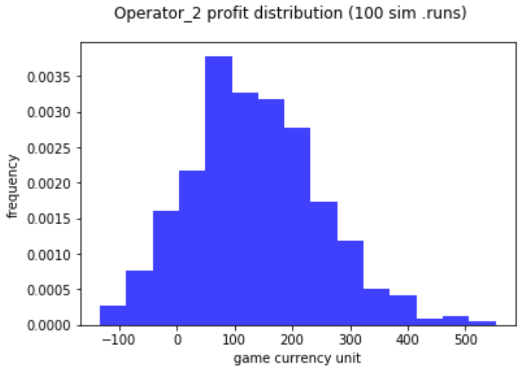


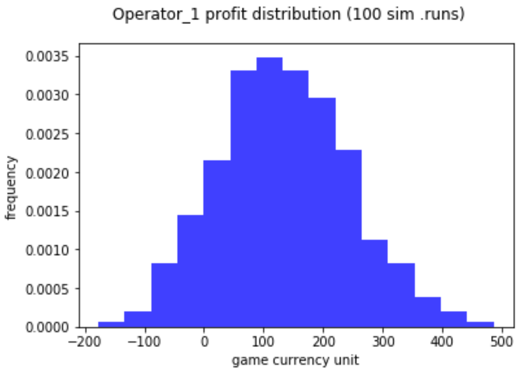
Performance per player











B.5. Example Simulation versus Optimization container routing

Random deck used for comparison

ID	Release da	Forwarder	Terminal	Destinatio	Expiry	ID	Release da	Forwarder	Terminal	Destinatio	Expiry
1	1	Blue	D	Duisburg	5	46	3	Red	D	Duisburg	6
2	1	Blue	E	Burghause	4	47	3	Red	D	Duisburg	7
3	1	Blue	E	Burghause	3	48	3	Red	D	Burghause	6
4	1	Blue	E	Duisburg	1	49	3	Yellow	A	Burghause	5
5	1	Blue	C	Duisburg	5	50	3	Yellow	C	Duisburg	4
6	1	Blue	B	Burghause	2	51	3	Yellow	C	Duisburg	3
7	1	Red	A	Burghause	3	52	3	Yellow	A	Burghause	6
8	1	Red	B	Duisburg	1	53	3	Yellow	B	Burghause	5
9	1	Red	E	Duisburg	4	54	3	Yellow	E	Burghause	5
10	1	Red	B	Duisburg	2	55	4	Blue	A	Burghause	6
11	1	Red	D	Duisburg	4	56	4	Blue	E	Burghause	8
12	1	Red	B	Duisburg	2	57	4	Blue	E	Duisburg	5
13	1	Yellow	C	Burghause	3	58	4	Blue	A	Burghause	6
14	1	Yellow	C	Burghause	2	59	4	Blue	D	Burghause	7
15	1	Yellow	C	Duisburg	5	60	4	Blue	C	Duisburg	8
16	1	Yellow	B	Burghause	2	61	4	Red	A	Burghause	5
17	1	Yellow	B	Burghause	2	62	4	Red	C	Duisburg	8
18	1	Yellow	A	Burghause	1	63	4	Red	A	Duisburg	7
19	2	Blue	B	Burghause	6	64	4	Red	B	Duisburg	5
20	2	Blue	B	Duisburg	2	65	4	Red	C	Duisburg	5
21	2	Blue	C	Burghause	2	66	4	Red	A	Duisburg	7
22	2	Blue	D	Burghause	2	67	4	Yellow	D	Duisburg	4
23	2	Blue	E	Duisburg	3	68	4	Yellow	D	Burghause	6
24	2	Blue	D	Burghause	3	69	4	Yellow	B	Burghause	5
25	2	Red	D	Duisburg	3	70	4	Yellow	E	Duisburg	6
26	2	Red	B	Burghause	4	71	4	Yellow	C	Burghause	8
27	2	Red	E	Burghause	4	72	4	Yellow	E	Burghause	6
28	2	Red	C	Burghause	4	73	5	Blue	B	Burghause	9
29	2	Red	A	Burghause	3	74	5	Blue	B	Burghause	8
30	2	Red	A	Burghause	5	75	5	Blue	B	Duisburg	6
31	2	Yellow	D	Burghause	2	76	5	Blue	D	Burghause	7
32	2	Yellow	C	Burghause	3	77	5	Blue	C	Duisburg	6
33	2	Yellow	E	Burghause	5	78	5	Blue	D	Duisburg	6
34	2	Yellow	C	Burghause	3	79	5	Red	D	Burghause	7
35	2	Yellow	D	Duisburg	4	80	5	Red	D	Duisburg	9
36	2	Yellow	B	Duisburg	3	81	5	Red	A	Burghause	8
37	3	Blue	C	Duisburg	3	82	5	Red	A	Burghause	8
38	3	Blue	E	Burghause	5	83	5	Red	D	Burghause	9
39	3	Blue	B	Burghause	6	84	5	Red	E	Burghause	5
40	3	Blue	D	Burghause	5	85	5	Yellow	B	Burghause	7
41	3	Blue	D	Duisburg	6	86	5	Yellow	E	Duisburg	5
42	3	Blue	E	Burghause	3	87	5	Yellow	B	Burghause	6
43	3	Red	A	Duisburg	6	88	5	Yellow	C	Burghause	6
44	3	Red	D	Duisburg	7	89	5	Yellow	B	Burghause	5
45	3	Red	D	Burghause	4	90	5	Yellow	C	Burghause	8

ID	Release da	Forwarder	Terminal	Destinatio	Expiry	ID	Release da	Forwarder	Terminal	Destinatio	Expiry
91	6	Blue	B	Duisburg	8	136	8	Red	D	Duisburg	11
92	6	Blue	E	Burghause	6	137	8	Red	A	Burghause	11
93	6	Blue	E	Duisburg	7	138	8	Red	C	Duisburg	12
94	6	Blue	D	Burghause	8	139	8	Yellow	A	Burghause	10
95	6	Blue	B	Duisburg	10	140	8	Yellow	D	Burghause	10
96	6	Blue	D	Duisburg	7	141	8	Yellow	A	Duisburg	11
97	6	Red	C	Duisburg	6	142	8	Yellow	C	Duisburg	8
98	6	Red	C	Burghause	10	143	8	Yellow	D	Burghause	9
99	6	Red	B	Duisburg	8	144	8	Yellow	D	Burghause	11
100	6	Red	C	Duisburg	10	145	9	Blue	A	Duisburg	10
101	6	Red	B	Duisburg	9	146	9	Blue	D	Duisburg	10
102	6	Red	A	Duisburg	9	147	9	Blue	B	Burghause	9
103	6	Yellow	E	Duisburg	9	148	9	Blue	A	Burghause	10
104	6	Yellow	C	Duisburg	7	149	9	Blue	A	Duisburg	9
105	6	Yellow	A	Burghause	6	150	9	Blue	B	Burghause	13
106	6	Yellow	B	Duisburg	9	151	9	Red	C	Duisburg	9
107	6	Yellow	B	Duisburg	6	152	9	Red	A	Burghause	9
108	6	Yellow	C	Burghause	9	153	9	Red	B	Duisburg	9
109	7	Blue	E	Burghause	7	154	9	Red	A	Duisburg	9
110	7	Blue	A	Duisburg	10	155	9	Red	E	Burghause	12
111	7	Blue	E	Burghause	7	156	9	Red	C	Duisburg	12
112	7	Blue	B	Duisburg	10	157	9	Yellow	B	Burghause	13
113	7	Blue	D	Burghause	7	158	9	Yellow	A	Burghause	9
114	7	Blue	E	Burghause	9	159	9	Yellow	E	Duisburg	13
115	7	Red	D	Duisburg	10	160	9	Yellow	B	Duisburg	9
116	7	Red	B	Burghause	7	161	9	Yellow	A	Burghause	13
117	7	Red	A	Duisburg	9	162	9	Yellow	D	Duisburg	10
118	7	Red	D	Duisburg	8	163	10	Blue	B	Burghause	10
119	7	Red	C	Burghause	11	164	10	Blue	C	Duisburg	11
120	7	Red	D	Burghause	9	165	10	Blue	B	Burghause	11
121	7	Yellow	D	Burghause	9	166	10	Blue	B	Burghause	12
122	7	Yellow	D	Burghause	8	167	10	Blue	C	Duisburg	11
123	7	Yellow	C	Duisburg	9	168	10	Blue	B	Burghause	10
124	7	Yellow	B	Duisburg	8	169	10	Red	B	Duisburg	12
125	7	Yellow	D	Duisburg	7	170	10	Red	D	Burghause	14
126	7	Yellow	B	Burghause	9	171	10	Red	E	Burghause	13
127	8	Blue	C	Burghause	12	172	10	Red	B	Burghause	11
128	8	Blue	C	Burghause	12	173	10	Red	E	Burghause	14
129	8	Blue	A	Burghause	9	174	10	Red	E	Duisburg	13
130	8	Blue	B	Burghause	10	175	10	Yellow	B	Duisburg	14
131	8	Blue	B	Duisburg	11	176	10	Yellow	D	Duisburg	14
132	8	Blue	D	Duisburg	8	177	10	Yellow	E	Duisburg	12
133	8	Red	C	Burghause	8	178	10	Yellow	C	Duisburg	12
134	8	Red	D	Burghause	9	179	10	Yellow	A	Burghause	11
135	8	Red	C	Burghause	8	180	10	Yellow	C	Duisburg	13

Dice outcome (maximum #Terminals allowed)		
	Operator 1	Operator 2
Round 1	3	2
Round 2	2	1
Round 3	3	2
Round 4	1	2
Round 5	2	3
Round 6	2	2
Round 7	2	2
Round 8	2	2
Round 9	1	2
Round 10	2	3

Always only one destination is allowed per round.

Simulation Routing

simulation											
Hamburg	60	66	72	77	78	83	84	89	90	95	96
	101	102	107	108	113	114	119	120	125	126	131
	132	137	138	143	144	149	150	155	156	161	162
	167	168	173	174	179	180					

Operator 1 Terminals/Destination choice per round					
	Terminal1	Terminal2	Terminal3		Destination
Round 1	1	4	2		1
Round 2	0	3			1
Round 3	4	2	3		0
Round 4	0				1
Round 5	0	1			1
Round 6	4	1			0
Round 7	4	3			1
Round 8	2	0			1
Round 9	2				0
Round 10	1	3			1
	(A=0, B=1, C=2, D=3, E=4)				(Du=0, Bu=1)

									(Train Capacity=10)	
Train op1	Slot 1	Slot2	Slot 3	Slot 4	Slot 5	Slot 6	Slot 7	Slot 8	Slot 9	Slot 10
Round 1	6	16	17	2	3	14	13	0	0	0
Round 2	7	29	30	22	24	31	0	0	0	0
Round 3	5	37	50	41	35	0	0	0	0	0
Round 4	55	61	52	49	0	0	0	0	0	0
Round 5	58	81	39	85	87	0	0	0	0	0
Round 6	70	103	75	99	106	0	0	0	0	0
Round 7	109	111	59	94	121	122	0	0	0	0
Round 8	127	128	98	129	0	0	0	0	0	0
Round 9	100	151	123	0	0	0	0	0	0	0
Round 10	163	165	166	172	170	0	0	0	0	0

Operator 2 Terminals/Destination choice per round					
	Terminal1	Terminal2	Terminal3		Destination
Round 1	1	3			0
Round 2	2				1
Round 3	2	3			0
Round 4	1	4			1
Round 5	3	1	2		0
Round 6	1	3			1
Round 7	0	1			0
Round 8	3	0			1
Round 9	1	0			1
Round 10	4	0	1		0
	(A=0, B=1, C=2, D=3, E=4)				(Du=0, Bu=1)

									(Train Capacity=10)	
Train op2	Slot 1	Slot2	Slot 3	Slot 4	Slot 5	Slot 6	Slot 7	Slot 8	Slot 9	Slot 10
Round 1	8	10	12	1	11	0	0	0	0	0
Round 2	21	28	34	0	0	0	0	0	0	0
Round 3	15	51	25	46	47	0	0	0	0	0
Round 4	19	26	53	56	27	33	54	0	0	0
Round 5	44	65	0	0	0	0	0	0	0	0
Round 6	73	74	76	79	68	0	0	0	0	0
Round 7	110	117	91	112	124	0	0	0	0	0
Round 8	134	140	82	139	0	0	0	0	0	0
Round 9	130	147	157	148	152	158	0	0	0	0
Round 10	159	169	175	0	0	0	0	0	0	0

Truck delay							Truck early		
Round 1	18	4	0	0	0		Round 1	0	0
Round 2	20	0	0	0	0		Round 2	0	0
Round 3	42	36	32	23	0		Round 3	43	0
Round 4	67	45	9	0	0		Round 4	64	71
Round 5	86	38	57	40	69		Round 5	88	0
Round 6	92	105	48	97	0		Round 6	63	0
Round 7	116	104	93	0	0		Round 7	0	0
Round 8	62	118	133	135	142		Round 8	0	0
Round 9	80	153	160	154	0		Round 9	0	0
Round 10	145	146	115	0	0		Round 10	0	0

Optimization routing

optimization											
Hamburg	60	66	72	77	78	83	84	89	90	95	96
	101	102	107	108	113	114	119	120	125	126	131
	132	137	138	143	144	149	150	155	156	161	162
	167	168	173	174	179	180					

Operator 1 Terminals/Destination choice per round					
	Terminal1	Terminal2	Terminal3		Destination
Round 1	1	3	4		0
Round 2	2	3			1
Round 3	2	3	4		0
Round 4	3				1
Round 5	1	4			0
Round 6	0	2			0
Round 7	1	4			1
Round 8	1	2			0
Round 9	0				1
Round 10	1	3			1
	(A=0, B=1, C=2, D=3, E=4)				(Du=0, Bu=1)

									(Train Capacity=10)	
Train op1	Slot 1	Slot2	Slot 3	Slot 4	Slot 5	Slot 6	Slot 7	Slot 8	Slot 9	Slot 10
Round 1	4	8	9	10	11	0	0	0	0	0
Round 2	13	14	21	22	24	28	31	32	34	0
Round 3	5	15	23	25	35	37	41	46	50	51
Round 4	40	45	48	59	0	0	0	0	0	0
Round 5	57	64	70	75	86	0	0	0	0	0
Round 6	43	63	97	100	104	0	0	0	0	0
Round 7	56	73	74	85	109	111	116	0	0	0
Round 8	91	99	112	123	124	142	0	0	0	0
Round 9	129	139	148	152	158	0	0	0	0	0
Round 10	130	140	157	163	165	166	170	172	0	0

Operator 2 Terminals/Destination choice per round					
	Terminal1	Terminal2	Terminal3		Destination
Round 1	0	1			1
Round 2	1				0
Round 3	0	4			1
Round 4	2	3			0
Round 5	0	1	3		1
Round 6	0	4			1
Round 7	3	4			0
Round 8	2	3			1
Round 9	0	1			0
Round 10	2	3	4		0
	(A=0, B=1, C=2, D=3, E=4)				(Du=0, Bu=1)

									(Train Capacity=10)	
Train op2	Slot 1	Slot2	Slot 3	Slot 4	Slot 5	Slot 6	Slot 7	Slot 8	Slot 9	Slot 10
Round 1	6	7	16	17	18	0	0	0	0	0
Round 2	12	20	36	0	0	0	0	0	0	0
Round 3	2	3	27	29	30	33	38	42	49	54
Round 4	1	44	62	65	67	0	0	0	0	0
Round 5	19	39	53	61	68	69	76	79	87	0
Round 6	52	55	58	81	82	92	105	0	0	0
Round 7	47	80	93	103	118	0	0	0	0	0
Round 8	71	94	98	121	122	127	128	133	134	135
Round 9	106	110	117	141	145	153	154	160	0	0
Round 10	115	136	146	159	164	176	177	178	0	0

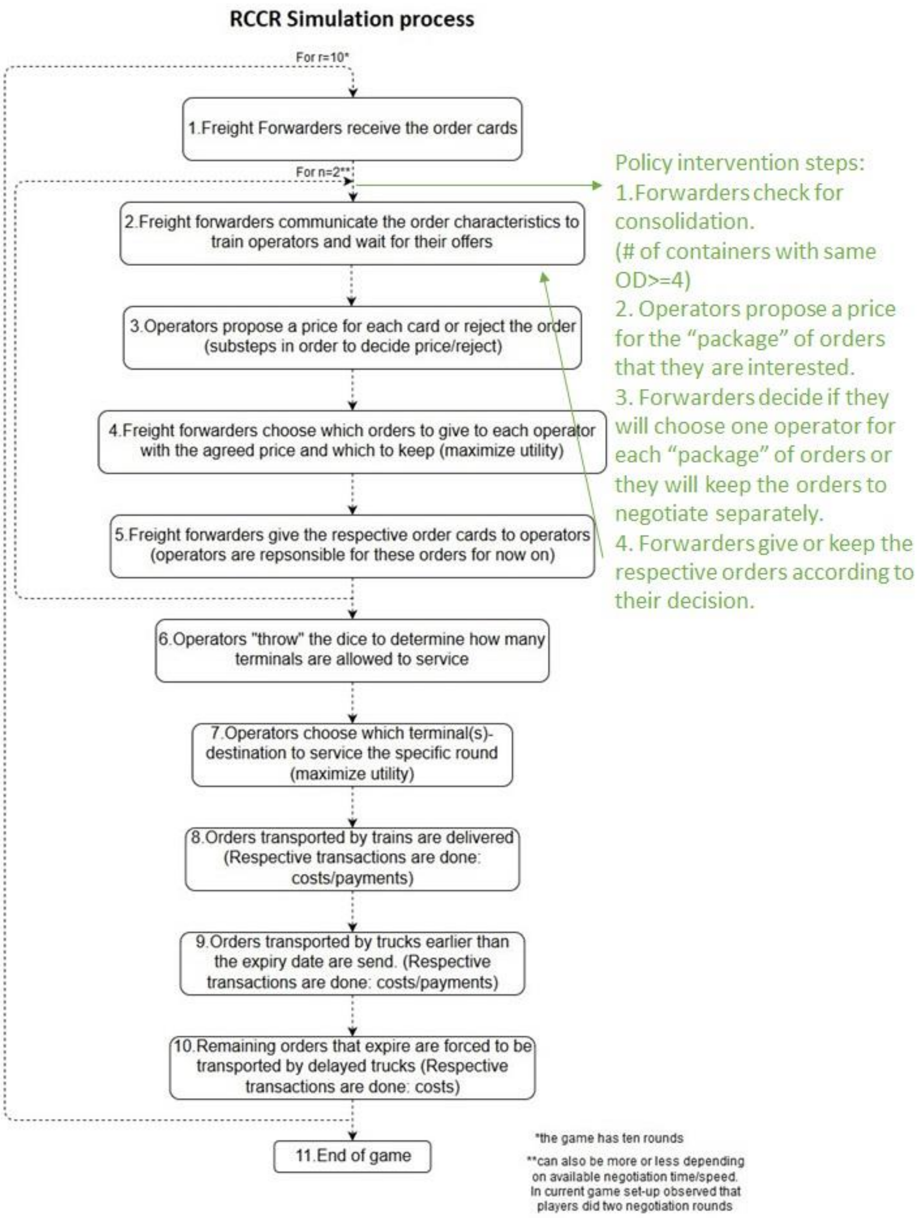
Truck delay					Truck early			
Round 1	0	0	0		Round 1	0	0	0
Round 2	0	0	0		Round 2	26	0	0
Round 3	0	0	0		Round 3	0	0	0
Round 4	0	0	0		Round 4	0	0	0
Round 5	0	0	0		Round 5	88	0	0
Round 6	0	0	0		Round 6	0	0	0
Round 7	0	0	0		Round 7	0	0	0
Round 8	0	0	0		Round 8	0	0	0
Round 9	147	151	0		Round 9	0	0	0
Round 10	0	0	0		Round 10	169	171	175

Appendix C. Performance of policies

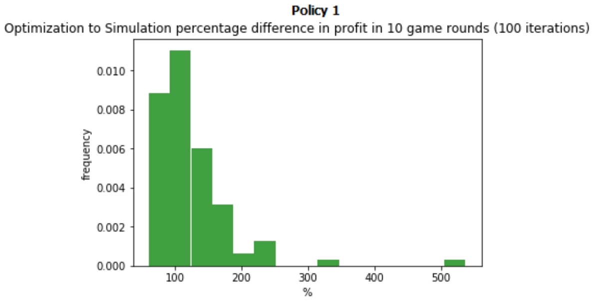
$$dif = \frac{(opt_{per} - policy_{per})}{policy_{per}} * 100$$

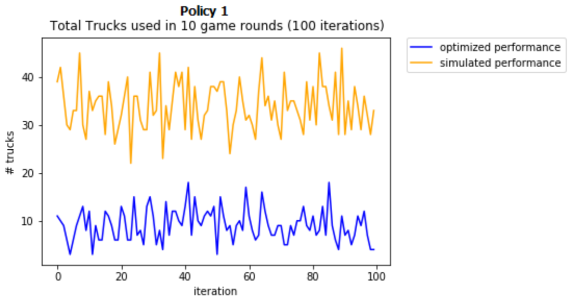
Policy 1

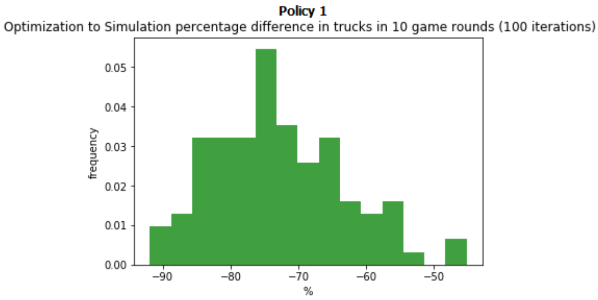
Policy 1 changes in simulation flowchart.



Performance of policy 1

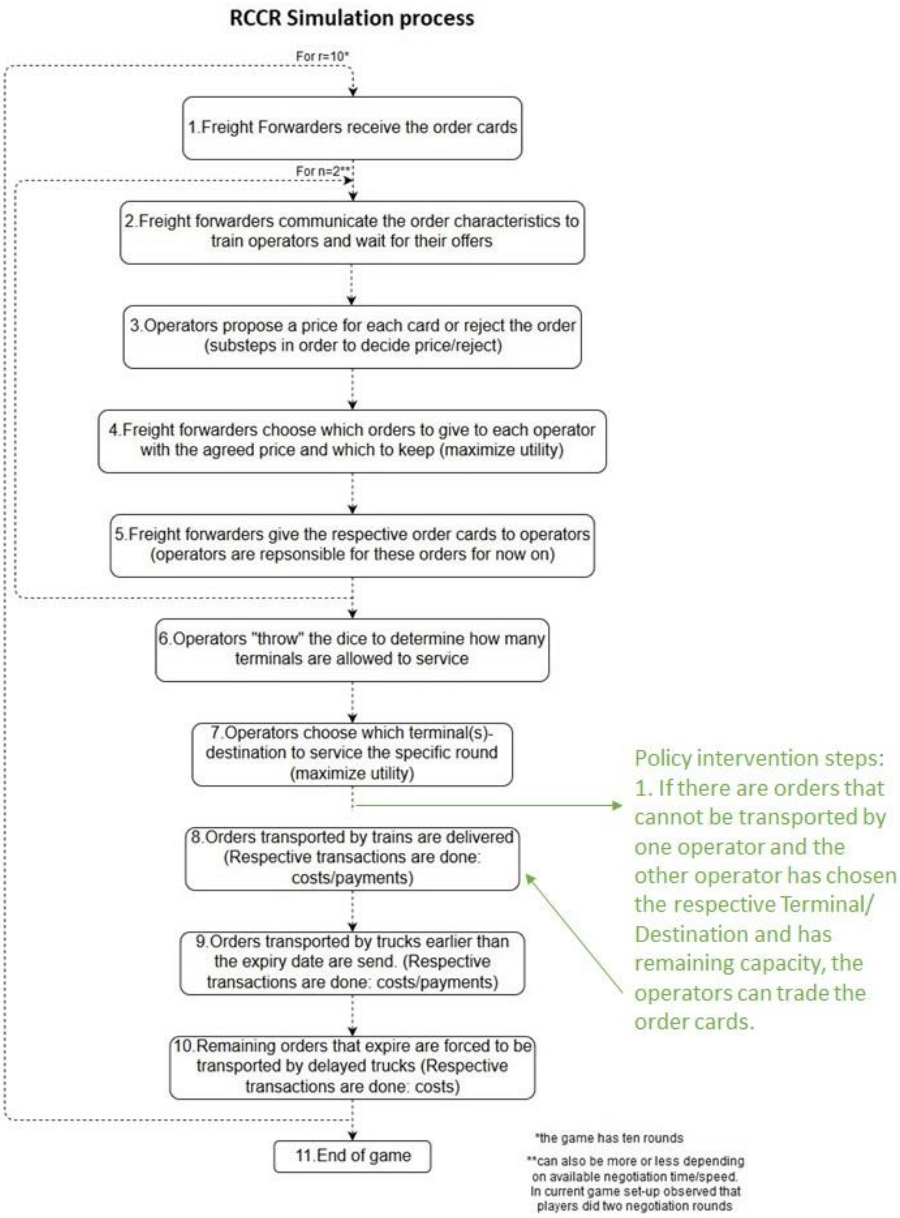




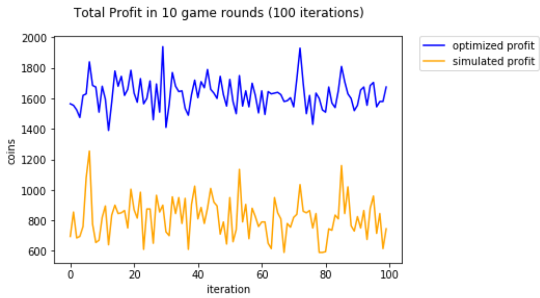


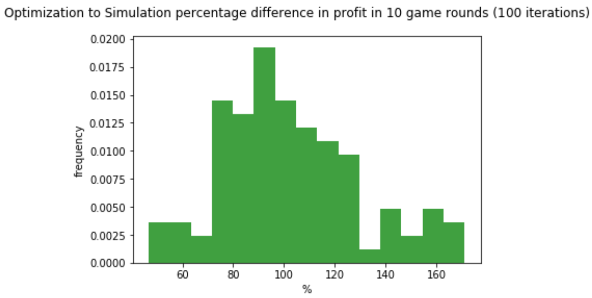
Policy 2

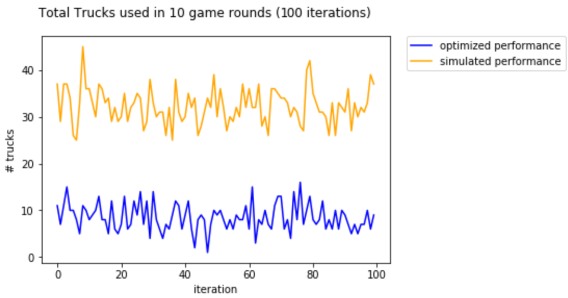
Policy 2 changes in simulation flowchart.

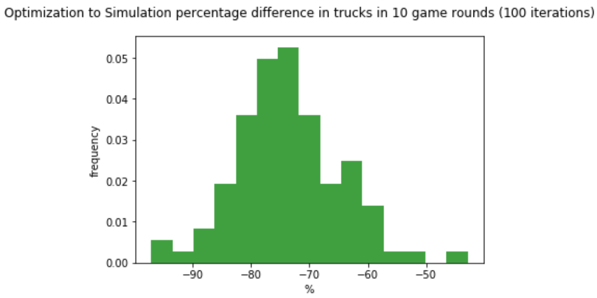


Performance of policy 2



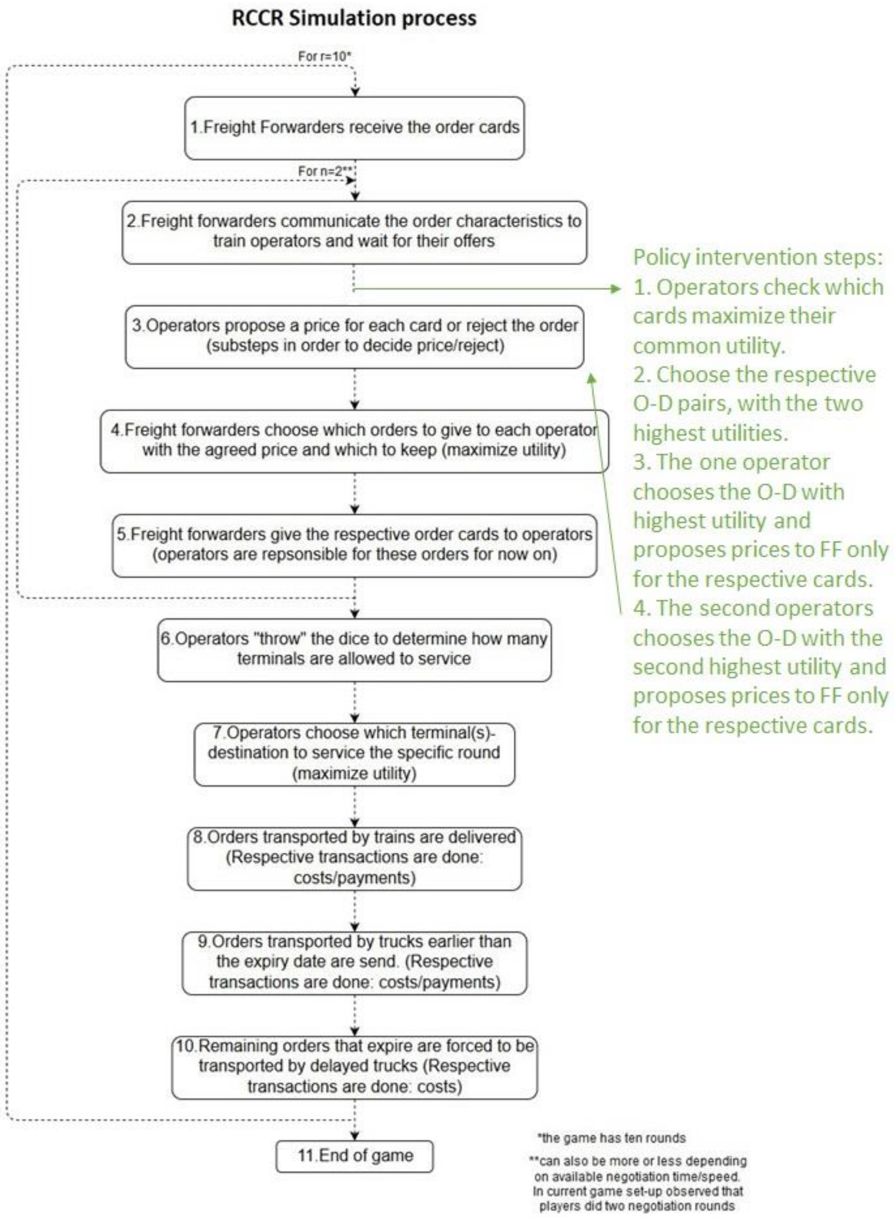




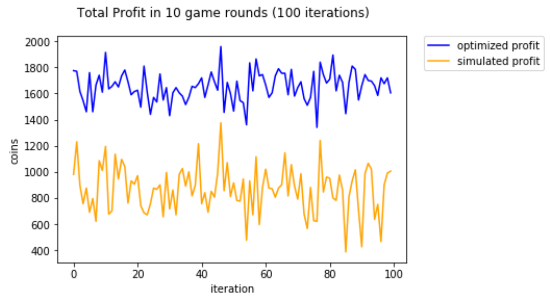


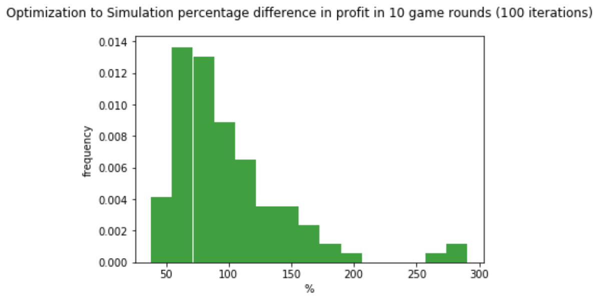
Policy 3

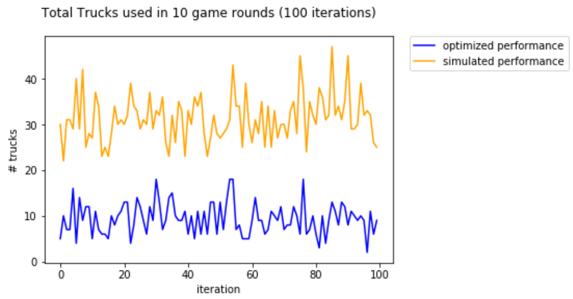
Policy 3 changes in simulation flowchart

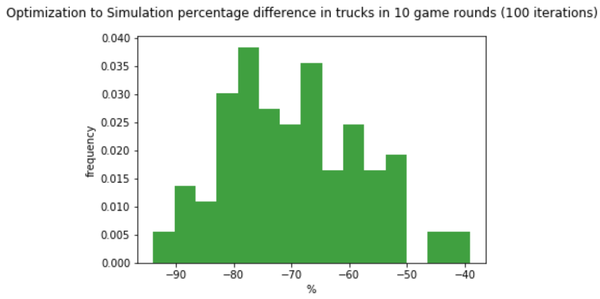


Performance of policy 3



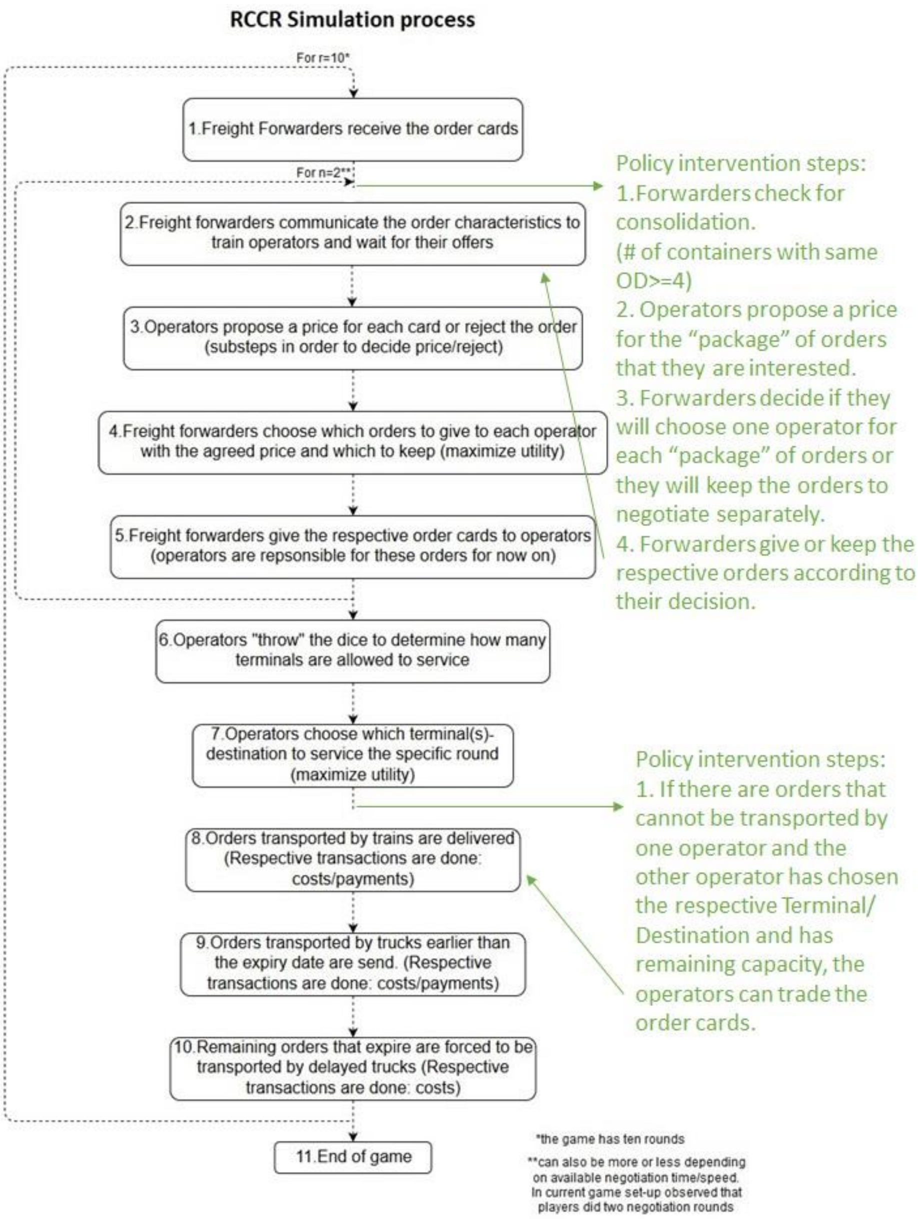




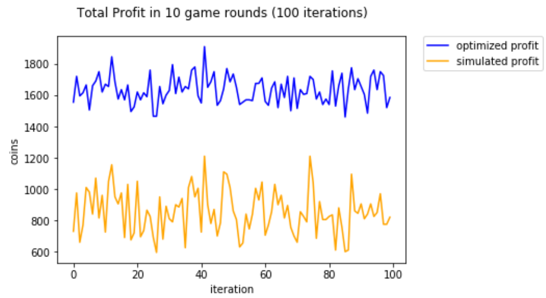


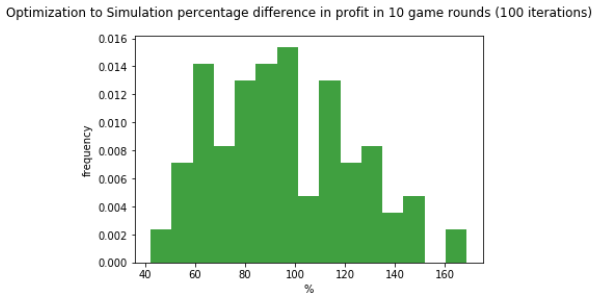
Policy 4

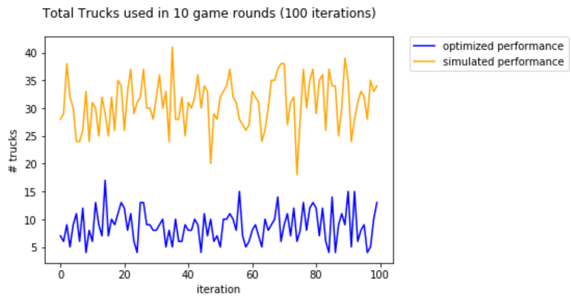
Policy 4 changes in simulation flowchart

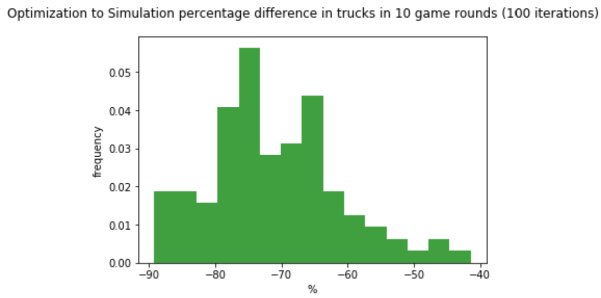


Performance of policy 4



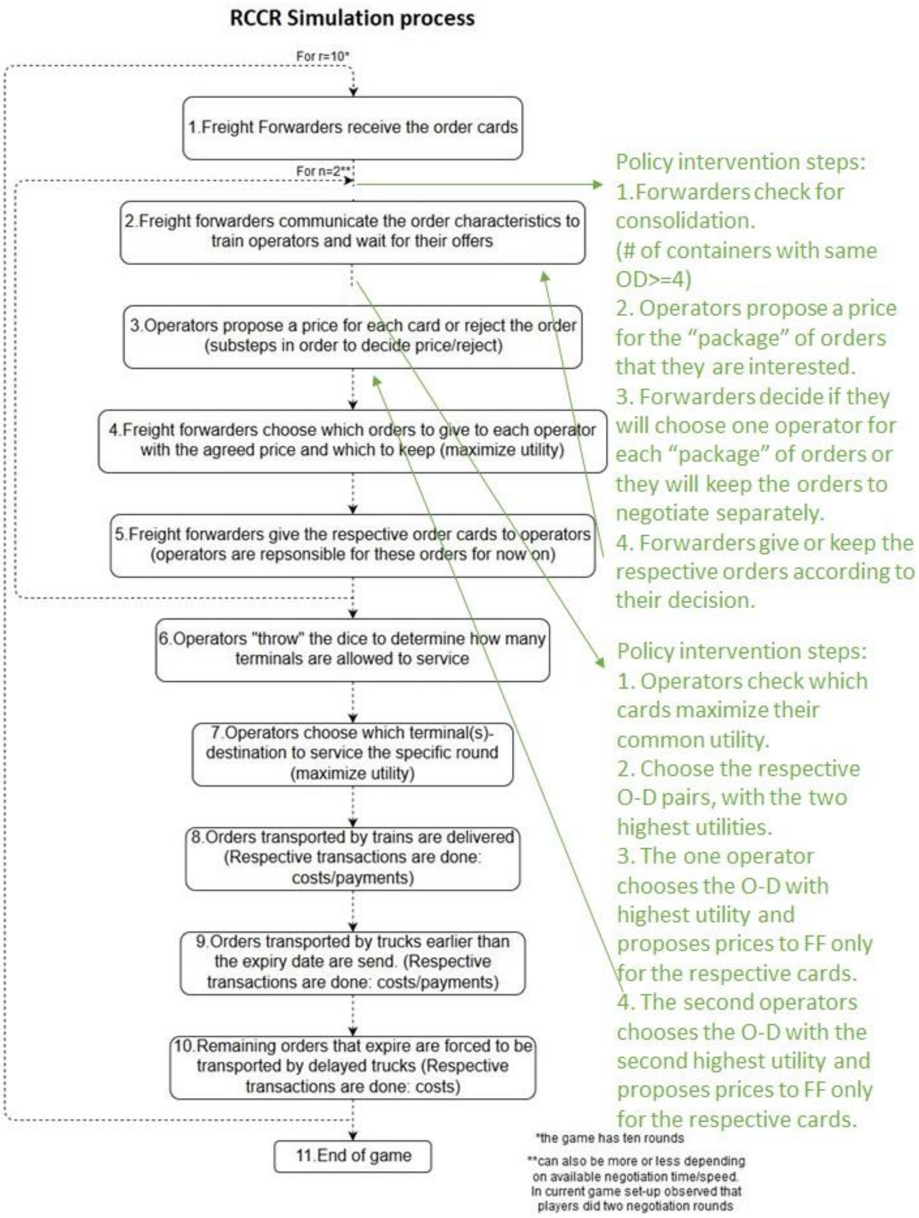




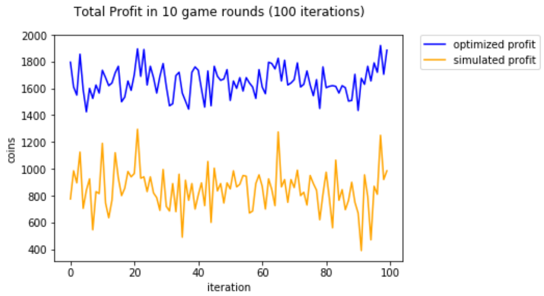


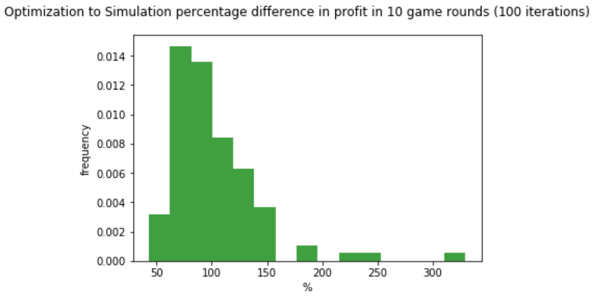
Policy 5

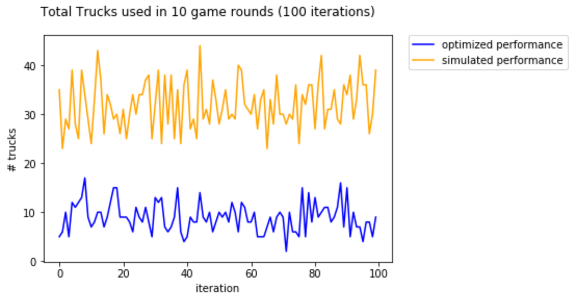
Policy 5 changes in simulation flowchart.

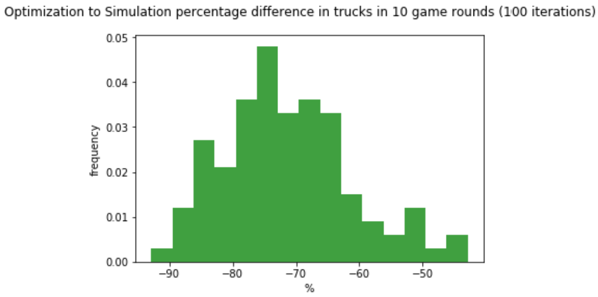


Performance of policy 5



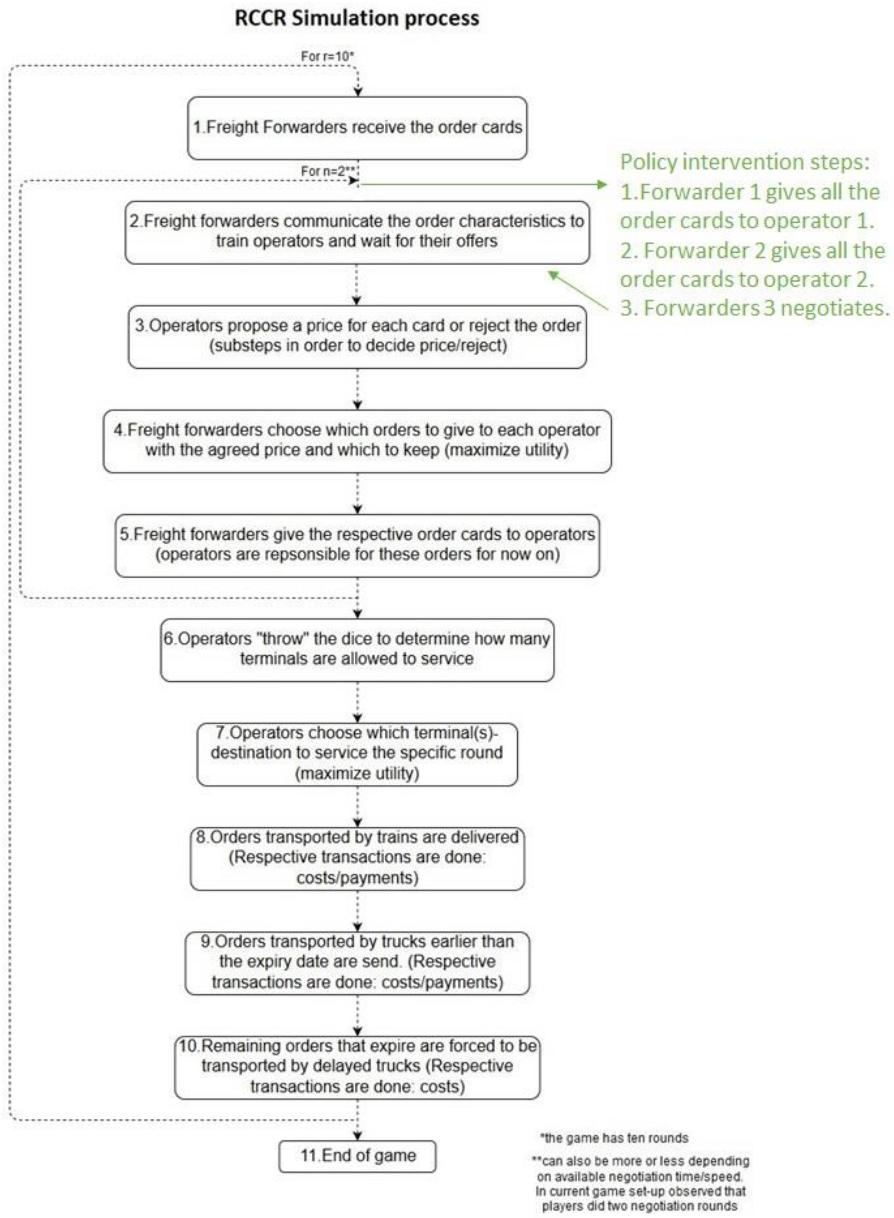




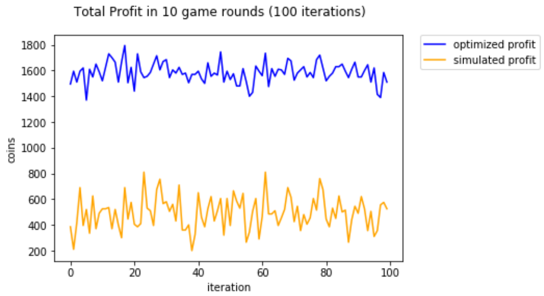


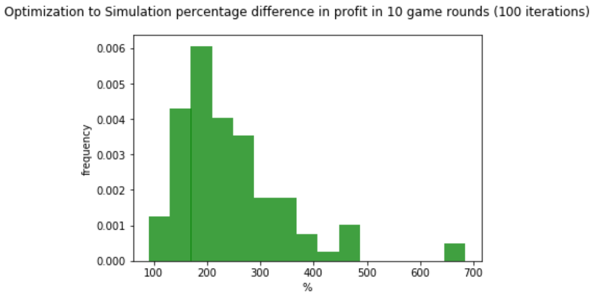
Policy 6

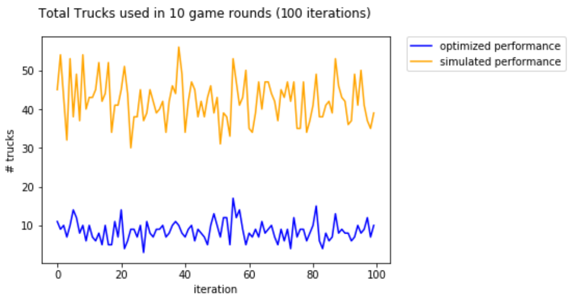
Policy 6 changes in simulation flowchart.

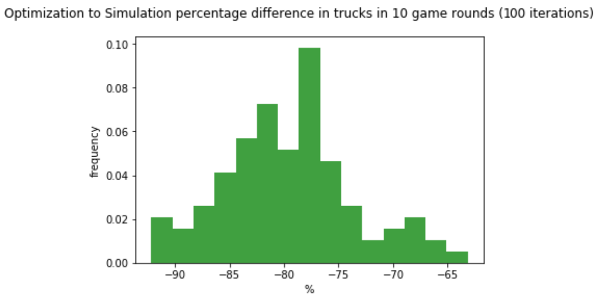


Performance of policy 6



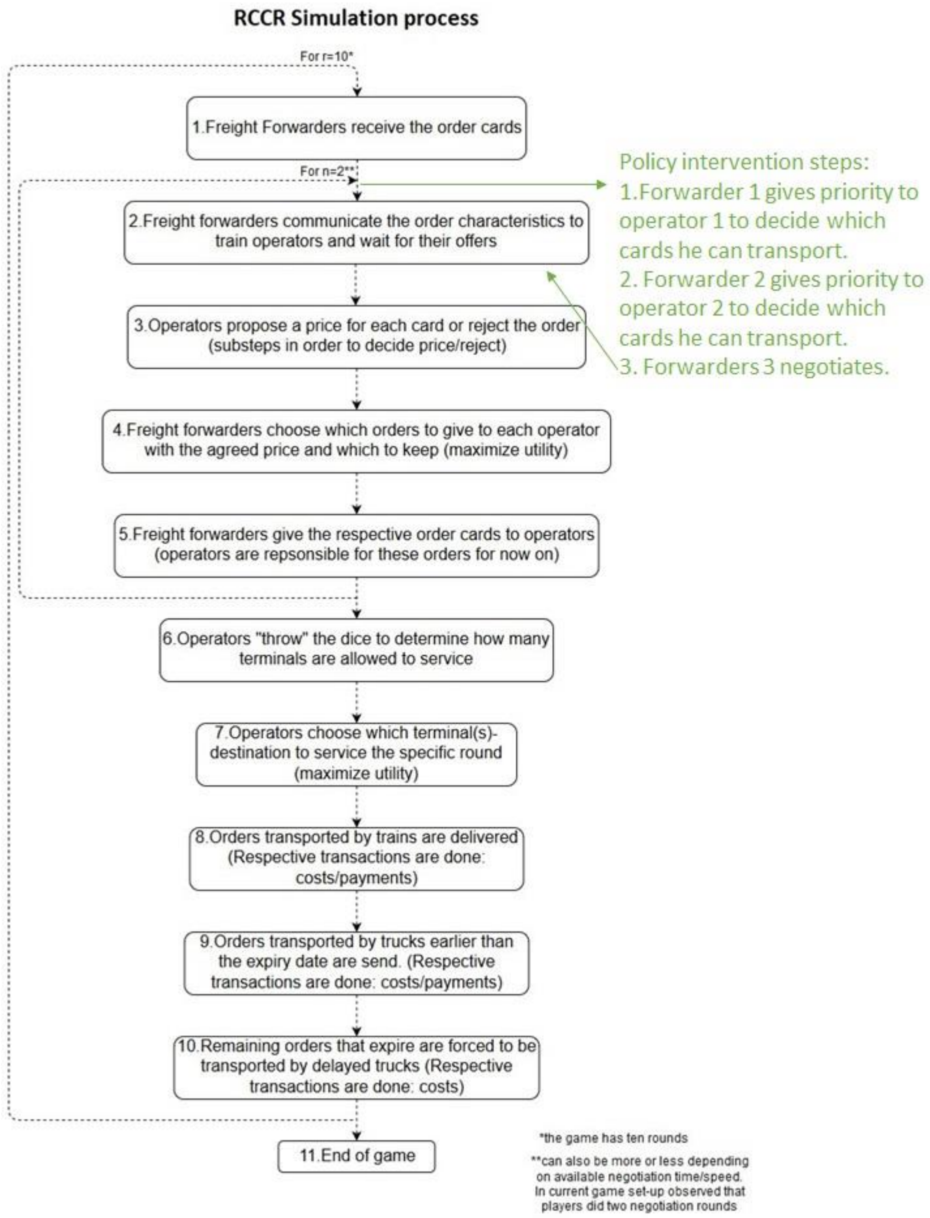




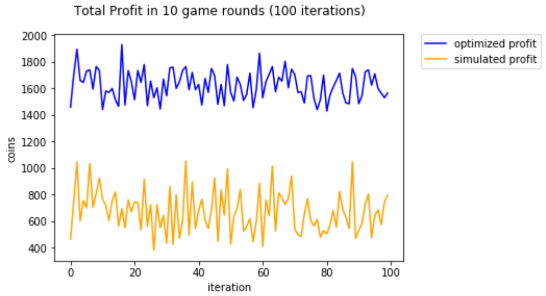


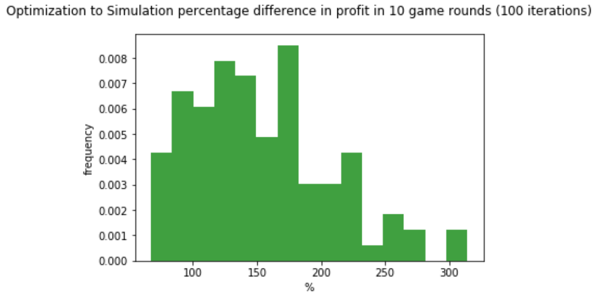
Policy 7

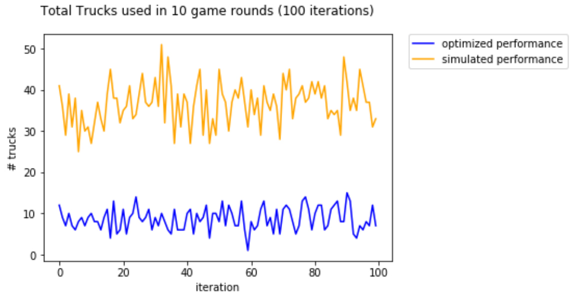
Policy 7 changes in simulation flowchart.

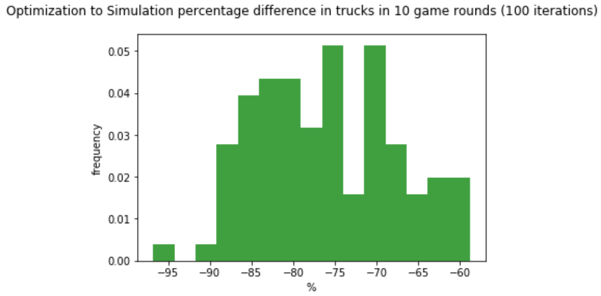


Performance of policy 7



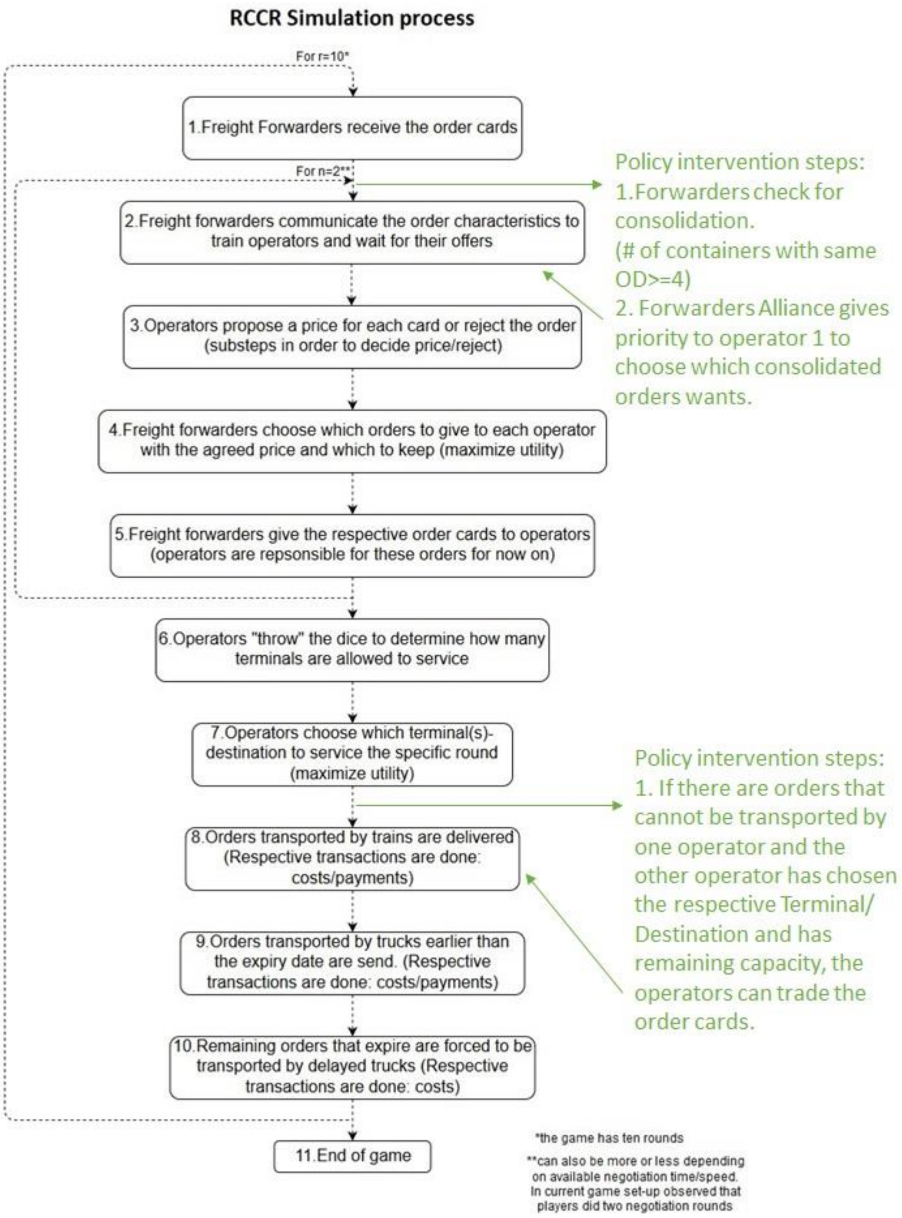




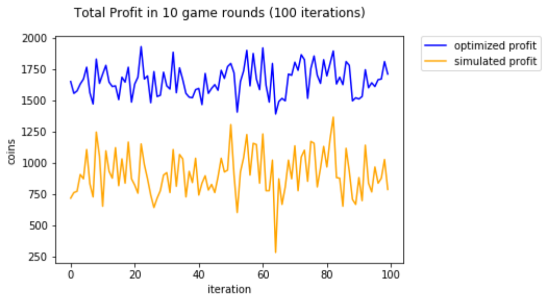


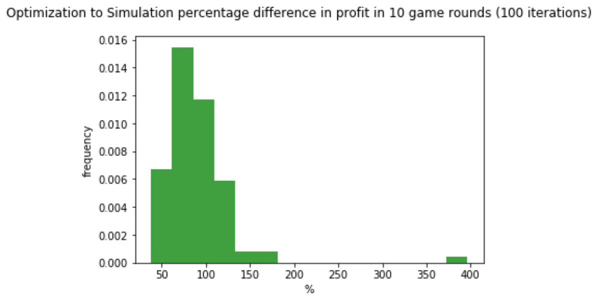
Policy 8

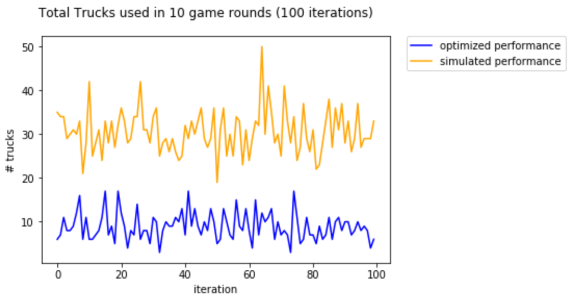
Policy 8 changes in simulation flowchart.

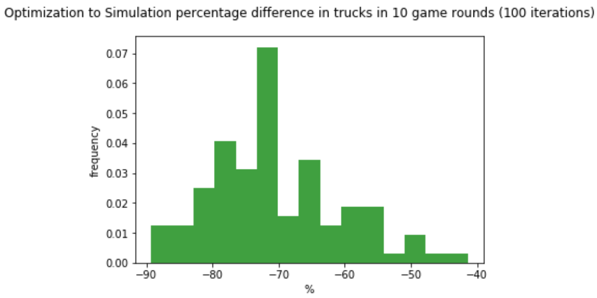


Performance of policy 8









Average performance and standard deviation of performance of Policies 1-8

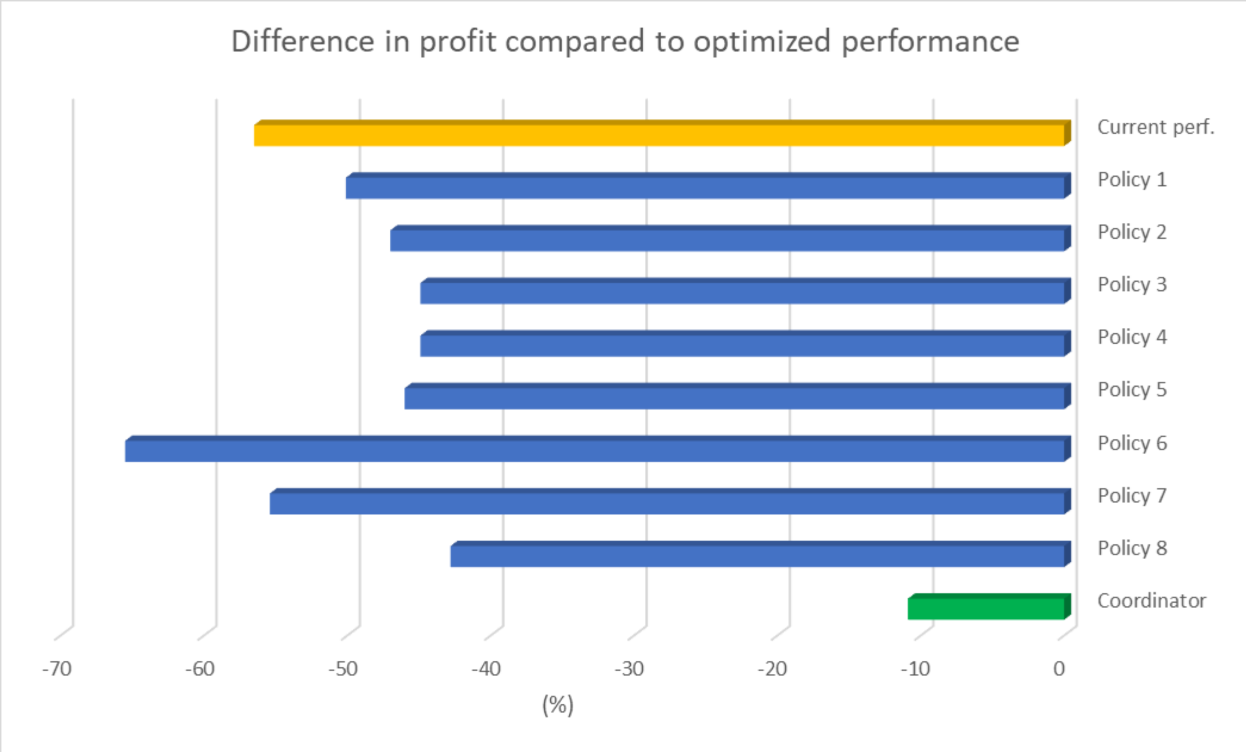
Note that the performance of the optimization increases as the performance of each policy increases. This happens as the optimization takes as input exactly the same number and type of orders as the policy in each case. As "better" is the policy, and the players achieve a higher reputation in each round, more containers reach to the port that have to be transported (demand increases). As soon as the input is the same for the optimization model, the more containers that transported the more the performance. For example, if the players by using policy 1, achieve a reputation per round that brings to the port 130 containers in total, the optimization model has as input 130 containers and optimizes the services for these 130 containers. If the players, using policy 8, achieve a reputation in each round that brings to the port 150 containers, the optimization model will also transport 150 containers. Thus, the more containers that become available to the port the higher the profitability. The reason that the optimization model is used is to see how "better" and more efficient can be the planning for the given demand. The coordinator's model, on the other hand, can seen as a policy as the coordinator "plays" the game in rounds and creates more demand when achieving higher reputation in each round.

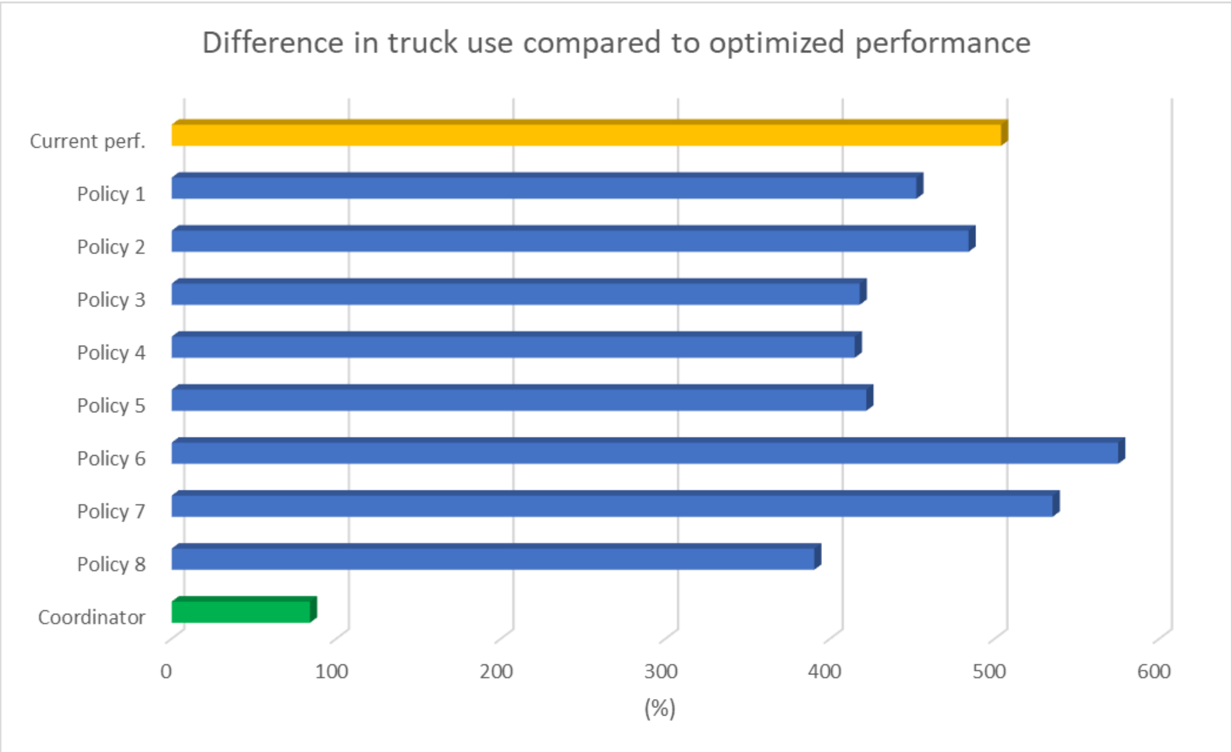
Profit comparison (policy- opt)/opt				
	profit mean	st.d.	Optimization mean with the same input	st.d.
Current perf.	688,9	139,9	1578	102,3
Policy 1	809,8	160,7	1618,1	112
Policy 2	862,5	126,3	1625,5	98,6
Policy 3	911,7	173,3	1653,1	115,9
Policy 4	902,4	136,2	1634,7	88,2
Policy 5	893,1	152,5	1652,4	108,9
Policy 6	546,3	126,8	1584,4	78,5
Policy 7	727,6	157,7	1625,6	109,8
Policy 8	954,4	175,7	1659,9	121,3
Coordinator	1903,3	208	2133	196

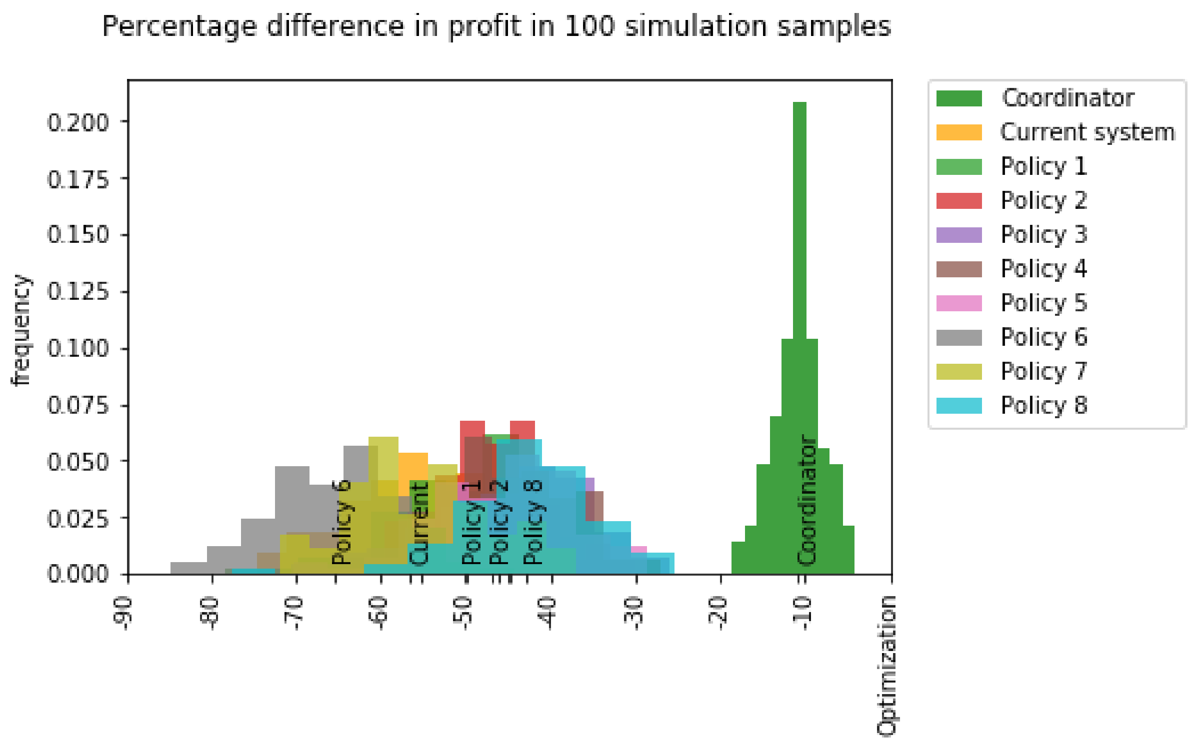
Truck comparison (policy- opt)/opt				
	truck use mean	st.d.	Optimization mean with the same input	st.d.
Current perf.	47,6	5,2	9,3	3,4
Policy 1	44,1	5,8	9,2	3,3
Policy 2	41,3	4,2	8,5	2,9
Policy 3	40,7	6,3	9,3	3,4
Policy 4	40,25	4,8	8,8	2,9
Policy 5	41,1	5,7	9	3
Policy 6	52,9	5,3	8,6	2,6
Policy 7	47,5	5,6	8,7	2,8
Policy 8	39,2	5	9	3,1
Coordinator	26,8	3,3	14,9	2,8

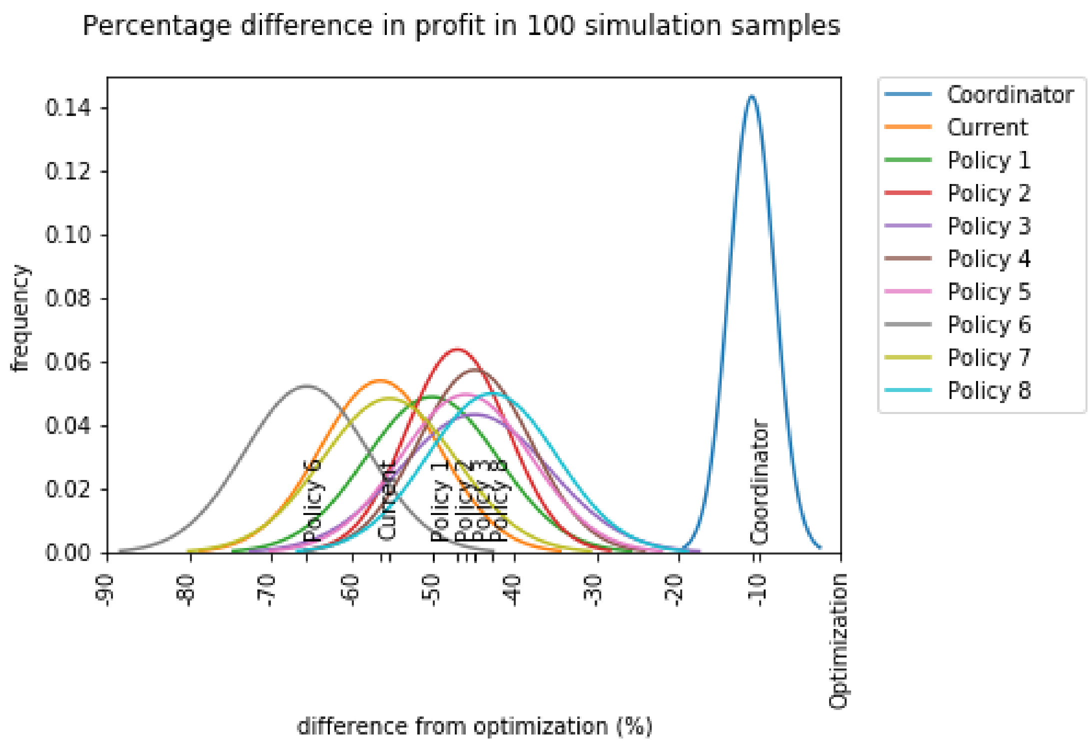
(policy- mpc)/mpc						
	profit (coins)				trucks (#)	
Current perf.	697,7	150,4		Current perf.	47,7	5,2
Policy 1	817,8	157,7		Policy 1	43,2	5,3
Policy 2	885,2	136,9		Policy 2	40,1	4,6
Policy 3	913,3	170,2		Policy 3	40,4	6
Policy 4	911	147,5		Policy 4	39,6	5,2
Policy 5	876,8	144,4		Policy 5	41	5,3
Policy 6	553,9	122,5		Policy 6	53,3	5,4
Policy 7	729,2	157,4		Policy 7	47,3	5,6
Policy 8	971,3	139,6		Policy 8	38,1	5
Coordinator	1924,6	178,2		Coordinator	27	3,3

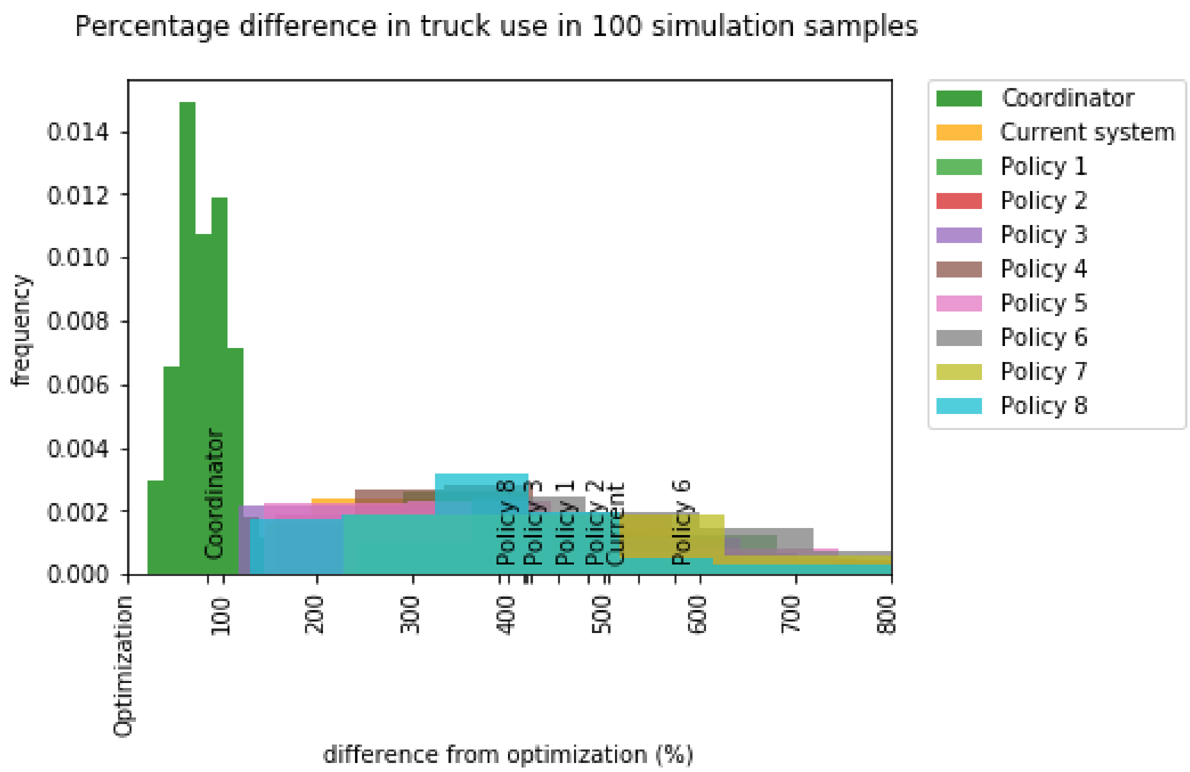
Comparison graphs of policies 1-8



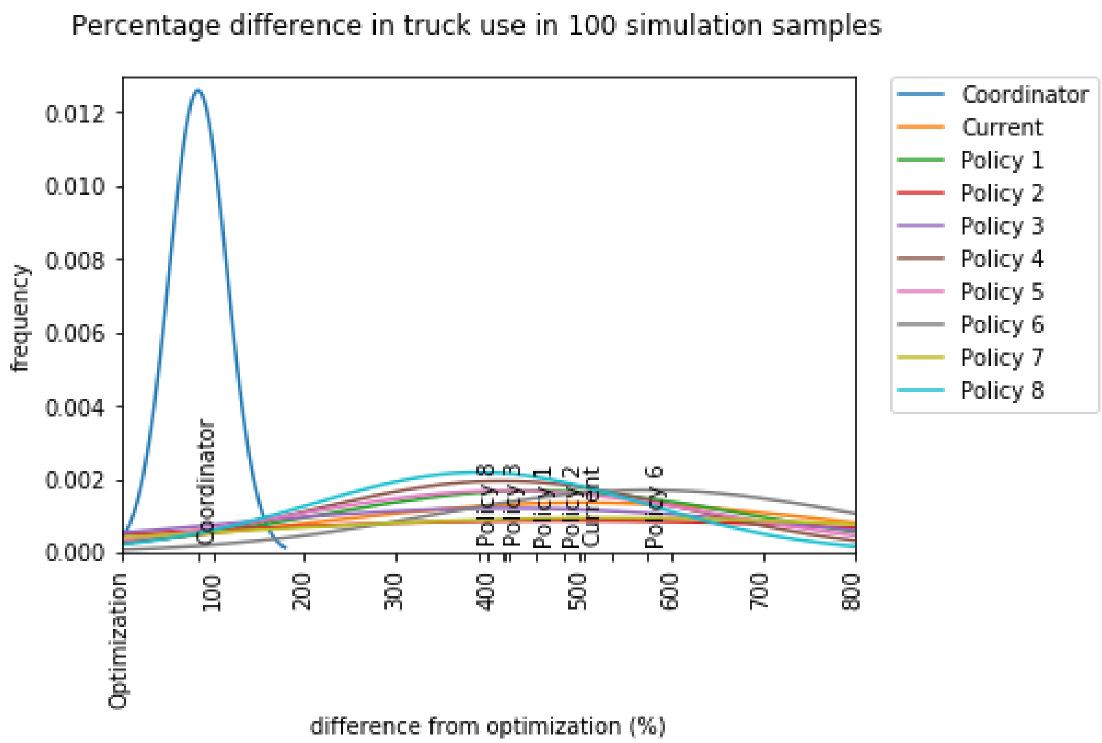



Percentage difference in profit in 100 simulation samples
frequency
difference from optimization (%)
Coordinator
Current system
Policy 1
Policy 2
Policy 3
Policy 4
Policy 5
Policy 6
Policy 7
Policy 8
Optimization

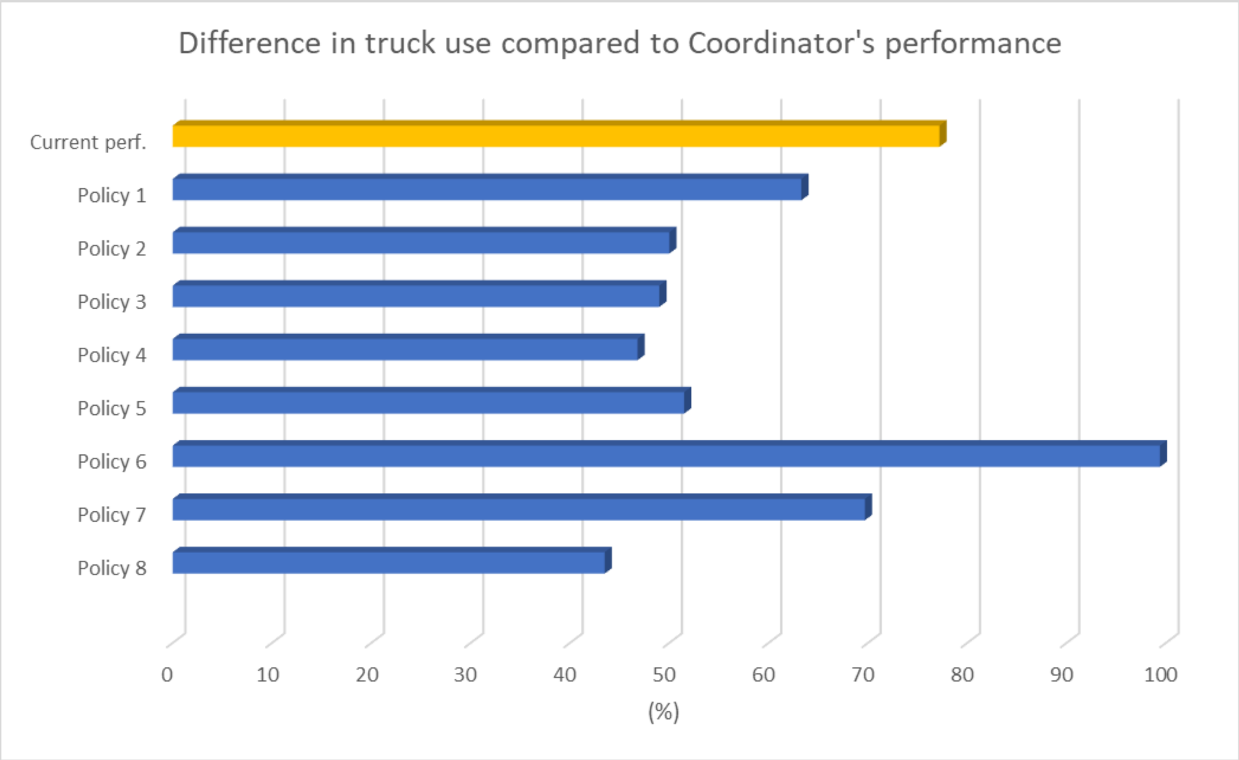

Percentage difference in profit in 100 simulation samples
frequency
difference from optimization (%)
Coordinator
Current
Policy 1
Policy 2
Policy 3
Policy 4
Policy 5
Policy 6
Policy 7
Policy 8
Optimization

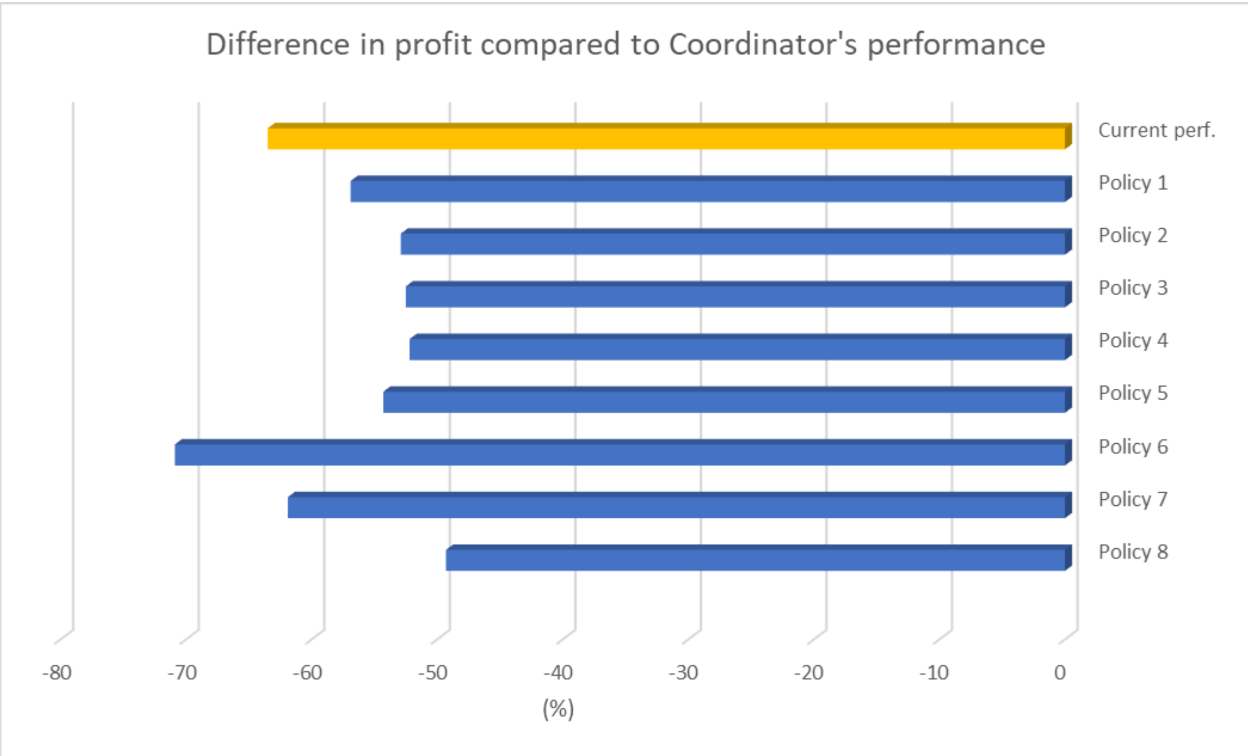


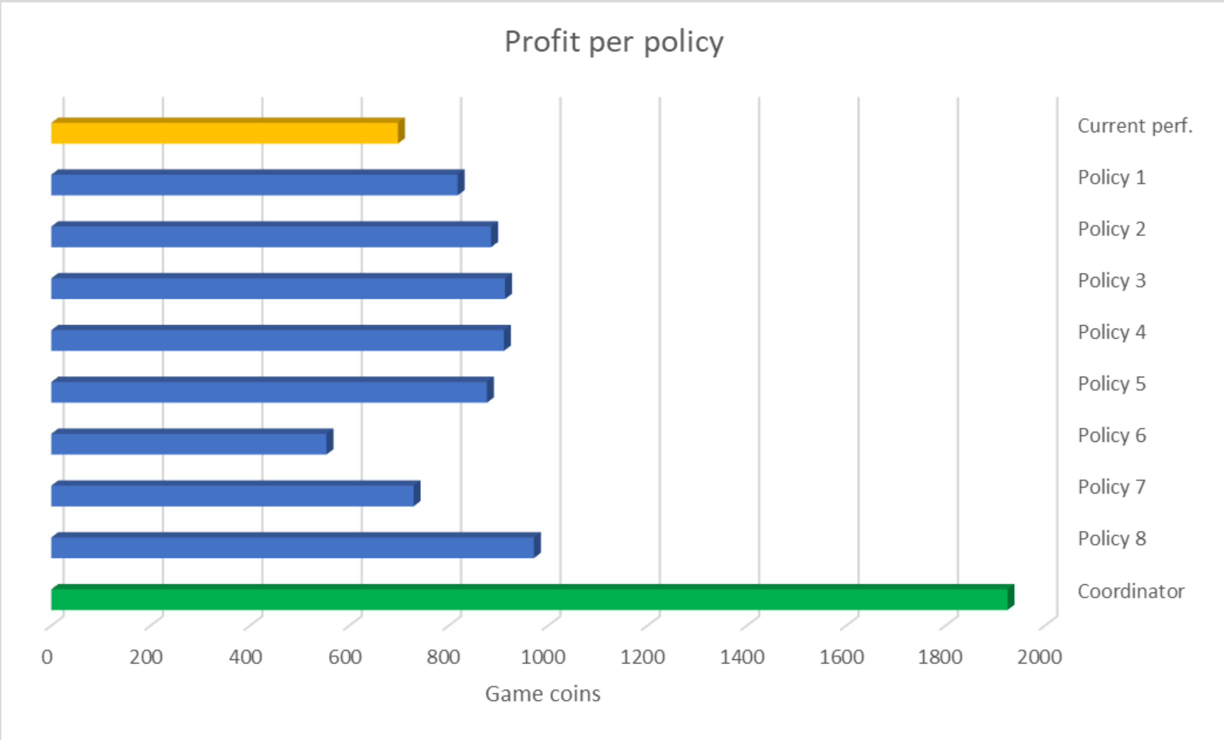
Percentage difference in truck use in 100 simulation samples
frequency
difference from optimization (%)
Optimization
Coordinator
Policy 8
Policy 3
Policy 1
Policy 2
Current
Policy 6
Coordinator
Current system
Policy 1
Policy 2
Policy 3
Policy 4
Policy 5
Policy 6
Policy 7
Policy 8

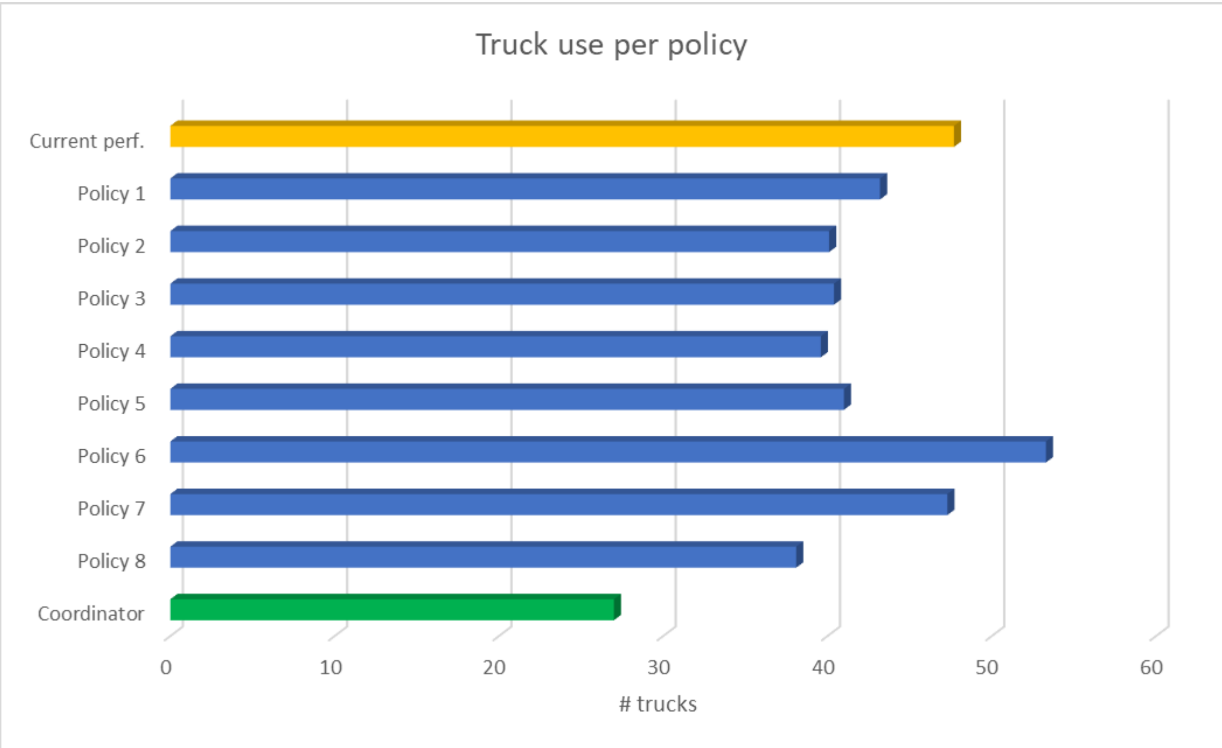


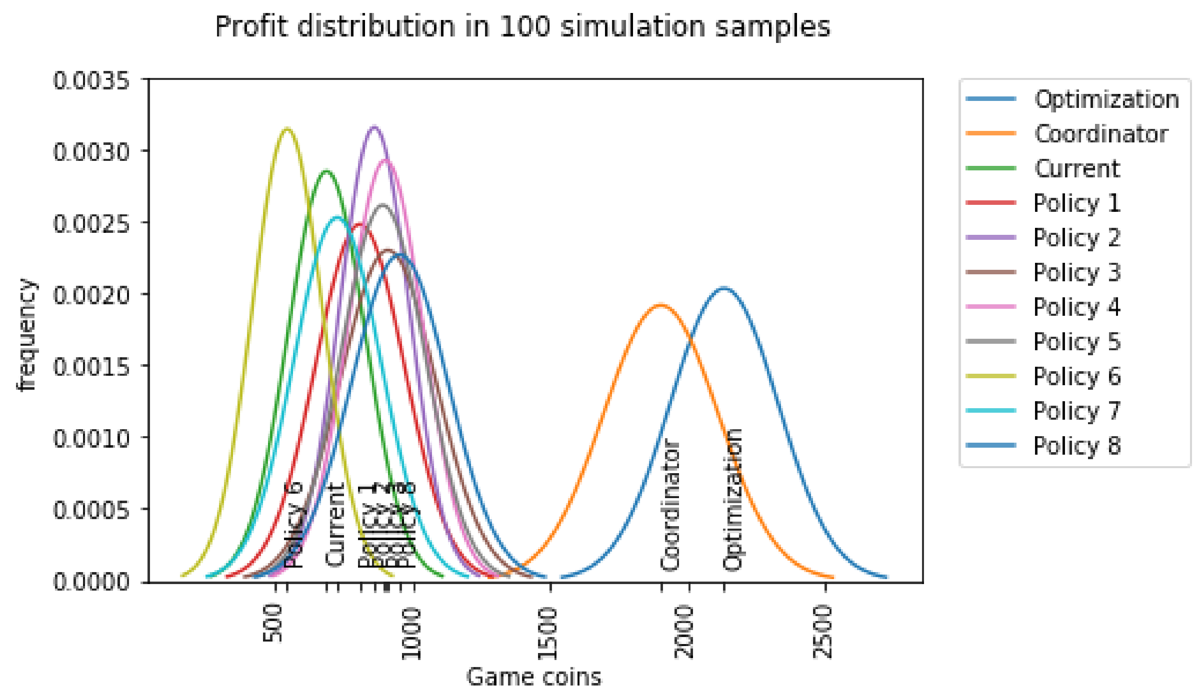
Percentage difference in truck use in 100 simulation samples
frequency
difference from optimization (%)
Optimization
Coordinator
Policy 8
Policy 3
Policy 1
Policy 2
Current
Policy 6
Coordinator
Current
Policy 1
Policy 2
Policy 3
Policy 4
Policy 5
Policy 6
Policy 7
Policy 8


Difference in truck use compared to Coordinator's performance
Current perf.
Policy 1
Policy 2
Policy 3
Policy 4
Policy 5
Policy 6
Policy 7
Policy 8
0
10
20
30
40
50
60
70
80
90
100
(%)

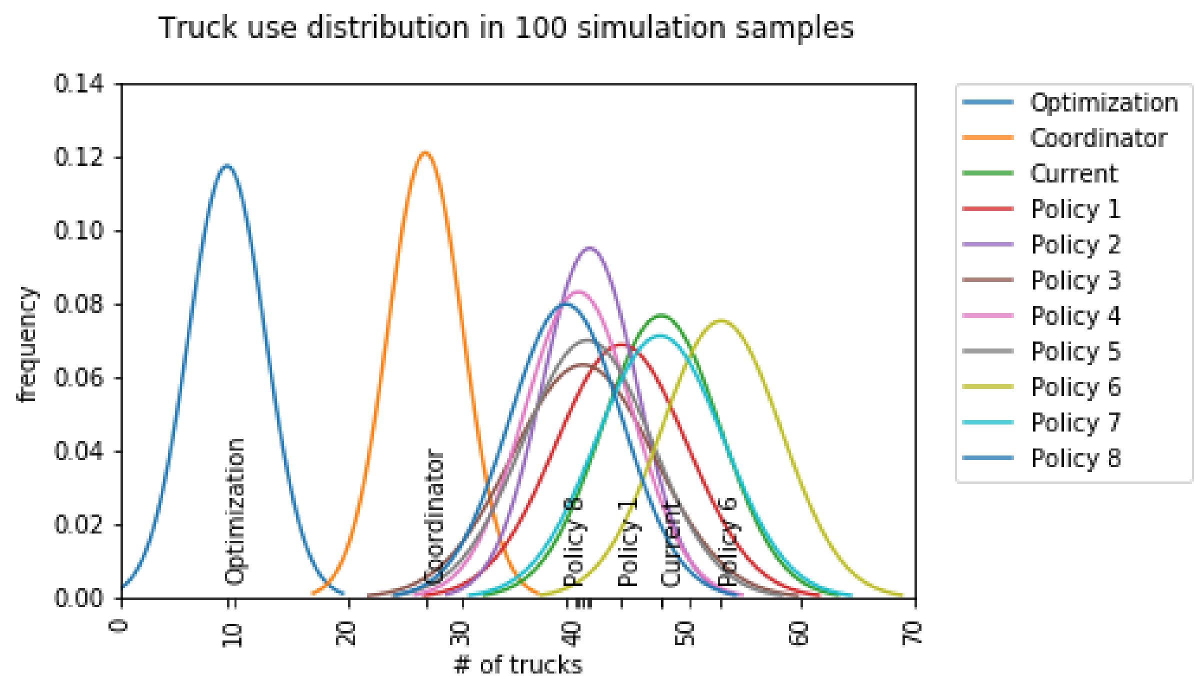

Difference in profit compared to Coordinator's performance
Current perf.
Policy 1
Policy 2
Policy 3
Policy 4
Policy 5
Policy 6
Policy 7
Policy 8
-80
-70
-60
-50
-40
-30
-20
-10
0
(%)


Profit per policy
Current perf.
Policy 1
Policy 2
Policy 3
Policy 4
Policy 5
Policy 6
Policy 7
Policy 8
Coordinator
0
200
400
600
800
1000
1200
1400
1600
1800
2000
Game coins


Truck use per policy
Current perf.
Policy 1
Policy 2
Policy 3
Policy 4
Policy 5
Policy 6
Policy 7
Policy 8
Coordinator
0
10
20
30
40
50
60
trucks

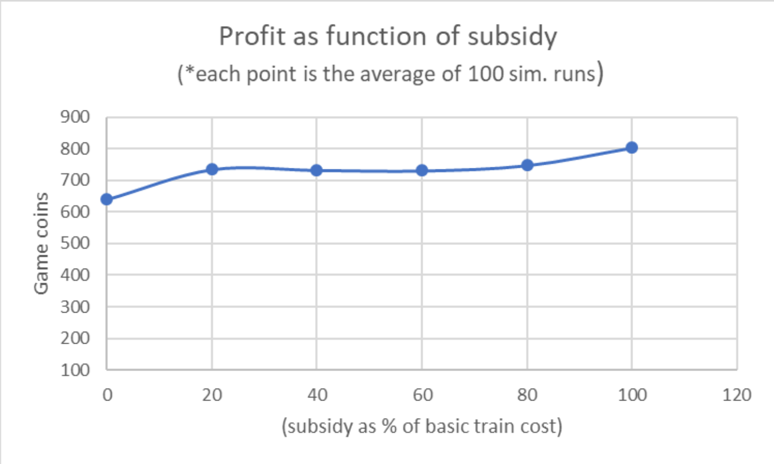


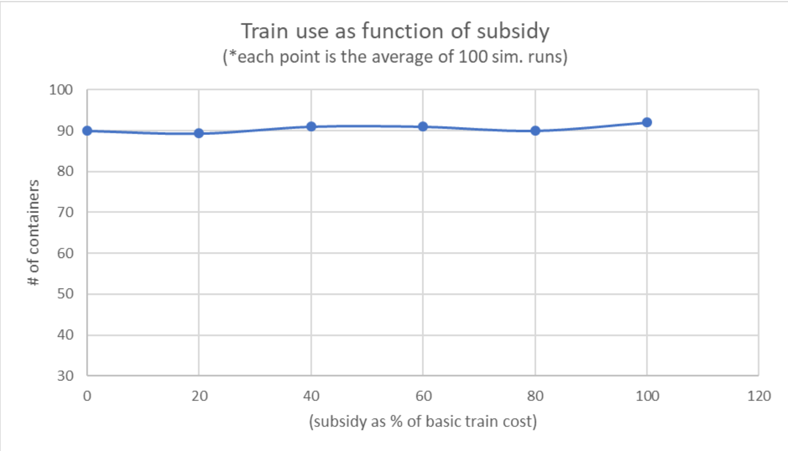
Profit distribution in 100 simulation samples
frequency
Game coins
Optimization
Coordinator
Current
Policy 1
Policy 2
Policy 3
Policy 4
Policy 5
Policy 6
Policy 7
Policy 8

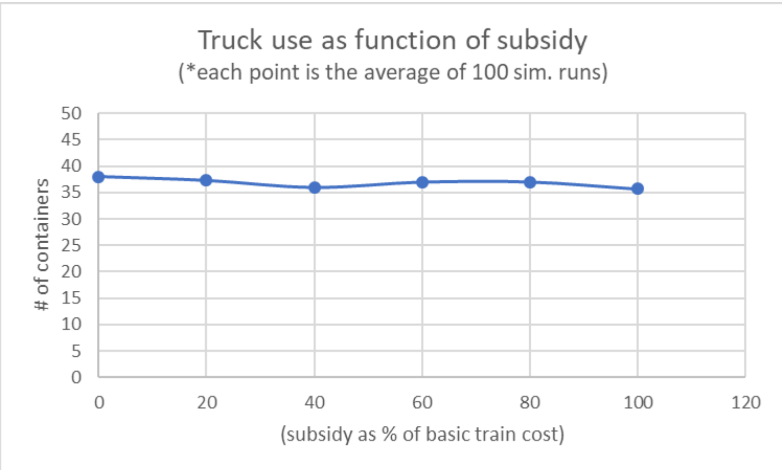


Truck use distribution in 100 simulation samples
frequency
# of trucks
Optimization
Coordinator
Current
Policy 1
Policy 2
Policy 3
Policy 4
Policy 5
Policy 6
Policy 7
Policy 8

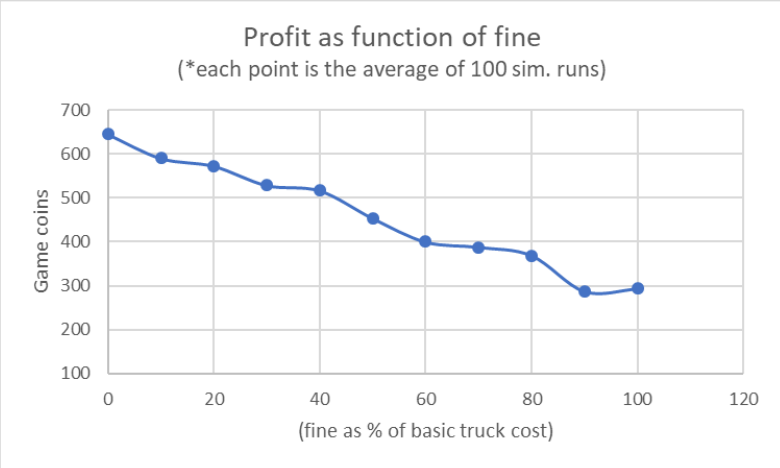
Policy 9

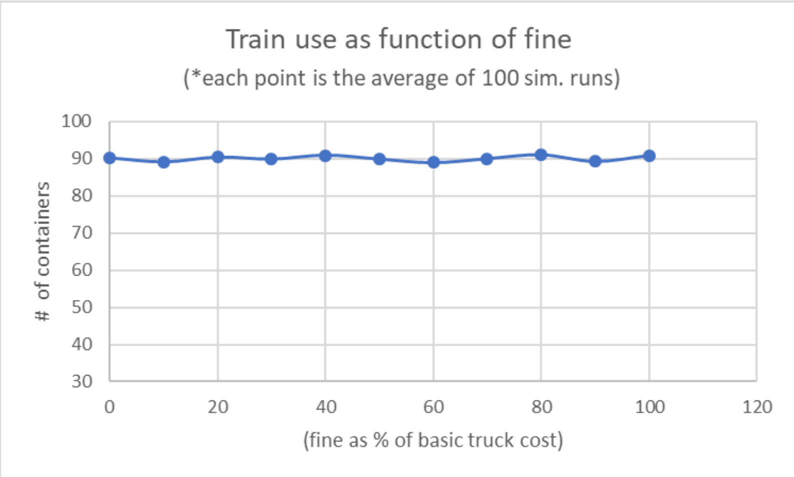

Profit as function of subsidy
(*each point is the average of 100 sim. runs)
Game coins
900
800
700
600
500
400
300
200
100
0
20
40
60
80
100
120
(subsidy as % of basic train cost)

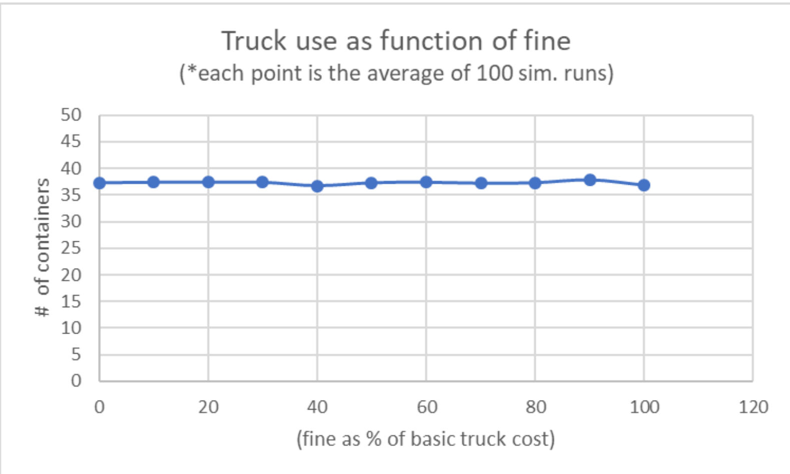

Train use as function of subsidy
(*each point is the average of 100 sim. runs)
# of containers
100
90
80
70
60
50
40
30
0
20
40
60
80
100
120
(subsidy as % of basic train cost)


Truck use as function of subsidy
(*each point is the average of 100 sim. runs)
# of containers
50
45
40
35
30
25
20
15
10
5
0
0
20
40
60
80
100
120
(subsidy as % of basic train cost)

Policy 10


Profit as function of fine
(*each point is the average of 100 sim. runs)
Game coins
700
600
500
400
300
200
100
0
20
40
60
80
100
120
(fine as % of basic truck cost)


Train use as function of fine
(*each point is the average of 100 sim. runs)
# of containers
100
90
80
70
60
50
40
30
0
20
40
60
80
100
120
(fine as % of basic truck cost)


Truck use as function of fine
(*each point is the average of 100 sim. runs)
# of containers
50
45
40
35
30
25
20
15
10
5
0
0
20
40
60
80
100
120
(fine as % of basic truck cost)

Appendix D. Paper

M.Sc. Transport, Infrastructure and Logistics thesis

Evaluating cooperation policies for rail utilization in the port to hinterland freight transport system. A combined method approach

Author: Dimitrios Karampelas
Committee: Lorant Tavasszy, Yousef Maknoon, Mark Duinkerken
Daily supervisor: Ioanna Kourounioti

Delft University of Technology.
Faculty of Civil Engineering and Geosciencies.
Faculty of Mechanical, Maritime and Materials Engineering.
Faculty of Technology, Policy and Management.

Abstract

As the margins for improvements in the current freight transport system become limited, researchers address more and more the importance of collaboration between the actors which is crucial for the implementation of new, more efficient transport concepts as synchromodality. In addition, rail is concerned as a sustainable mode of transport that can also achieve economies of scale due to its ability to haul large quantities of goods. This study investigates cooperation policies that affect actors' behavior to better utilize the rail use and lead to a more efficient system. We propose an innovative approach that combines gaming, simulation and optimization as a mixed method to test and evaluate these policies. The port to hinterland freight transportation system in the range of Port of Rotterdam is used as a case study. First, gaming sessions are organized in order to observe actors' behavior and collect data. The game that is used was initiated by Port of Rotterdam, especially to identify the problems in this system. Subsequently, by assessing the observed data, a simulation model is developed and different policy scenarios are simulated to quantify their performance. In addition, the optimization model is developed, which sets the upper bound for performance and used as a solid base for comparison between the policy alternatives. Finally, the explanation of the difference between the policies' and the optimized performance can give an insight on what are the root causes of the inefficiency, what is the best allocation of the resources and where the solutions should be focused.

Keywords: Cooperation; Policies; Freight transport; Port to hinterland; Collaboration; Gaming; Simulation; Optimization

1. Introduction

Every company and organization is trying to achieve the highest possible profits while catching up with government regulations. After the COP21 agreement on the environment and the aim of European Union to reduce climate gas emissions by 80-95% until 2050, and specifically in transport related emissions by 54-67% comparing to 1990 (European Commission, 2011), current solutions proved to be inadequate for the companies and transportation firms. Focusing on the ports and the freight transport to hinterland terminals, there is an ongoing necessity for modal shift towards more environmentally friendly modes in transport. Many European Port authorities are aiming to reduce truck-use and have cargo transported by rail or barge. Largest Europe's ports as port of Rotterdam and Antwerp have set truck reduction targets of 15-20% until 2035 and 2020 respectively, while port of Hamburg has set a target of 5% shift from truck to rail until 2025 (Van den Berg and De Langen, 2014). For this reason, several concepts have been proposed for freight transportation to promote sustainability. Researchers have introduced synchomodality concept as a development of "traditional" intermodal and multimodal concepts.

Synchromodality is "*a concept of optimising all network transportation in an integrally operated network, making of all transportation options in the most flexible way*." (Van Riessen et al., 2015). Furthermore, synchromodal concept is described as a freight transport system that provides a service independent of the mode, but as a range of customized services and requirements (Tavasszy et al., 2015). As described by Behdani et al. (2014) synchromodal transportation promotes an integrated view of freight transport in two dimensions, vertical and horizontal. “Vertical” dimension describes the integration of the logistic services (e.g. same shipping bill) while the “horizontal” dimension refers to the integration of the modes that are used for transport. As there are several papers that focus on the vertical integration of logistic services, the main distinctive feature of synchromodality is the horizontal dimension (Behdani et al., 2014), that integrates the transport service on different modalities as one transport mode.

A key factor to make synchromodal concept feasible and successful is the cooperation of the involved actors (Pfoser et al., 2016). However, these actors have much different businesses and involved in different aspects of freight transportation. This diversity of the actors makes their coordination a difficult task but can lead to potentially high benefits for all of them (Pfoser et al., 2016).

The need for cooperation is also addressed by Kourounioti et al. (2018), focusing on the in-game behavior of the Rail Cargo Challenge Rotterdam (RCCR) board game, who states “*Game playing results show that the inability of stakeholders to cooperate results in lower profits and lower reputation rates.*” (Kourounioti et al., 2018). There are several studies to record the preferences of the actors in synchromodalilty using games (see Kurapati et al. (2018); Kourounioti et al. (2018); Buiel et al. (2015)). However, there are not many papers that extent the gaming tool to test and evaluate different policies in freight transportation. This is proposed as future research by Kurapati et al. (2017) by changing parameters of the game and capture the effects on the performance indicators. This could give deep insight of different policy interventions (Kurapati et al., 2017). This is also an aim of this thesis: to investigate serious gaming as a policy validation tool.

Combining the aforementioned aspects, this study has as research objective to examine cooperation policies between the involved actors that can lead to a higher level of performance in port to hinterland freight transport system, using a mixed method based on gaming to test and evaluate these policies.

2. Research Approach

The general framework that will be followed in this thesis is based on the combination of gaming and simulation as used by Kurapati et al. (2017) and Kourounioti et al. (2018) for capturing the behavior and decision making of the stakeholders in gaming sessions for synchromodality. At first the games are used to let participants express their attitudes and preferences and then the simulation metamodel is developed using the same design of the game and the observed choices of the players (Kourounioti et al., 2018).

In this study the aforementioned framework will be enhanced with an optimization model in order to set a base for comparison and it will be used iteratively in order to test, evaluate and validate different policies and their level of performance. The optimized performance will set the upper limit and will be used as a reference point for comparison. The general framework can be seen in figure 1.

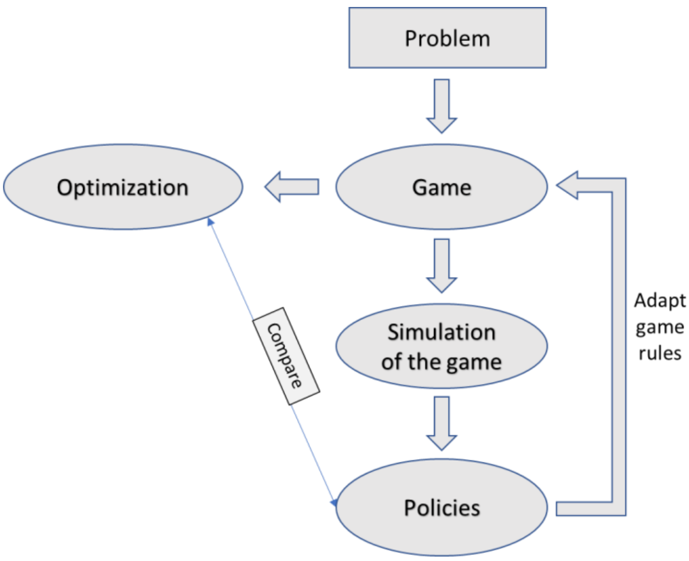


Figure 1 General framework

Based on the general framework a more detailed description of the methodological framework that will be followed is described in this paragraph. The first step is the development of the game. The Rail Cargo Challenge Rotterdam board game is already developed and some game sessions have already been done (see Kouronioti et al., 2018 ; Kurapati et al., 2017). After the development of the game, two independent branches follow. The first branch is associated with the creation of a reference point of the highest possible performance aiming in a system optimum state while the second branch includes observation and simulation of actors' behavior, behavioral policy implementation and evaluation. The "highest", reference point is needed to compare the policy alternatives. The planning to achieve this highest performance could be done by a coordinator that would have access to all the available information and could bypass the negotiations of actors, that lead to an inefficient system. The decisions of the coordinator are only based on the efficient planning to achieve system optimality and not to maximize individuals' profit. Subsequently, the steps on the second branch aim to find policies and incentives that will move actors towards more cooperative behavior and through cooperation and information exchange could approach the "optimal" system performance described above. In order to achieve this, several steps will be applied. First, game sessions are organized to observe players' behavior and performance. Observations captured in these sessions are used to develop a simulation model of the behavior of the players in the game (representation of in-game behavior) (step 2). For these two steps there is already some data available, as mentioned previously, from the research of Kurapati et al. (2017) and Kourounioti et al. (2018). The first simulation approach of RCCR, found in the work of Kurapati et al. (2017), uses probabilistic distributions of negotiated prices accepted by the train operators in-real games. In that way the negotiations are expressed by randomly drawing prices from these distributions and compare them with the respective prices of the freight forwarders. The third step of this branch is to find policies that can influence players' behavior towards collaboration. Subsequently, depending on the policies that will be chosen, the simulation model will be changed to identify the respective changes in performance (step 4). Simulation is used here as it is relatively easier and faster to change parameters and identify the results comparing to gaming. Then, a comparison of this performance with the reference performance (in coordinated system) is done (step 5). This simulation modification and performance comparison will be done for all the selected policies. After this iterative process, an evaluation of the results follows (step 6). The best of the above policies will be selected to be used in game sessions with changed player behavioral rules (step 7-9). Their new performance will be then measured and compared to the highest achievable score found by the optimizer of the game. In this way, it will be examined if the policies have the desired outcomes on actors' choices and if this performance was in accordance with the simulation model.

3. Game

The base method that is used to represent the port to hinterland freight transport system and actor's behavior in this study is gaming. Games are used from practitioners to better understand the value of flexibility in freight transport and by educational institutes to teach intermodal container logistics (Van Riessen, 2018). Furthermore, gaming is used as a way to raise actor's awareness towards new transport systems as synchromodality that is expected to increase efficiency in freight transportation (Kourounioti, 2018). This tool (gaming) has three objectives for synchromodality according to Buiel et al. (2015):
1) Let the actors experience synchromodal planning,
2) Show to the actors the benefits and
3) Achieve the mind shift towards cooperation between actors.

The game that is used is Rail Cargo Challenge Rotterdam. Rail Cargo Challenge Rotterdam is a game developed by TU Delft gamelab, The Barn, ProRail and TNO within the "Synchro-gaming" project (TU Delft gamelab site, 2018) and in collaboration with stakeholders of port of Rotterdam.
Acoording to Kourounioti et al. (2018), *"The key research objective of the Rail Cargo Challenge Rotterdam (RCCR) is to assess the attitudes and behavior of stakeholders in the freight transport domain with respect to the efficient bundling of containers to be transported to their final destination using rail".*

Gaming has the advantage that can give an actual – and not modeled- human behavior, while can also provide a discussion with the actors on the results and their individual reflection on the system operation. The main disadvantages of gaming, is that it has a high simplification level compared to the "real" world and it is difficult to take many samples, due to the availability of players and the gameplay time itself. As an indication a gaming session of RCCR game requires at least 5 players and 1 game master and has a duration of about 3 hours.

4. Simulation

The simulation model is used as a representation of the game. The simulation model gives the opportunity, by changing simulation structure or parameters, to model different game scenarios according to new policies, without the need of organizing multiple gaming sessions. Of course, ideally all the scenarios would be more realistic to be tested in gaming sessions, but due to time restrictions, the simulation alternative is preferred.

A sample of 100 simulation runs lasts a few minutes, while only one game session needs 2.30-3 hours. The disadvantage of the simulation is the fact that it is a model of the game, that is already an abstraction of reality. However, this method is used due to the convenience of testing different alternatives in a very short time, compared to gaming.

A first approach of a simulation meta-model of RCCR game was done by Kurapati et al. (2017). In their study, the simulation is based on a probabilistic comparison of the proposed prices in the negotiation phase between the players. In the current study, the simulation model is approached differently than the aforementioned work. First, the flowchart of the game was constructed and the simulation model was made according to the game steps. A very important element lays on the decision making of the players on what mode to choose, during the negotiation phase of the game. These decisions are modeled using Discrete Choice Modeling and specifically the Multinomial Logit model (MNL). According to Ben-Akiva and Lerman (1985) Discrete Choice analysis is the most used methodology for travel decisions and mode choice. In addition, the proposed negotiation prices were drawn from a distribution, using observed prices from gaming sessions.

In order to choose the most important factors to include in the utility functions of the decision model, literature is used. The most important factors for mode choice in port to hinterland freight transportation found to be cost, transport time, reliability, transport quality and in some cases frequency of the service. As in the game RCCR transport time, transport quality and frequency of service are not included, the factors that are finally chosen in the utility functions are cost and reliability.

The simulation model was coded in python 2.7. The parameters used for the Discrete Choice model were based on observed data from gaming sessions and were estimated using the software BIOGEME 1.8 (see Bierlaire, 2008). BIOGEME package is distributed free in order to develop the research area of Discrete Choice Models (Bierlaire, 2003).

4.1. Freight forwarders decision modeling

In the simulation model freight forwarders make their decision for each order card separately. The important assumptions for the used Discrete Choice Model (see Ben-Akiva & Bierlaire, 2009) in this case are:

- The decision maker: Freight forwarder
- The alternatives: depend on the expire date (see next)
- The attributes: cost, reliability (transport time and quality are not included in RCCR game)
- The decision rule: utility maximization, MNL model

The alternatives for freight forwarders depend on the expiry round of the order card.

➢ If it is the last round (day) before the order expires, the discrete choices for each freight forwarder are:
1) train operator 1,
2) train operator 2 or
3) delayed truck.

And the respective utility functions are:

$$U_{Train_1} = \beta_{price} * (revenue - operator1price) + \beta_{reliability} * reliability1 + (\beta_{train})$$
$$U_{Train_2} = \beta_{price} * (revenue - operator2price) + \beta_{reliability} * reliability2 + (\beta_{train})$$
$$U_{truck\_delayed} = \beta_{price} * (revenue\_delay - cost\_delay) + \beta_{truck\_delayed}$$

➢ If it is not the last day before the order expires, the discrete choices for each freight forwarder are:
1) train operator 1,
2) train operator 2,
3) early truck or
4) keep the order to decide next day.

And the respective utilities are:

$$U_{Train_1} = \beta_{price} * (revenue - operator1price) + \beta_{reliability} * reliability1 + (\beta_{train})$$
$$U_{Train_2} = \beta_{price} * (revenue - operator2price) + \beta_{reliability} * reliability2 + (\beta_{train})$$
$$U_{truck\_early} = \beta_{price} * (revenue\_early - cost\_early) + \beta_{truck\_early}$$
$$U_{keep\_order} = +\beta_{keep\_order}$$

The parameters for each utility function were estimated using observed data from the game sessions. The values of the parameters can be seen in Table 1.

β_{price}	0.108
$\beta_{reliability}$	0.146
β_{train}	0 (train set as base case)
$\beta_{truck\_delayed}$	-1.45
β_{truck_early}	-2.44
β_{keep_order}	-1.06

Table 1 estimation of parameters in Utility functions

Note that as the truck cost and revenue are constant, these prices were incorporated in the alternative specific parameter. Thus, $U_{truck\_delayed} = +\beta_{truck\_delayed}$ and $U_{truck\_early} = +\beta_{truck\_early}$. Furthermore, it is worth noting that the parameter for the early trucks ($\beta_{truck_{early}}$) found to be less than the parameter for delayed truck. This is justified from the game sessions, as the early truck alternative found to be the most rarely used, as the players prefer to keep the order cards for the next rounds most of the times.

4.2. Train operator's decisions modeling

Train operators' decisions modelling is included in simulation, as well. For this model, simple utility maximization is used as the decision rule, as the operators do not choose among a set of mode alternatives, but decide which origin-destination pair will service to achieve the highest benefits. The weights in the utilities (paramters) for the price and for the delayed orders are assumed to be the same as estimated for freight forwarders in the previous subsection.

5. Optimization and a coordinated system perspective

Optimization model is used in order to find the upper bound of performance and identify the potential benefits of a coordinated or fully-cooperative system. Two approaches of optimized performance are used in this study. The first model uses full information, excludes stochasticity and sets the upper bound, while the second uses only the exact information that players have and gives a coordinated system perspective. The second model can be also assumed as a policy measure of a central coordinator and is closer to the simulation of the game, as the coordinator takes the decisions per round. However, as the coordinated model is based on optimization and does not include human behavior, it is described with the optimization part.

The first model, referred as optimization model, assesses all information of the system and excluding stochasticity by taking the results of the stochastic elements as input. This optimization model has no physical meaning, as excludes stochasticity, which is not realistic. However, the practical usefulness of the model is that sets the theoretical upper bounds of the game performance in each case, in order to quantify the potential for system improvements and set a basic element for comparison between the different policy scenario. In a way the optimization model can give a quantification of how "worse" is the planning of the players compared to the highest performance that they could have achieved, with the specific demand and resources.

The second model, referred as coordinator's model, is a combination of the aforementioned optimization model and a Model Predictive Control (MPC). This model has a physical meaning and represents a version of a coordinated system that assesses only the available information each time. The information of the coordinator is exactly the same as players' information and released at the same time that become available to the players, as well. As a result, coordinator's performance falls under stochasticity. The difference of the coordinated system and the current system is that the coordinator takes decisions to maximize system's KPIs and bypasses players' negotiations that lead to inefficient decisions for the system.

The main difference of the two models is that the optimization model guarantees the highest performance, as makes the planning under full information. On the other hand, MPC coordinator takes and performs the decisions on each round separately under stochasticity. This makes coordinator's performance lower compared to the optimized performance. However, this difference can give an insight of the impact of the stochastic elements on performance and consequently separate this difference with the impact of players' negotiations.

In order to compare the simulated results with the performance of the optimization model that assess full information, first the simulation model was executed for one sample, the information for the stochastic elements were saved and then the optimization model was executed with all the information as input. This was used to find the highest possible performance for this sample, with the specific number of orders, order characteristics and stochastic element outcomes. It becomes obvious, that the performance of the optimization model does not take one single value, but depends on the input that differs for each sample.

On the other hand, the coordinated system's model (MPC) was executed after each simulation step (game round) and not at the end of the sample. In this way the coordinator had as input exactly the same information at each round as the simulation model -and the players at each round- and not full information, as the optimization model. In this way the coordinator included the uncertainty of the stochastic elements and can be assumed as a special case of policy of centralized control center, that bypasses players' negotiations.
The optimization approach is based on the arc-based Service network design or "capacitated multicommodity network design" (CMND) as described by several articles (Andersen et al., 2007; Crainic, 2000) with some adaption.

Coordinator's decisions on the coordinated system's model are based on the aforementioned optimization model combined with Model Predictive Control (see Camacho & Alba, 2013; Kouvaritakis & Cannon, 2016). The main elements that are used from the MPC is that the coordinator makes the planning for a planning horizon (e.g. four rounds) by assessing all the currently-available information, but applies only the decision for the current round. Every new round that new information become available to the system, a new planning is done for the planning horizon. In this way, stochasticity is handled as the disturbances on the MPC concept (see Kouvaritakis & Cannon, 2016).

The optimization model and coordinator's model were first formulated as Linear Programming problems using mathematical terms and then solved in python 2.7 using the external library and application programming interface (API) of IBM CPLEX.

5.1. Optimization model

The optimization approach is based on the arc-based Service network design or "capacitated multicommodity network design" (CMND) as described by several articles (Andersen et al., 2007; Crainic, 2000), with some adaption. The aforementioned model is changed to better fit the specific problem. Firstly, a profit maximization formulation is considered, instead of cost minimization, as the train services have a fixed cost, independent of the arc that is used. Secondly, to reduce the decision variables and as the arcs have no cost of use (fixed cost per train), each train service is not described with design arcs but with design nodes ($xter_{in}^{tr}$, $xdest_j^{tr}$) that represent the terminals/destination that each train can visit each round. In the case of flow arcs the decision variables of rail service could be represented as r_{iklj}^{tpr} as each train t∈T can service up to three terminals (e.g. i,k,l∈O) to transport the containers p∈P in round r∈R to destination j∈D. However, this would require about T*P*R*O*O*O*D=2*18*4*5*5*5*2=36000 decision variables, only for the rail flows. As there are no cost for using each arc and in order to reduce the required decision variables, the flow arcs of rail service (r_{inj}^{tpr}) are represented as binary variables that train t∈T transports container p∈P in round r∈R from terminal i∈O, which is the nth terminal choice of the operator (n∈N), to destination j∈D. In this case, the decision variables for rail flows are reduced to T*P*R*O*N*D=2*18*4*5*3*2=4320 instead of 36000. The flow decision variables are binary as each commodity p∈P represents only one container; thus, flow is either zero or one.

The Integer programming optimization is presented next.

Sets:	
T	Set of trains that are operating (t∈T).
P	Set of containers (IDs) (p∈P).
O	Set of origin terminals (i∈O).
D	Set of destination (j∈D).
R	Set of planning horizon rounds (days) (r∈R)
N	Set of possible choices in priority order for terminals (n∈N). (e.g. 1st choice, 2nd choice, 3rd choice for a maximum of 3 out of 5 Terminals) (Equals to the dice alternatives)
Parameters:	
$dest_j^p$	Binary parameter: 1 if container p∈P has j∈D as destination, 0 otherwise.
$term_i^p$	Binary parameter: 1 if container p∈P has i∈O as destination, 0 otherwise.
$train\_term^{tr}$	Non-negative integer: maximum number of terminals that train t∈T is allowed to service on planning round r∈R.
$profit\_rail$	Revenue for a successful container transport by train (as train has constant cost for operating, cost not included)

$profit\_truck\_early$	Profit for each container transported by an on-time truck (revenue -cost)
$profit\_truck\_delay$	Profit for each container transported by a delayed truck (revenue -cost)
$expire^{pr}$	Binary parameter: 1 if container order p∈P has expired on round r∈R, 0 otherwise. (The indicated round shown in the order cards is the last round that the container can be transported, thus expire=0 at the specific and previous rounds and expire=1 the following days).
$release^{pr}$	Binary parameter: 1 if container order p∈P has released on round r∈R, 0 otherwise. (The round that the container reaches the origin terminal and the following rounds, release=1. Before this round release=0)
Variables:	
r_{inj}^{tpr}	Binary variable: 1 if train t∈T transports container p∈P from origin terminal i∈O, which is the n^{th} (n∈N) terminal choice, to destination j∈D in round r∈R, 0 otherwise.
$xter_{in}^{tr}$	Binary variable: 1 if train t∈T services terminal i∈O as n^{th} choice (n∈N) in round r∈R, 0 otherwise.
$xdest_{j}^{tr}$	Binary variable: 1 if train t∈T has as destination j∈D in round r∈R, 0 otherwise.
te^{pr}	Binary variable: 1 if on-time (early) truck transports container p∈P in round r∈R, 0 otherwise. (trucks can service all terminals and destinations at all rounds)
td^{pr}	Binary variable: 1 if delayed truck transports container p∈P in round r∈R, 0 otherwise.

$Objective\ Function$ (maximize profit):

$$max \sum_{t\in T}\sum_{p\in P}\sum_{r\in R}\sum_{i\in O}\sum_{n\in N}\sum_{j\in D} r_{inj}^{tpr} * profit\_rail + \sum_{p\in P}\sum_{r\in R} te^{pr} * profit\_truck\_early + \sum_{p\in P}\sum_{r\in R} td^{pr} * profit\_truck\_delay \qquad (1)$$

$Subject\ to$:

$$\sum_{t\in T}\sum_{r\in R}\sum_{i\in O}\sum_{n\in N}\sum_{j\in D} r_{inj}^{tpr} + \sum_{r\in R} te^{pr} + \sum_{r\in R} td^{pr} = 1, \quad \forall\, p \in P \qquad (2)$$

$$\sum_{p\in P}\sum_{i\in O}\sum_{n\in N}\sum_{j\in D} r_{inj}^{tpr} \le 10, \quad \forall\, t \in T, r \in R \qquad (3)$$

$$r_{inj}^{tpr} \le dest_j^p, \quad \forall t \in T, p \in P, r \in R, i \in O, n \in N, j \in D \qquad (4)$$

$$r_{inj}^{tpr} \le term_i^p\ , \quad \forall t \in T, p \in P, r \in R, i \in O, , n \in N\ j \in D \qquad (5)$$

$$r_{inj}^{tpr} \le xter_{in}^{tr}\ , \quad \forall t \in T, p \in P, r \in R, i \in O, n \in N, j \in D \qquad (6)$$

$$r_{inj}^{tpr} \le xdest_j^{tr}\ , \quad \forall t \in T, p \in P, r \in R, i \in O, n \in N, j \in D \qquad (7)$$

$$r_{inj}^{tpr} \le (1 - expire^{pr}), \quad \forall t \in T, p \in P, r \in R, i \in O, n \in N, j \in D \qquad (8)$$

$$te^{pr} \le (1 - expire^{p(r+1)}), \quad \forall p \in P, r \in R \qquad (9)$$

$$td^{pr} \le (1 - expire^{pr}), \quad \forall\, p \in P, r \in R \qquad (10)$$

$$r_{inj}^{tpr} \le release^{pr}, \quad \forall t \in T, p \in P, r \in R, i \in O, n \in N, j \in D \qquad (11)$$

$$te^{pr} \leq release^{pr}, \qquad \forall p \in \mathrm{P}, r \in \mathrm{R} \tag{12}$$

$$td^{pr} \leq release^{pr}, \qquad \forall\, p \in \mathrm{P}, r \in \mathrm{R} \tag{13}$$

$$\sum_{i \in \mathrm{O}} \sum_{n \in \mathrm{N}} xter_{in}^{tr} \leq train\_term^{tr}\ , \qquad \forall t \in \mathrm{T}, r \in \mathrm{R} \tag{14}$$

$$\sum_{n \in \mathrm{N}} xter_{in}^{tr} \leq 1\ , \qquad \forall t \in \mathrm{T}, r \in \mathrm{R}, i \in \mathrm{O} \tag{15}$$

$$\sum_{i \in \mathrm{O}} xter_{in}^{tr} \leq 1\ , \qquad \forall t \in \mathrm{T}, r \in \mathrm{R}, n \in \mathrm{N} \tag{16}$$

$$\sum_{j \in \mathrm{D}} xdest_{j}^{tr} \leq 1\,, \qquad \forall t \in \mathrm{T}\,, r \in \mathrm{R} \tag{17}$$

$$r_{inj}^{tpr}, xter_{in}^{tr}, xdest_{j}^{tr}, te^{pr}\ , td^{pr}\ \in \{0,1\}, \qquad \forall t \in \mathrm{T}, p \in \mathrm{P}, \mathrm{r} \in \mathrm{R}, i \in \mathrm{O}, n \in \mathrm{N}\ , j \in \mathrm{D} \tag{18}$$

Objective function (1), maximizes the profit. The first term represents the profit obtained by the successful transport of containers by train, the second term includes the profit by on-time (early) trucks and the third term the profit by delayed trucks.
Constraint (2) ensures that each container is transported only once and only by one of the available modes/services: train "t", on-time truck or delayed truck.
(3) is the container capacity constraint for each train t∈T and for each round r∈R.
Constraint (4) ensures that each container p∈P can only reach the destination that is assigned to.
Constraint (5) ensures that each container p∈P can only be picked up by the terminal that is assigned.
Constraints (6)-(7) ensure that each container p∈P can only be transported by train t∈T on the round r∈R, if the specific train is servicing the respective terminals/destinations on the specific round.
Constraints (8)-(10) ensure that each container p∈P will reach destination before expire. Also, constraint (9), by using r+1 in $expire^{p(r+1)}$ ensure that an on-time (early) truck cannot be used on the last day that the order is released. In this case only a delayed truck can be used by the rules of the game.
Constraints (11)-(13) ensures that each container p∈P cannot be delivered before the day of release.
Constraint (14) limits the number of terminals that each train can service. A different limit for each train applies per round, depending on the conditions (dice value) in each round.
Constraint (15) restricts each train t∈T to choose each terminal i∈O on each round r∈R no more than one time.
Constraint (16) ensures that each train t∈T on each round r∈R has as n^{th} choice (n∈N) no more than one terminal i∈O.
Constraint (17) restricts the train to have at most one destination.
(18) is a constraint that sets the type of variables to binary.

5.2. Coordinated system

Several coordinator strategies can be defined to control the system. In this thesis, coordinator's decisions are based on the optimization model that was described in the previous section combined with Model Predictive Control (see Camacho & Alba, 2013; Kouvaritakis & Cannon, 2016). The main elements that are used from the MPC is that the coordinator makes the planning for a planning horizon (e.g. four rounds) by assessing all the available information, but applies only the decision for the current round. Every new round that new information become available to the system, a new planning is done for the planning horizon. In this way, stochasticity is handled as the disturbances on the MPC concept (see Kouvaritakis & Cannon, 2016).

As the container information become available only in the "current" round and the demand is unknown for the "future" rounds, the optimization model is used in every new round of the game and the planning for a planning horizon is performed with all the available information until this round. Then, according to the model results, only the decisions for the "current" round are taken, the respective containers are transported and the round ends. Subsequently, in the new round, the input information of the model is readapted including information of the new round and the planning is redone, performing only the decisions for the "new" round. The planning horizon is chosen until the round of the latest expiring order.

As the “future” rounds of the game include some stochasticity due to the dice that determines the maximum number of the terminals that each train is allowed to service, the profit calculated from the planning is not “guaranteed”. For this reason, we implement “expected” profit in the optimization model which is the profit multiplied by the probability (expected_profit=chance*profit) of this profit to happen. The objective function of the model is then modified to:

$Objective\ Function$ (maximize expected profit for the planning horizon):

$$max \sum_{t\in T}\sum_{p\in P}\sum_{r\in R}\sum_{i\in O}\sum_{n\in N}\sum_{j\in D} r_{inj}^{tpr} * chance_n^r * profit\_rail$$
$$+ \sum_{t\in T}\sum_{p\in P}\sum_{r\in R}\sum_{i\in O}\sum_{n\in N}\sum_{j\in D} r_{inj}^{tpr} * expire^{p(r+1)} * (1 - chance_n^r) * profit\_truck\_delay$$
$$+ \sum_{p\in P}\sum_{r\in R} te^{pr} * profit\_truck\_early$$
$$+ \sum_{p\in P}\sum_{r\in R} td^{pr} * profit\_truck\_delay$$

,where $chance_n^r$ is the chance (depending on dice) that the train is allowed to service up to n∈N terminals in round r∈R.

The objective function in this case maximizes the expected profit (chance*profit) for the entire planning horizon. The first term represents the profit that can be obtained by the successful transport of containers by train up to the respective probability $chance_n^r$. The second term expresses the risk that the dice can determine less terminals than the number of terminals the coordinator has decided to service. In this case the expiring orders that cannot be transported by train have to be sent by a delayed truck. This probability is (1-$chance_n^r$). The third term calculates the expected profit by on-time (early) trucks and the fourth term the expected profit by delayed trucks.

6. Policies

Based on literature and expert consultation, the policies that have been selected to be tested are divided in information sharing policies and momentary adjustment policies.

6.1. Information sharing policies

6.1.1. Horizontal collaboration of actors

6.1.1.1. Alliance between freight forwarders:

Policy (1). Freight forwarders consolidate their containers to achieve economies of scale and have discount in train transport by train operators. Requires information sharing between alliance forwarders.

6.1.1.2. Alliance between operators:

Policy (2). Operators can trade the containers that cannot transport by themselves, if the other operator has chosen the respective terminal-destination.

Policy (3). Operators decide together which terminal(s)-destination to service each train in order to maximize their total benefits, then negotiate with forwarders for the respective orders and at the end of the round share the profits.

6.1.1.3. Alliance between forwarders and alliance between operators (combination of 6.1.1.1.-6.1.1.2.):

Policy (4). Freight forwarders can consolidate their containers and operators can trade their containers between them.

Policy (5). Freight forwarders can consolidate their containers and operators co-decide trains’ terminal(s)-destinations.

6.1.2. Vertical collaboration of actors.

Alliance between freight forwarder and operator:

Policy (6). A freight forwarder deals to transport all his containers with a specific operator for a predefined price, and the operator decides which to send by truck and which by train.

Policy (7). Forwarder gives priority to a specific operator to choose which containers will take in a predefined price and then can negotiate with the other operator for the rest.

6.1.3. Vertical and horizontal collaboration of actors.

Policy (8). Forwarders make alliances to consolidate their freight and give their orders to specific operator in predefined price and operators can trade their containers to the other operator if they cannot fulfil the order.

6.2. Monetary adjustment policies

Policy (9). Subsidize the utilization of trains above a percentage (e.g. 70%). *Note that this policy may not have a very high effect as the in-game operator profitability is almost proportional with train utilization (if the deviations in negotiated prices are neglected), and thus operators try to utilize their train anyway, even without subsidy.

Policy (10). Fine the use of truck (by operators and freight forwarders). *Note that this would probably raise the fees for train use, as the operators would ask for higher prices, that forwarders could accept in order to avoid fine.

7. Results

7.1. Policies' performance

For the first eight policies the comparison, the base for comparison is the optimization model's performance and thus the comparison between the policies is set as the percentage difference from this reference point.

$$dif = \frac{(policy_{per} - opt_{per})}{opt_{per}} * 100$$

For policies 9 and 10, which are the subsidize of train-use and fine of truck-use respectively, a sensitivity analysis is chosen in order to check the performance in different levels of subsidies and fines. On the next tables the performance of each policy can be seen compared to the optimization model.

Profit comparison between each policy and optimization model		
	Mean Dif. (%) (100 samples)	St. Deviation
current performance	-56,5	7,4
Policy 1	-50,1	8,1
Policy 2	-47	6,2
Policy 3	-44,9	9,2
Policy 4	-44,9	6,9
Policy 5	-46	8
Policy 6	-65,5	7,6
Policy 7	-55,4	8,2
Policy 8	-42,8	7,9
MPC controller	-10,9	2,77

Table 2 Profit comparison between policies and optimization model

Truck use comparison between each policy and optimization model		
	Mean Dif. (%) (100 samples)	St. Deviation
current performance	503,9	293
Policy 1	452,4	235,5
Policy 2	484,1	455,6
Policy 3	418	329
Policy 4	415	203
Policy 5	422	235,9
Policy 6	575	233
Policy 7	535,2	422
Policy 8	390,4	182,2
MPC controller	84	31,6

Table 3 Truck-use comparison between policies and optimization model

In figures 2 and 3, the performance of each policy in terms of profit and truck-use compared to the optimized performance is represented graphically.
As can be seen, all the policies except “policy 6” have a better performance than the current situation. The best performance is achieved by the application of “policy 8”, which represents the highest level of cooperation, vertical and horizontal at the same time. Furthermore policies “3” and “4” approach the performance of “policy 8”. These two policies concern only horizontal collaboration, that is collaboration between the same kind of actors. At last, it is worth mentioning that only the cooperation between forwarders (policy 1) and only vertical collaboration (policies 6 and 7) are not enough to improve the current system in a high level.

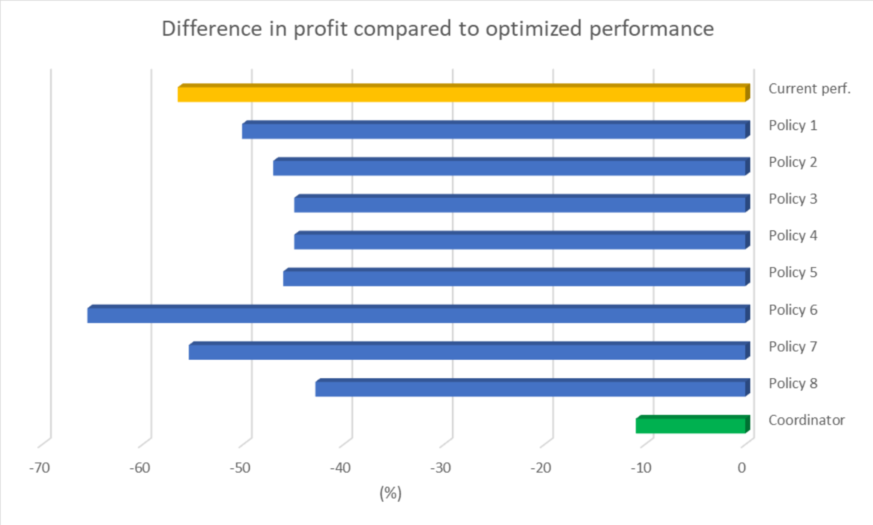


Figure 2 Profit comparison between policies

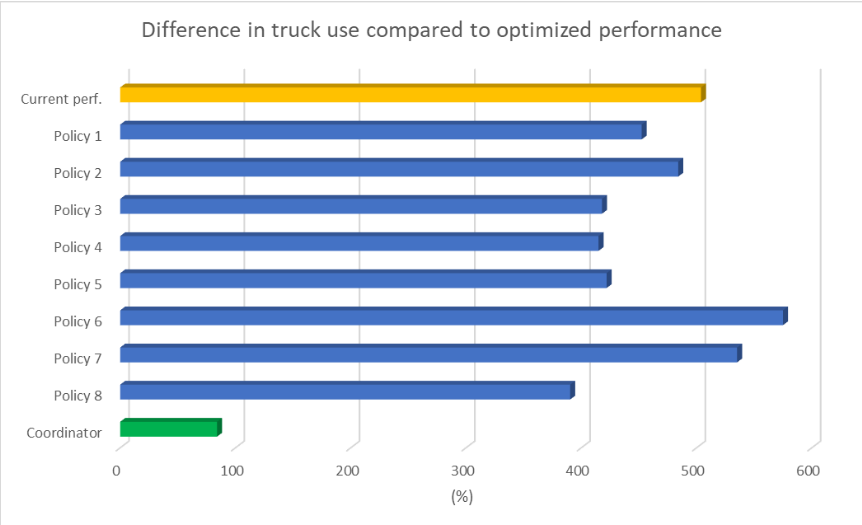


Figure 3 Truck-use comparison between policies

Policy 9 is a subsidy policy for the train utilization rate. When the utilization rate overcomes a specific percentage (e.g. 70%), extra benefits are given to train operators. A sensitivity analysis is done for different prices of subsidy, as percentage of the basic train cost. The impact of the subsidies as function of the subsidy amount is illustrated in figure 4. The subsidy amount is assumed that comes into the port system from external resources (e.g. government). Also, note that 0% subsidy describes the current system, without any subsidy.

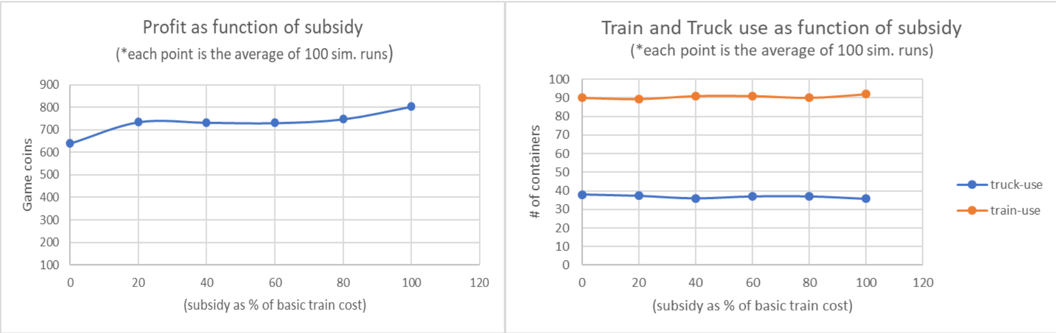


Figure 4 Profit, train-use and truck use as function of subsidy

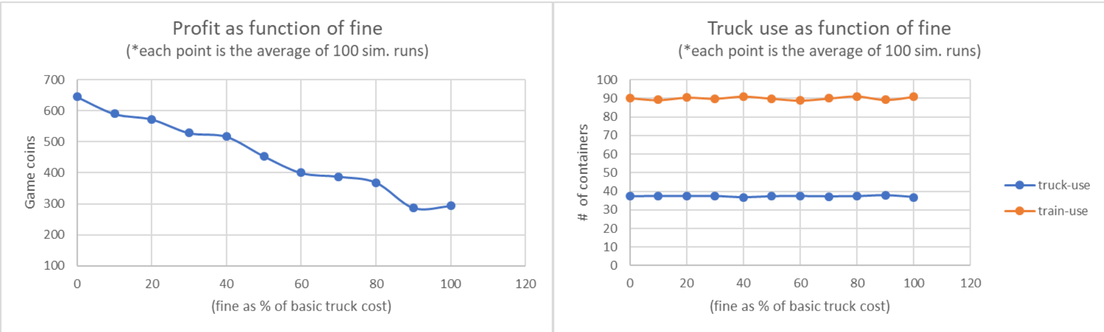


Figure 5 Profit, train-use and truck use as function of subsidy

In the same way as the subsidize policy (policy 9), policy 10 fines the use of truck by freight forwarders. As in the previous policy, in this case as well, the fine is set as a proportion of the basic truck cost and assumed to be paid in an external actor (out of the port system). Using penalty in truck use does not have a significant effect on promoting train use and avoiding truck, as can be seen in figure 5.

7.2. Remaining challenge to reach coordinator's performance

Due to the big gap between coordinated system's performance and the rest of the policies an explanation of this difference is done in this section. For this reason, a sensitivity analysis on two parameters that assumed constant on the negotiation phase of simulation model is done, to explore how the change of these parameters could affect system's performance. These are not relevant for the coordinator's model as the negotiation phase of the players is bypassed.

The two parameters are the negotiation time between the players, that is translated in negotiation rounds, and the minimum number of containers that assumed the consolidation effects and economies of scale are achieved. The negotiation time is set to five minutes, according to the game rules. It was observed from the game sessions that the players had time for about 2 negotiation rounds in five minutes. One negotiation round is defined as the interval between the proposal of a transport price by the train operator, the acceptance or decline of this price from the freight forwarder and the trade between the accepted orders. In the simulation model, as shown on the simulation flow chart, this number was set as constant to 2 rounds.

The number of containers (n) that consolidation effects started for the operators and discount that was given to the freight forwarders due to the economies of scale, assumed also constant in the simulation model. It was observed from the game sessions that above 3 to 4 containers, the operators proposed prices in discount to the freight forwarders. The discount is only relevant in the form of alliances that the players consolidate their containers. The number of containers (n) was chosen as 4 containers for the simulation model. As a base for the sensitivity analysis, policy 8 is chosen.

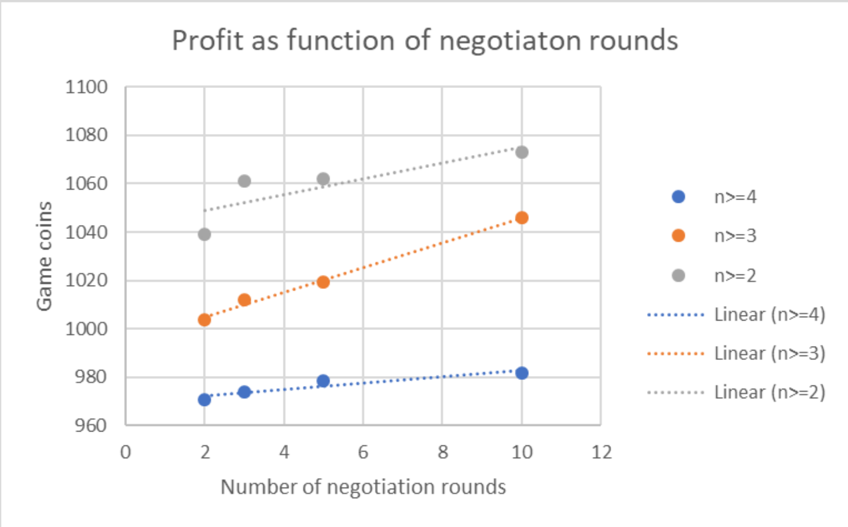


Figure 6 Profit as function of negotiation rounds and number of consolidated containers.

As can be seen in figure 6, as the negotiation time increases and as the consolidation point drops the profit is increased. By dropping the consolidation point from 4 (current simulation) to 2 containers and by increasing the negotiation rounds from 2 (current simulation) to 5, the performance can be increased about 10%. However, there is still a remaining gap between policy performance and coordinator. This can be caused by several other reasons. First, there is still competition for the unconsolidated containers. Second, the players do not have a central plan for a planning horizon, but plan individually for their orders. On the other hand, coordinator plans for all the available orders at the same time and for a planning horizon. At last, the simulation model is based on the current game with the basic rules. The new policies allow for new interactions between the players that may not be incorporated in the most realistic way in the current simulation. This can be a recommendation for future research, to observe players' behavior under the new policy implementation and re-simulate the game.

7.3. Implementation of policy 4 in game session

Policy 4 was chosen to play in the last game session to find the result of the policy. This policy was chosen as has a high performance and included the participation of all players. Policy 4 sets parallel horizontal collaboration of freight forwarders and train operators. As can be seen in figures 7, the profit of the players reached 910 game currency units compared to 717 that achieved in the first to games (average). Also, the truck use dropped to 36 compared to 46 in the previous games and train use increased to 107 from 91 containers.

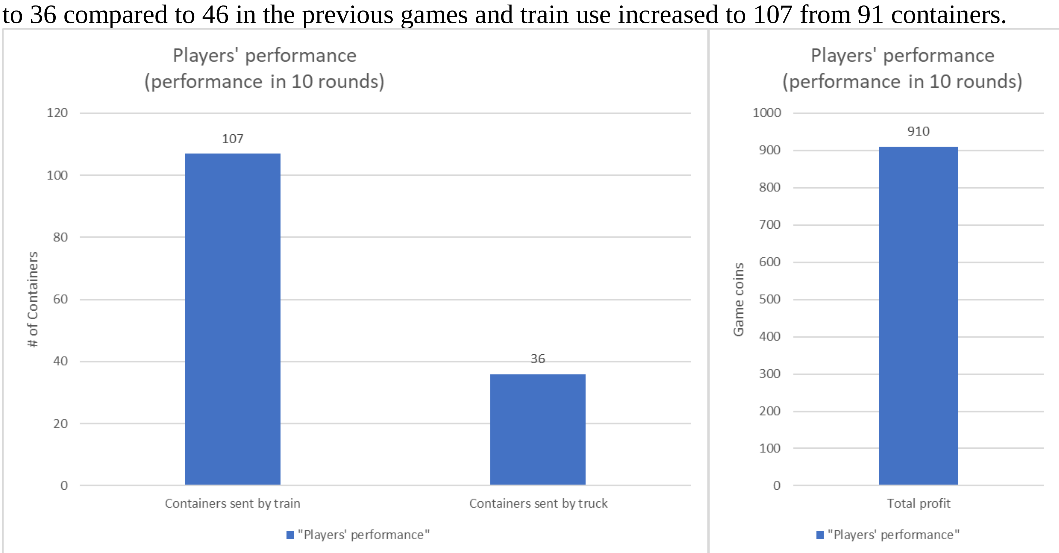


Figure 7 Performance of players in game session with policy 4 applied

8. Conclusions and Recommendations for future research

8.1. Conclusions

This section addresses the most important outcomes of this study. On the methodological part, this study showed that the combined use of gaming, simulation and optimization allowed to extract each method's benefits, while skipping the main drawbacks. The combined methods were not independent on each other but were chosen in such a way that the advantages of the one method could cover the disadvantages of the others. The proper functioning of the combination appeared on the results, as well. After the analysis that compared different policies, on the last game session for this study, the players responded on the expected way on the in-game policy implementation.

The analysis also indicated that the current system is far from the optimal state and the involved actors achieve much lower profits and port reputation rates. The source of this low performance lays on the lack of information sharing, the inability of the stakeholders to cooperate and the conflicting interests of the stakeholders. The uncertainty of delays and the stochastic demand themselves only lead to a small proportion of the inefficiency. All the rest difference in performance is due to the ineffective planning. This was shown in the results, as a coordinator that operated under the aforementioned stochastic elements, but by-passed player's negotiations, could achieve a much higher performance that approached the optimal solution in about 10% deviation. Thus, the near-optimal planning can be done by a coordinator that has access to all available information and is accepted by all the involved actors.

Generally, the higher the level of collaboration between the players the higher the performance that they can achieve. A simultaneous vertical and horizontal collaboration can lead to an improved performance compared to the current system. However, port managers and stakeholders should be careful on choosing which cooperation policy to implement as not all cooperation policies have a positive effect on performance. Some vertical collaboration interventions that do not include all the involved actors can even have negative outcomes for the system. This happens as the agreements between separate small alliances create more restrictions on the decision-making, that do not guarantee that these are the most effective for the system.

There is still a big difference on coordinator's performance and policies' highest performance. This is mainly because there is still competition for the unconsolidated containers. In addition, most players try to send their orders as soon as possible and do not plan for multiple rounds in cooperation with the other players, by taking the probabilities for the stochastic aspects into account. This can have short term benefits for the players, but in long-term it can lead to reduction of system profitability and port reputation. However, it should be noted that a coordinated system is much more difficult to apply as it requires the acceptance and the compliance of all the involved actors, which is a much stricter agreement than any cooperation policy.

Finally, the results show that penalty and subsidy policies do not have a significant effect on overall performance, as the companies already try to achieve the highest individual profits by utilizing the transport mean with the highest benefits and avoiding the expensive alternatives. As stated previously, the inefficiency comes from the lack of cooperation and information sharing and not from the price differences of the different transport alternatives.

8.2. Recommendation for future research

As this study includes a number of different models and due to the low samples provided by the game sessions, the models should be further validated with more observations.

The optimization of the game does not include any human behavior and was developed according the game rules that were clearly stated on the gaming instructions. Thus, the validation of the optimization model for the purpose that was developed is considered sufficient. As a further research it could be proposed an optimization model that would include the decision making of the players.

On the other hand, the simulation model includes a Discrete Choice Model for the decision making of the players. As the parameters for this model were based only in two game session with the same players, in the future observations from more game sessions and different players could be used for parameter estimation.

In addition, as future research is proposed the more detailed observation on the interaction of the players. The new observations could lead to a more reliable decision model that is included in the simulation model. For example, different decision rules could be tested in the simulation model for the negotiation phase between freight forwarders and operators (e.g. game theory) and be compared with the Discrete Choice Model that is currently used, to find which model fits better to the decision making of the players.

Also, the simulation model is based on the current basic rules. The new policies allow for new interactions between the players that may not be incorporated on the current model in the most realistic way. Thus, using new observations on players' interactions from game sessions, after the in-game policy implementation, a simulation meta-model could be developed, especially to model the behavior of the players under the new policy.

Furthermore, as the costs for information sharing and forming of alliances was not included in the policy performance of this study, in a future study it could be examined how transaction costs can affect the policy performance and implementation.

Finally, as the game sessions were organized with university students due to the low availability of port's stakeholders, it is recommended to validate the results in game sessions with professionals from the field of port to hinterland freight transport.

Bibliography

Behdani, B., Fan, Y., Wiegmans, B., & Zuidwijk, R. (2014). Multimodal schedule design for synchromodal freight transport systems.

Ben-Akiva, M., & Bierlaire, M. (1999). Discrete choice methods and their applications to short term travel decisions. In *Handbook of transportation science* (pp. 5-33). Springer, Boston, MA.

Ben-Akiva, M. E., Lerman, S. R., & Lerman, S. R. (1985). *Discrete choice analysis: theory and application to travel demand* (Vol. 9). MIT press.

Beuthe, M., & Bouffioux, C. (2008). Analysing qualitative attributes of freight transport from stated orders of preference experiment. *Journal of Transport Economics and Policy (JTEP)*, *42*(1), 105-128.

Bierlaire, M. (1998). Discrete choice models. In *Operations research and decision aid methodologies in traffic and transportation management* (pp. 203-227). Springer, Berlin, Heidelberg.

Bierlaire, M. (2003). BIOGEME: a free package for the estimation of discrete choice models. In *Swiss Transport Research Conference* (No. TRANSP-OR-CONF-2006-048).

Bierlaire, M. (2008). Estimation of discrete choice models with BIOGEME 1.7. biogeme. epfl. ch.

Bradley, S., Hax, A., & Magnanti, T. (1977). Applied mathematical programming.

Brandenburger, A. M., & Nalebuff, B. J. (1996). Co-opetition. New York, Bantam Doubleday Dell Publishing Group. *Inc.*

Brooks, M. R., McCalla, R., Pallis, A. A., & van der Lugt, L. M. (2009). Coordination and cooperation in strategic port management: The case of Atlantic Canada's ports. *Atlantic Gateway Initiative Working Paper*

Buiel, E., Visschedijk, G., Lebesque, L. H. E. M., Lucassen, I. M. P. J., Riessen, B. V., Rijn, A. V., & te Brake, G. (2015, January). Synchro mania-design and evaluation of a serious game creating a mind shift in transport planning. In *46th International Simulation and Gaming Association Conference, ISAGA* (pp. 1-12).

Camacho, E. F., & Alba, C. B. (2013). *Model predictive control*. Springer Science & Business Media.

Crozet, Y. (2017). Rail freight development in Europe: how to deal with a doubly-imperfect competition?. *Transportation research procedia*, *25*, 425-442.

Cruijssen, F., Bräysy, O., Dullaert, W., Fleuren, H., & Salomon, M. (2007). Joint route planning under varying market conditions. International Journal of Physical Distribution & Logistics Management, 37(4), 287-304.

Cullinane, K., & Toy, N. (2000). Identifying influential attributes in freight route/mode choice decisions: a content analysis. *Transportation Research Part E: Logistics and Transportation Review*, *36*(1), 41-53.

Dai, B., & Chen, H. X. (2009). A benders decomposition approach for collaborative logistics planning with LTL transportation. In The third international conference on operations and supply chain management, Wuhan, China.

Dai, B., & Chen, H. (2011). A multi-agent and auction-based framework and approach for carrier collaboration. Logistics Research, 3(2-3), 101-120.

Dai, B., & Chen, H. (2012). Mathematical model and solution approach for carriers' collaborative transportation planning in less than truckload transportation. International Journal of Advanced Operations Management, 4(1-2), 62-84.

Duke, R. D. (1974). Gaming: Thefuture's language.

European Commission. (2011). A roadmap for moving to a competitive low carbon economy in 2050. Communication from the commission to the European parliament, the council, the European economic and social committee and the committee of the regions.

Feo-Valero, M., García-Menéndez, L., Sáez-Carramolino, L., & Furió-Pruñonosa, S. (2011). The importance of the inland leg of containerised maritime shipments: An analysis of modal choice determinants in Spain. *Transportation Research Part E: Logistics and Transportation Review*, *47*(4), 446-460.

Flodén, J., Bärthel, F., & Sorkina, E. (2017). Transport buyers choice of transport service–A literature review of empirical results. *Research in Transportation Business & Management*, (23), 35-45.

Harteveld, C. (2011). *Triadic game design: Balancing reality, meaning and play*. Springer Science & Business Media.

Holguín-Veras, J., Xu, N., De Jong, G., & Maurer, H. (2011). An experimental economics investigation of shipper-carrier interactions in the choice of mode and shipment size in freight transport. *Networks and spatial economics*, *11*(3), 509-532.

Kourounioti, I., Kurapati, S., Lukosch, H., Tavasszy, L., Verbraeck, A. (2018). Simulation Games to Study Transportation Issues and Solutions: Studies on synchromodality, *98th Annual Meeting of the Transportation Research Board*.

Kouvaritakis, B., & Cannon, M. (2016). *Model predictive control*. New York: Springer.

Krajewska, M. A., Kopfer, H., Laporte, G., Ropke, S., & Zaccour, G. (2008). Horizontal cooperation among freight carriers: request allocation and profit sharing. Journal of the Operational Research Society, 59(11), 1483-1491.

Kurapati, S., Kourounioti, I., Lukosch, H., Tavasszy, L., & Verbraeck, A. (2018). Fostering Sustainable Transportation Operations through Corridor Management: A Simulation Gaming Approach. *Sustainability*, *10*(2), 455.

Kurapati, S., Kourounioti, I., Lukosch, H., Tavaszzy, L., Verbraeck, A., van Veen, L., & van Nuland, B. (2017, June). Exploring challenges and solutions for container transportation using rail: A modelling and simulation gaming study. In *Models and Technologies for Intelligent Transportation Systems (MT-ITS), 2017 5th IEEE International Conference on* (pp. 158-163). IEEE. Available at: https://ieeexplore.ieee.org/abstract/document/8005657/ [Accessed on 15/03/2018].

Maier, G., Bergman, E.M., & Lehner, P. (2002). Modelling preferences and stability among transport alternatives. *Transportation Research Part E: Logistics and Transportation Review*, 38(5), 319–334.

Mason, R., Lalwani, C., & Boughton, R. (2007). Combining vertical and horizontal collaboration for transport optimisation. *Supply Chain Management: An International Journal*, *12*(3), 187-199.

Meers, D., Macharis, C., Vermeiren, T., & van Lier, T. (2017). Modal choice preferences in short-distance hinterland container transport. *Research in Transportation Business & Management*, *23*, 46-53.

Pfoser, S., Treiblmaier, H., & Schauer, O. (2016). Critical success factors of synchromodality: Results from a case study and literature review. *Transportation Research Procedia*, *14*, 1463-1471.

Reis, V. (2014). Analysis of mode choice variables in short-distance intermodal freight transport using an agent-based model. *Transportation research part A: Policy and practice*, *61*, 100-120.

Saeedi, H., Wiegmans, B., Behdani, B., & Zuidwijk, R. (2017). Analyzing competition in intermodal freight transport networks: The market implication of business consolidation strategies. *Research in Transportation Business & Management*, *23*, 12-20.

Singh, P., van Sinderen, M., & Wieringa, R. (2016). Synchromodal transport: pre-requisites, activities and effects. In *ILS Conference* (pp. 1-4).

Smith, R. (2010). The long history of gaming in military training. *Simulation & Gaming*, *41*(1), 6-19.

Sudarsanam, S. (2003). *Creating value from mergers and acquisitions: The challenges: An integrated and international perspective*. Pearson Education.

Tavasszy, L. A., Behdani, B., & Konings, R. (2015). Intermodality and synchromodality. Available at: https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2592888 [Accessed 10/03/2018].

Tavasszy L. and G. de Jong. Modelling Freight Transport. Elsevier, 2013.

Van den Berg, R., & De Langen, P. W. (2014). An exploratory analysis of the effects of modal split obligations in terminal concession contracts. *International Journal of Shipping and Transport Logistics*, *6*(6), 571-592.

Van Der Horst, M. R., & De Langen, P. W. (2008). Coordination in hinterland transport chains: a major challenge for the seaport community. *Maritime Economics & Logistics*, *10*(1-2), 108-129.

Van Riessen, B., PhD Dissertation (2018), Optimal Transportation Plans and Portfolios for Synchromodal Container Networks.

Van Riessen, B., Negenborn, R. R., & Dekker, R. (2015, September). Synchromodal container transportation: an overview of current topics and research opportunities. In *International Conference on Computational Logistics* (pp. 386-397). Springer, Cham.

Wolfe, J., & Crookall, D. (1998). Developing a scientific knowledge of simulation/gaming. *Simulation & Gaming*, *29*(1), 7-19.