Bachelor Thesis Quantitative Logistics

Lowering CO_2 Emissions of Companies by Collaborative Planning of Freight Transport

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Abstract

Society deals with worrying environmental changes, partially caused by high CO_2 emissions of freight transport. In this research we investigate whether collaborative freight transport planning can lower the emissions of companies. We focus on collaborations where companies share costumers to reduce travel distance. Our aim is to compare emissions of each company in the case that it collaborates and does not collaborate. To assign emissions to companies in both cases, we consider the five emission allocation methods introduced by Naber et al. (2018). These methods can allocate emissions to various targets, such as the costumers of a company or to the companies themselves. To choose one of the emission allocation methods to work with we determine which method allocates emissions to costumers best. Therefore we evaluate each method on stability, consistency, robustness and computation time by performing a case study. We conclude that the Equal Profit+ method performs best. Using this method we performed a case study in which two or three companies can collaborate. We concluded that when two companies cooperate the emissions of both companies decrease, with 48.2% on average. When three companies cooperate it can happen that one company observes an emission increase. However, the emission decrease of the remaining companies is on average equal to 56.3%, which is higher than when two companies cooperate.

Contents

1 Introduction and literature review

In our current society, freight transport is dealt with by trucks, airplanes and ships. Transport activities have been increasing immensely over the past decades. From 1990 to 2010, the greenhouse gas emission in Europe has risen with 23% according to the European Commission Directorate-General for Energy and Transport (2009). As a consequence, tons of greenhouse gasses are released into the air, mostly consisting of carbon dioxide. This gas causes the temperature on earth to rise dramatically; according to IPCC (2013), our current pace will lead to a 1 to 2 Celcius increase in mean global temperature in 2100. This is not the only negative consequence. In Patz et al. (2000), extreme weather conditions such as heat waves and humans inhaling polluted air are two of the many situations that we can expect to occur due to the carbon dioxide. In fact, it already is occurring.

The world now finally realizes that this is a major problem. Therefore action needs to be taken; for instance, transportation vehicles should become less polluting and, even better, less needed. One way to realize this goal might be to plan freight transport collaboratively. Companies can do this by different means. For instance, companies can share trucks such that full capacity is used, or companies can let a different company serve some of its costumers to reduce travel distance. However, companies are not too keen on such collaborations since it involves sharing private information with their competitors. It therefore is important to investigate what the possible benefits of collaborative freight transport planning in terms of emissions are. Based on results of such research, companies can decide whether these benefits outweigh the disadvantages and can be persuaded to cooperate.

We will first review some of the studies that did research on this topic. In Frisk et al. (2010), the benefits of collaborative freight transport planning in terms of costs are investigated. Since costs and distance are positively correlated and distance and emissions are positively correlated, this study is linked to ours. In the paper, two methods are introduced that construct companies' transportation routes for two cases whilst minimizing costs. In the first case companies plan their transport collaboratively, and in the second case each company plans their own transport. Both methods create these routes by solving a vehicle routing problem. For one method the formulation of the problem is flow-based, and for the other method the problem concerns backhauling. Backhauling refers to the situation where transportation vehicles deliver a load to and pick up load from a point at the same time, which lowers the travelled distance. To test if collaboration can lower the costs of a company, a case study is performed. The case study concerns eight wood selling companies in Sweden. Using both methods, the authors compute the costs for each company in both cases. To assign costs to a company for the collaborative case, several cost allocation methods are used. It turned out that collaborative freight transport planning can lower total costs of a company up to 14.2%. This shows that such collaboration may also lead to lower emissions.

Xu et al. (2012) investigate the benefits of collaborative freight transport planning in terms of costs as well as in terms of emissions. They perform a case study involving the supply of two French retailers, which is taken care of by four different suppliers. The possible benefits of collaboration for these suppliers are determined by solving a mixed integer linear problem. Based on the study, the authors conclude that in a time period of 33 weeks costs can be reduced with 26% and emissions with 13.6 tonnes when freight transport is planned collaboratively.

One of the first studies that focuses entirely on the possible benefits of collaborative freight transport planning in terms of emissions is done by Verstrepen and Jacobs (2012). The study concerns two different companies, *JSP* and *HF-Czechforge*. Both companies ship their products on a regular base from Czech Republic to Germany with trucks. Using full capacity of these trucks is difficult for both; the first company produces lightweight and voluminous beads, whilst the latter sells heavy metal components. To enable themselves to use full capacity, it may be interesting for these companies to plan their freight transport collaboratively. The authors have investigated this, and estimate that a collaboration could lead to a reduction of emissions of about 11%.

Danloup et al. (2015) study the possible benefits of collaborative freight transport planning in terms of emissions in the food supply industry. The authors use simulation to establish that the emissions are reduced by at least 26% when trucks are shared. Despite of the conclusions of all these articles, companies still aren't convinced to cooperate. Investigating this topic such that more incentives to collaborate are created is thus extra motivation for us.

There also are studies which introduce methods to appoint possible benefits of collaborative freight transport planning. However, these papers did not perform a case study. One of these studies is by Özener et al. (2014). These authors introduce a method that can collaboratively plan freight transport whilst keeping transport and emission costs as low as possible. This method iteratively solves a vehicle routing problem by first generating as many clusters as trucks available. Then it executes a set partitioning problem to assign costumers to clusters. This is done such that the packages of costumers in a cluster do not exceed the truck capacity. Based on these clusters, several feasible delivery patterns are generated. Next, for each pattern a route is found by solving a travelling salesman problem. This problem minimizes transport and emission costs. Finally, the set partitioning problem is used to choose the patterns such that each costumer is served and emissions and costs are minimal. A similar study is done by Guajardo (2018). In this study, a method is introduced that solves a vehicle routing problem whilst minimizing emissions.

To determine the benefits of collaborative transport planning for companies in terms of emission, we compare for individual companies its emission in the case of collaborative transport planning with its emission in the case of non-collaborative planning. Based on the reviewed literature, we propose to calculate company emissions for both cases using one of the five emission allocation methods introduced by Naber et al. (2018). These methods can be used to assign emissions to various targets, such as the costumers of a company or companies themselves. To choose between these methods, we determine which method allocates emissions to costumers of companies best. For this we perform a case study with generated data on individual companies and their costumers, and evaluate each method on stability, consistency, robustness and computation time. With the chosen emission allocation method we allocate emissions to companies when they collaborate and don't collaborate, and compare these emissions. For this we also perform a case study, with generated data on multiple companies and their costumers.

To allocate emissions to companies, we need the total amount of emission that needs to be distributed among the companies. Naber et al. (2018) computes this using the emission function of Ligterink et al. (2012). We decide to use this function as well. The function calculates the total amount of emission based on distribution routes, thus we need to construct routes first in order to compute emission. Constructing routes for the case in which companies do not collaborate involves solving a travelling salesman problem for each company, for which we use the Christofides (1976) heuristic. When companies do collaborate, the construction of the routes involves solving a multi-depot vehicle routing problem. For this we have created an algorithm that solves this problem heuristically.

Four of the considered emission allocation methods are developed based on the *emission allocation game*. In this game, the players are the targets to which emissions need to be allocated. To evaluate these four methods' emission allocations to costumers, we need the version of the emission allocation game in which the players are the costumers. To assign emissions to companies with each of these four methods, we need the version of the game in which the players are the companies. We elaborate on both versions in our paper.

The rest of the paper has the following outline: in Section 2 we describe our research problem, and we explain the two versions of the emission allocation game in which the players are costumers or companies. Also, we elaborate on our algorithm to construct routes for the case in which companies collaborate. Next we elaborate on the five allocation methods and the evaluation methods in Section 3. In Section 4 an overview of the data that we use is given. We show our results on the evaluation of the allocation methods and on collaborative transport planning in Section 5. We end our paper with concluding remarks in Section 6.

2 Problem description

In this paper we investigate whether collaborative transport planning by companies can be beneficial in terms of emission. Every company has a set of costumers, $N_1 = \{1, \ldots, n\}$, each costumer characterized by its location and its order size. Each company also has a depot that is characterized by its location. The companies deliver the orders of these costumers by truck, which follows a certain route. When constructing this route each company aims to keep the costs as low as possible.

Constructing routes can be done in two different settings: a collaborative setting, in which companies plan their freight transport together, and a non-collaborative setting, in which each company plans its own freight transport. From now on, we will refer to the first setting as the *cooperative case*, and to the second setting as the *non-cooperative case*. Our aim of this research is to compare the emissions of individual companies in both cases by performing a case study. For this generated data is used on multiple companies and their costumers. We let the set of companies that can collaborate be $N_2 = \{1, \ldots, m\}$, each company characterized by its depot location and by the locations and order sizes of its costumers. To compute emissions of companies in the case study, we use one of the five emission allocation methods introduced by Naber et al. (2018). These methods can allocate emissions to various targets, for example costumers of a company or companies themselves. To choose between these methods, we determine which method allocates emissions to costumers best. For this we evaluate each method on stability, consistency, robustness and computation time. To test each allocation method for stability, consistency and computation time we perform a case study with data on individual companies and their costumers. We use data with similar content to measure robustness, only in this data there exists a costumer of which order size and location is fixed. With the method that performs best according to the evaluation, we allocate emissions to companies in the cooperative and non-cooperative case.

In order to allocate emissions to companies, we need the total emission that needs to be distributed among the companies. We compute this total emission with the emission function of Ligterink et al. (2018). This function computes the total emission based on the distribution routes. Thus we need to construct these routes first in order to compute emission. When companies do not collaborate, the construction of the route involves solving a travelling salesman problem for each company over its costumers, which we solve with the Christofides (1976) heuristic. More on this heuristic can be found in the Appendix. Constructing routes in the cooperative case involves solving a multi-depot vehicle problem, for which we propose an algorithm that solves the problem heuristically. This algorithm is explained in Section 2.2. Since we don't have any information on the costs of transport, we can't construct minimum-cost routes. Thus we create routes such that the distance is minimized, defined as the two-dimensional Euclidian distance.

Four of the considered emission allocation methods are developed based on the emission allocation game. The players in this game are the targets to which emission needs to be allocated. To evaluate which method allocates emission to costumers best and to allocate emissions to companies in the cooperative and non-cooperative case, we use two versions of the emission game: one in which the players are the costumers, and one in which the players are the companies. We first explain concepts of cooperative game theory that are used to develop the emission allocation game in Section 2.1. Then we elaborate on the first version of the game in Section 2.1.2 and on the second version of the game in Section 2.1.1.

2.1 Emission allocation game

The emission allocation game is developed by Naber et al. (2018) using concepts of cooperative game theory. We first discuss cooperative game theory. Then we elaborate on the emission allocation game for which the players are the costumers of a company in Section 2.1.2, and for which the players are the companies in Section 2.1.1.

Cooperative game theory concerns games in which players can choose to cooperate with other players, leading to competition between groups. Such a group of players is called a coalition. This is a subset, which we call S, of the set containing all the players, also referred to as the grand coalition. After competing in groups, the payoff of each coalition needs to be redistributed among its members. In a cooperative game, the main assumption is that the only coalition that will form is the grand coalition. Thus the main focus in cooperative game theory is the allocation of payoff to each grand coalition member.

2.1.1 Emission allocation game for which players are costumers

In this game the grand coalition is the set of costumers of a company, N_1. Serving these costumers concerns transport emissions. The aim of the game is to allocate these emissions to the costumers. This is accomplished by setting requirements for the allocation. Since these requirements need to hold for all possible coalitions, we first need to introduce some notation on coalitions before we can discuss them.

When a company serves the members of a coalition S, a minimum-cost route is constructed that starts and ends at the depot and visits each member. We let the order in which each of these costumers is served be equal to $\sigma(S)$. Since finding an optimal route is often difficult, we find $\sigma(N)$ instead and let the costumers in $\sigma(S)$ be visited in the same order as in $\sigma(N)$. We determine $\sigma(N)$ by solving a travelling salesman problem, of which the solution is the least-cost route that starts and ends at the depot and visits every costumer exactly once. Since this problem is NP-hard, we solve it with the heuristic of Christofides (1976). More on this heuristic can be found in the Appendix. Because we don't have any information on travelling costs we decide to solve the problem whilst minimizing distance, defined as the two-dimensional Euclidian distance.

Based on $\sigma(S)$ we calculate the transport emission concerned when serving S, $e(S)$. As mentioned before, we use the emission function of Ligterink et al. (2012) for this. In the Appendix a more detailed description of the computation of $e(S)$ can be found.

With $e(S)$ defined, we can introduce the requirements that an allocation needs to meet in the emission allocation game. The game aims to find an emission allocation $x = (x_i)_{i \in N}$, where x_i is the amount of emission allocated to costumer i, such that no member of any coalition is unsatisfied and wants to withdraw from the route. This is called a stable emission allocation. For this we make the assumption that $\sum_{i \in N} e(\{i\}) \geq e(N)$ to assure that an efficient emission allocation exists. There are two requirements that an allocation needs to meet to assure that it is stable. The first requirement is that the total of emissions allocated to the members of the grand coalition is equal to $e(N)$. The second requirement is that for each coalition S, the total of emissions allocated to coalition members is smaller than or equal to $e(S)$. The set containing the stable emission allocations is called the core of the game. We let $x(S) = \sum_{i \in S} x_i$. Then the definition of the core is:

$$core(e) = \{x \in R^n : x(N) = e(N), x(S) \leq e(S), \forall S \subset N\} \tag{1}$$

We aim to choose an emission allocation that is in the core. However, the core can be empty, which can make this difficult. To find a proper emission allocation that preferably is in the core, we can use the allocation methods described in Section 3.1.

2.1.2 Emission allocation game for which players are companies

This game is very similar to the game described in the previous section. Here, the grand coalition is the set of companies, N_2. Each company emits CO_2 when serving its costumers. In the game, the total emission that is emitted by the companies is distributed among the companies. For this an emission allocation is chosen that preferably is in the core. To find such an allocation, we can use the allocation methods described in Section 3.1. We want to find emission allocations for the cooperative and non-cooperative case.

The main difference with the previously described game is the computation of $e(S)$. In this case, $e(S)$ equals the total emission of transport when the companies S serve their costumers. To compute this we use the emission function of Ligterink et al. (2012). As can be seen from the Appendix, this function computes emission based on routes. We thus will explain how we construct routes to compute $e(S)$ for the cooperative and non-cooperative case when $|S| = 1$ and when $|S| > 1$.

When $|S| = 1$, the construction of the route is done in the same way for both cases. We solve a travelling salesman problem with the Christofides (1976) heuristic whilst minimizing distance, defined as the two-dimensional Euclidian distance.

When $|S| > 1$, we construct routes differently for the cooperative and non-cooperative case. For the cooperative case we construct routes by solving a multi-depot vehicle routing problem, for which we propose an algorithm. We elaborate on this algorithm in the next section. For the non-cooperative case, we construct for each company a route that visits all its costumers and starts and ends at its depot using the Christofides (1976) heuristic. For both cases we construct routes such that distance is minimized.

2.2 Algorithm to solve a multi-depot vehicle routing problem

In the following paragraphs, we introduce our algorithm to solve a multi-depot vehicle routing problem. With this we can construct routes for the case when multiple companies plan their freight transport collaboratively.

For this algorithm we assume that the collaborating companies have the same products in stock at their depots. This makes it easy for these companies to serve a costumer of a different company. We also assume that each company has one truck, which makes it impossible to let multiple routes start from the same depot of a company.

Based on these assumptions we create an algorithm that first assigns costumers to depots and then creates a transport route for each depot. For this algorithm we would like to construct routes that lead to lower emissions of companies than in the non-cooperative case. Considering that we use the emission function of Ligterink et al. (2012) to compute emissions, we therefore decide to create routes whilst minimizing distance.

Our first step is to determine which depot will serve which costumer. To minimize distance, we want each costumer to be served by the nearest depot. Therefore we assign each costumer to the nearest depot such that truck capacity, which we assume to be equal to 507 units, isn't exceeded. If a costumer can't be assigned to the nearest depot due to truck capacity, the costumer will be assigned to the second-to-nearest depot.

With costumers assigned to a depot, we create a route that starts and ends at the depot and visits each costumer whilst minimizing distance. This concerns solving a travelling salesman problem, for which we use the Christofides (1976) heuristic.

3 Allocation and evaluation methods

The five allocation methods are introduced in Section 3.1. We want to evaluate each method based on its stability, consistency, robustness and computation time. In Section 3.2 we explain each criterion and how we measure it.

3.1 Allocation methods

The allocation methods that we consider are the Star method, which is a commonly used method, and the Shapley value, the nucleolus, the Lorenz+ Allocation and the Equal Profit+ Method, which are all developed using cooperative game theory. The plus sign indicates that we slightly changed the original method for our convenience. In this section we briefly explain each method.

3.1.1 Star method

The Star method is a proportional allocation method. It uses the following equation:

$$x_i = \frac{e(\{i\})}{\sum_{i \in N} e(\{i\})} e(N). \tag{2}$$

The method is straightforward, making it easy to understand. Also, it clearly can be seen how a certain alternation affects allocations created with this method. The downside is that the allocations developed by this method are not always in the core of the game, which can lead to instability. On top of that, this method does not take into account the order in which the costumers are visited and the distance between two costumers.

3.1.2 Shapley value

According to Shapley (1953), costumers should be assigned to a share of the emission proportional to their marginal contribution to the emission. The Shapley value realizes this by allocating to each costumer its average marginal emission over all coalitions. We let $m_i(S) = e(S \cup i) - e(S)$, which is equal to the marginal emission of adding costumer i to coalition S. The weights used to calculate the average are based on three axioms, on which you can find more in Shapley (1953). With these weights, the emission allocated to costumer $i \in N$ equals:

$$x_i = \sum_{S \subseteq N \setminus i} \frac{|S|(n - |S| - 1)!}{n!} m_i(S). \tag{3}$$

The disadvantage of this method is that its allocation isn't necessarily in the core.

3.1.3 Nucleolus

The nucleolus is introduced by Schmeidler (1969). To explain what the nucleolus is, we set the excess of coalition S equal to $e(S) - x(S)$. Let $\theta(x)$ be the vector containing the excesses of each possible coalition S when allocation x is used, in non-decreasing order. For the definition of the nucleolus, we also need to explain lexicographic ordering. Let x and x' be possible emission allocations. $\theta(x)$ is lexicographically smaller than $\theta(x')$ if there exists a j such that $\theta_i(x) = \theta_i(x'), i < j$ and $\theta_j(x) < \theta_j(x')$. The nucleolus of the emission allocation game is the allocation x such that $\theta(x)$ is the lexicographic minimum among all allocations. When the core is non-empty, the nucleolus is located in it.

Now that we know what the nucleolus is, we need a method to find it. For this, Engevall et al. (1998) developed a method that concerns iteratively solving linear programming problems. In each such problem, an allocation is found by maximizing the smallest excess. If it turns out that this allocation is not unique, we check which coalitions have dual variables greater than zero. For these coalitions, we fix the excess obtained. Then we maximize the smallest excess again, but now only for the coalitions for which the excess is not fixed yet. We repeat solving this linear programming problem until a unique solution is found. This solution is the nucleolus.

Let's now introduce the mathematical notation of the linear programming problems. We set δ to be the decision variable equal to the smallest excess among all allocations for which the excess is not fixed. On top of that, we create δ_l and set it equal to the optimal value of δ in iteration l. Finally, we let F_l be the set of coalitions for which the excess is fixed after the problem is iteration l has been solved. This set is initialized as an empty set at each iteration. The linear programming problem in iteration l is equal to:

$$
\begin{aligned}
\delta_l = \quad & \max \quad \delta && && (4)\\
& \text{s.t.} \quad x_i \leq e(\{i\}) && \forall\, i \in N, && (5)\\
& \qquad x(S) + \delta \leq e(S) && \forall S \subset N, S \notin (\cup_{m<l} F_m), && (6)\\
& \qquad x(S) + \delta_m = e(S) && \forall m < l, S \in F_m, && (7)\\
& \qquad x(N) = e(N). && && (8)
\end{aligned}
$$

Constraints (5) make sure that the emission allocated to a costumer is never greater than its stand-alone emission. δ is set smaller than or equal to the smallest excess among all coalitions for which excess is not fixed in constraints (6). Constraints (7) fix the excess of the coalitions for which this should be done. The final constraint (8) makes sure that the total amount of emission assigned to costumers is equal to the total amount of emission emitted when serving these costumers. The objective (4) maximizes the smallest excess. When the problem is solved, all the coalitions for which the dual variable of the constraints (6) is greater than zero are added to F_l. A unique solution is found if the constraint matrix of the constraints (7) and (8) has rank $|N|$, and the algorithm stops.

3.1.4 Lorenz+ Allocation

The Lorenz allocation is introduced by Aguirre and Javier (2003). It is defined as the emission allocation in the core with minimal difference between the largest and smallest amount of emission assigned to any costumer. This results in a commonly known "egaliterian solution", which can be preferred. We introduce the decision variable f, which is set equal to this difference. With this variable, we can find the Lorenz allocation by solving the following linear programming problem:

$$
\begin{aligned}
\min \quad & f && && (9)\\
\text{s.t.} \quad & x_i - x_j \leq f && \forall\, i, j \in N, && (10)\\
& x(S) \leq e(S) && \forall S \subset N, && (11)\\
& x(N) = e(N). && && (12)
\end{aligned}
$$

Constraints (10) set f greater than or equal to the largest absolute difference between two amounts of allocated emission. Constraints (11) and (12) make sure that the allocation is in the core (1). The objective (9) minimizes the largest difference. From its formulation we can conclude that the problem does not give a solution when the core is empty, which is inconvenient. We fix this by slightly altering the Lorenz allocation method: when the core is empty, we use the nucleolus to find an emission allocation since this method is still defined then.

3.1.5 Equal Profit+ Method

This method is introduced by Frisk et al. (2010) and is quite similar to the Lorenz+ allocation. The only difference is that this method minimizes the difference between the largest and smallest amount of allocated emission relative to the stand-alone emission of the associated costumer. This problem is also solved with a linear programming problem that uses the decision variable g to represent the largest difference. The problem then becomes:

$$
\begin{aligned}
\min \quad & g && && (13)\\
\text{s.t.} \quad & \frac{x_i}{e(\{i\})} - \frac{x_j}{e(\{j\})} \leq g && \forall\, i, j \in N, && (14)\\
& x(S) \leq e(S) && \forall S \subset N, && (15)\\
& x(N) = e(N). && && (16)
\end{aligned}
$$

Here, constraints (14) set g greater than or equal to the largest difference between two amounts of allocated emission relative to the stand-alone emission of the associated costumers. Constraints (15) and (16) again make sure that the allocation is in the core (1). The largest difference g is minimized by the objective (13). Again, we note that solving this problem does not give a solution when the core is empty. Therefore we use the nucleolus to find an emission allocation in such cases since this method is still defined then.

3.2 Evaluation methods

We want to evaluate the introduced emission allocation methods on stability, consistency, robustness and computation time. In this section, we briefly explain each criterion and our methods to test for each criterion. These criteria and methods are introduced by Naber et al. (2018).

3.2.1 Stability

As stated before, a stable allocation is an allocation for which no subset of costumers is unsatisfied and wants to withdraw from the route. All these allocations can be found in the core of the game. Thus, to test for the stability of the different allocation methods we perform a case study with generated data instances. Since the nucleolus, the Lorenz+ Allocation and the Equal Profit+ method always find an allocation that is the core, we leave these methods out of the case study. In the case study we apply the remaining methods to every instance, and check for each method what percentage of the created allocations is in the core of the game.

3.2.2 Consistency

A costumer can be located far away from the other costumers or close to them. When the locations of the other costumers are identical in both cases, a costumer may expect the emission allocated to him or her to be greater in the first case than in the second case. We would like to have an emission allocation method that is consistent with such costumer expectations.

We determine the consistency of each allocation method by first applying the method to every generated data instance. With these results, we execute an OLS regression. The dependent variable is the allocated emission and the explanatory variables are a constant, the distance to the depot in kilometer and the average distance to the other costumers in kilometer. Naber et al. (2018) also include the order size of costumers and two cross-terms that concern order size as explanatory variables. We leave these variables out of the regression since in our data instances the order size of the costumers is constant, on which we elaborate in Section 4.1. With the results of the regressions, we can determine for each allocation method which explanatory variables are significant for the explanation of the dependent variable at a 5% significance level, and if their effects on the allocation of emissions are consistent with costumer expectations. On top of that, we can determine for which allocation method the explanatory variables explain the dependent variable best using R^2.

3.2.3 Robustness

There can be cases in which a costumer places similar orders from time to time. When this costumer is assigned significantly different amounts of emission at each order, he will not be pleased. There is a possibility that this can happen, since the total emission of transport depends on for instance the locations of the other costumers on the route. An allocation method that can prevent this from happening is called a robust method.

To evaluate the robustness of each allocation method we investigate whether the allocated emissions of one targeted costumer, with fixed location and order size, stay the same when the locations and order sizes of the other costumers change. One way to check this is by computing the standard deviation of the emission allocated to this targeted costumer. However, this would lead to insufficient results since the Star method often assigns less emission to this costumer than the other allocation methods do. Therefore we use the Coefficient of Variation to evaluate robustness. In order to determine the Coefficient of Variation for each allocation method, we perform a case study with randomly generated data instances.

3.2.4 Computation time

When emissions of transport frequently have to be allocated to costumers, short computation times are useful. To measure these times, we will perform a case study where we apply each method to every generated data instance and time its performance. Next, we will take for each method the average over its computation times.

4 Data

For our research, we need three different data sets. Our first data set is needed for the measurement of stability, consistency and computation time. The second data set is necessary for the measurement of robustness. We use the third data set to compare emissions of companies in the cooperative and non-cooperative case. We generate each data set randomly, of which the process is explained in the next sections.

4.1 Data set for stability, consistency and computation time

To measure stability, consistency and computation time we generate data instances, each containing information on one company and its costumers. Each company has a depot and 5, 10 of 15 costumers. The depot of the company is characterized by its location, and every costumer is characterized by its location and order size. The locations are expressed in clusters and in a vertical and horizontal coordinate. The order size of a costumer is expressed in loading units, each weighing 0.01 ton, and is the same for all costumers in the instance. This order size can be low, equal to 1.4 units, medium, equal to 7.1 units, or high, equal to 35.7 units.

The locations of the depot and the costumers of an instance are generated in the following way. First, three groups that need to be located are formed: the depot, a target costumer and the other costumers. Next, we need to decide for each group where we locate them. We can choose to put the groups close together, such that transportation vehicles can avoid highways most of the time, or further apart, in which case these vehicles do use highways. Our decision on location therefore affects the covered distance and average speed of the transporting vehicles, which influences the emission of transport.

We do the locating of each group by uniformly distributing the members of the group over a square with sides of length 10 kilometer. Then we construct a square with sides of length 100 kilometer and randomly place each of the smaller squares in the bottom left corner, the center or the top right corner of the bigger square. Multiple smaller squares can be positioned at the same cluster. If groups are located in the same cluster the driving speed between these groups is 35 kilometers per hour, and is 70 kilometers per hour between the groups that are located in different clusters. Since only the distance between the three groups is important for the emissions and not the cluster in which they are placed, we can locate the three groups in ten different ways. This gives us 90 different data instances. For a visualization of the locating of the groups, see Table 1. The categories mentioned in this table are used for the second data set, on which we elaborate in the next section.

4.2 Data set for the robustness measurements

To generate data for the measurement of robustness we follow the data generating process described in Section 4.1, except for two aspects: the order size and the location of the target costumer. We need both to be constant over the data instances. Therefore we set the order size of the target costumer equal to 7.1 units in each data instance, whilst the order size of the other costumers can still be low, medium or high. To assure that the location of the target costumer is the same in each data instance, we make use of the fact that a fixed target costumer location means a fixed distance between the target costumer and the depot. Thus we categorize the created instances based on this distance: in type I, the depot and the target costumer are located in the same cluster, in type II they are located in clusters that lie next to each other, and in type III they are two clusters apart. In each category the location of the target costumer is somewhat fixed. For a visualization of this categorization, see Table 1. We measure robustness of each method by determining the Coefficient of Variation per category.

Category	Location config. name	Bottom left	Center	Top right
Type I	1	D, T, C		
	2	D, T	C	
	3	D, T		C
Type II	4	D, C	T	
	5	D	T, C	
	6	D	T	C
	7	C	D	T
Type III	8	D, C		T
	9	D	C	T
	10	D		T, C

Table 1: Visualization of the locating of the groups and the categorization of the data instances. D stands for depot, T stands for target costumer and C stands for other costumers.

4.3 Data set to compare emissions of companies

For the comparisons of companies' emissions in the cooperative and non-cooperative case we need data instances containing information on multiple companies and their costumers. We generate data for this by combining several single-depot instances of the data set of Section 4.1 into one multi-depot instance. It is important to notice that combining many instances might lead to a collaboration that is too complicated for companies. Therefore we decide to combine two or three single-depot instances. We also need to be careful when choosing the single-depot instances to combine. For example, it probably isn't beneficial in terms of emission to combine two instances of which the depot is located close to its costumers. Thus we set three requirements: (1) when combining instances, at least for two instances its other costumers are not located in the same cluster as the depot, (2) when single-depot instances are combined it should be true for at least one depot that the distance between its other costumers and itself is greater than the distance between these costumers and a different depot, and (3) the depots of the instances shouldn't all lie in the same cluster.

Based on these requirements we create the multi-depot instances. First we discuss how we can make multi-depot instances out of two single-depot instances. For this we can't use data instances with location configuration 1, 4 and 8 since this violates the first requirement. Of the seven remaining location configurations, six have a depot placed in the bottom left cluster. A combination of two data instances with these location configurations will conflict with our third requirement. We therefore decide to 'flip' the location configuration of one of the instances horizontally and vertically. For an instance with the depot in the bottom left cluster, this flipping would cause the depot to become located in the top right cluster. In this way we can make 21 different combinations of two location configurations such that all three requirements are met. For each of these combinations, we decide to create a multi-depot instance consisting of two single-depot instances that have the associated location configurations. Which single-depot instances that are is chosen randomly. To create the multi-depot instances consisting of three single-depot instances, we repeat this process and add to each of the 21 created multi-depot instances one of the 90 data instances. This data instance is randomly chosen. This gives us 42 multi-depot data instances in total.

5 Results

In this section we show our results. Firstly, we discuss the results of the evaluation of the emission allocation methods on stability, consistency, robustness and computation time in Section 5.1. Also, we compare these results with the evaluation results of Naber et al. (2018). Based on this evaluation, we will choose one emission allocation method to continue with. Secondly, we present our results of the comparisons between emissions of companies in the cooperative and non-cooperative case in Section 5.2. We have implemented the allocation methods and our method to construct routes for the cooperative case using Eclipse Neon 4.6.0 for Java (2016), and we used CPLEX 12.8 (2017) to solve the linear programming problems. To run the programs, we used an Intel(R) Core(TM) i5 @ 2.30 GHz with 8 GB of RAM.

5.1 Evaluation allocation methods

5.1.1 Stability

First, we checked for each generated data instance if the core is non-empty. For two instances the core turned out to be empty. In both instances the depot is located in the central cluster, the other costumers in the bottom left cluster and the target costumer in the top right cluster. A truck that visits all these costumers somewhat passes the depot along the way. Thus breaking the route of this truck apart into two routes probably leads to a emission reduction. This might explain the empty cores.

With this in mind, we started our case study to test for stability. We conclude that the Star Method provided allocations of which 33.3% are in the core, and is therefore quite unstable. For the Shapley value, we found that 98.7% was a core solution. This means that the Shapley value finds a core solution for all the data instances with a non-empty core. Our results on stability are in line with the results of Naber et al. (2018).

5.1.2 Consistency

The results of the regressions can be found in Table 2. We see that, except for the Star method, the constant, the distance to the depot and the average distance to other costumers explain the allocated emissions. The signs of the coefficients belonging to the distance to the depot and the average distance to other costumers are consistent with costumer expectations. In the table we can find the R^2 values of each regression as well. We can conclude from these values that the variables explain the allocated emissions best for the nucleolus, followed by the Equal Profit+ method, and worst for the Lorenz+ Allocation. This means that the nucleolus is the most consistent method according to our findings.

The obtained coefficient and R^2 values differ greatly from the results of Naber et al. (2018). There are two possible explanations for this. The first possible explanation is that we use a different method to find $\sigma(N)$; we use the Christofides (1976) heuristic, and Naber et al. (2018) use the software package Response. The decision on this method affects the values that we find for the dependent and explanatory variables. The second possible explanation is that we don't know the units in which Naber et al. (2018) express the dependent and explanatory variables. The units that we use might deviate from their units, causing our results to be different.

Table 2: Results of the regressions to test for the consistency of the allocation methods.

	Star		Shapley		nucleolus		Lorenz+		Equal Profit+	
Explanatory variable	Coeff.	p val.	Coeff.	p val.	Coeff.	p val.	Coeff.	p val.	Coeff.	p val.
Constant	-54.91	0.32	-677.13	0.00	-659.02	0.00	-707.79	0.00	-590.80	0.00
Dist. to depot	17.39	0.00	6.22	0.00	20.74	0.00	21.88	0.00	20.67	0.00
Avg. dist. to other cust.	25.51	0.00	48.51	0.00	51.20	0.00	50.84	0.00	47.43	0.00
R^2	0.48		0.55		0.60		0.23		0.58	

5.1.3 Robustness

In Naber et al. (2018) the Coefficient of Variation (CoV) is calculated using the data instances with a non-empty core, and using all instances. The authors made this distinction because the Lorenz+ Allocation and the Equal Profit+ method allocate emissions differently when the core is empty, and 20 out of 90 instances had an empty core. Thus we first checked for each generated data instance if the core is empty or non-empty. We found that two instances have an empty core. For both instances, the depot and the other costumers are located in the bottom left cluster. For one instance the target costumer is located in the center, and for the other instance the target costumer is situated in the top right cluster. When the target costumer is located far away from the rest, we expect the emission allocated to the target costumer to be the highest. For coalitions S containing the target costumer, this could make it difficult to meet the requirement of the core that $x(S) \leq e(S)$, which may lead to an empty core. Since we only have two instances with an empty core, we decide to not make the same distinction as Naber et al. (2018) and only calculate the CoV using all instances.

Our results on this can be found in Table 3. When we compare the CoV values of the different allocation methods, we conclude that for each category the nucleolus has the lowest CoV. Therefore, this method is according to us the most robust method. The nucleolus is closely followed by the Equal Profit+ method. The Lorenz+ Allocation performs worst in terms of robustness for each category.

Our results on robustness deviate from the results of Naber et al. (2018). These authors state that the Star method performs worst in terms of robustness for type I and III instances. As mentioned before, in our results the Lorenz+ Allocation is the least robust method for these instances. We think that these dissimilarities are mainly caused by our different methods to construct routes. We use the Christofides (1976) heuristic for this, and Naber et al. (2018) used the software package Response. These methods greatly affect the emission allocation, which

Table 3: *The Coefficient of Variation of each allocation method per category and other results.*

Instance type	Allocation method	Average emission	Std. dev. of emission	% alloc. in core	CoV
Type I	Star method	168	120	11.1	0.717
	Shapley	299	231	100.0	0.772
	nucleolus	500	288	100.0	0.576
	Lorenz+	394	334	100.0	0.847
	Equal Profit+	349	228	100.0	0.654
Type II	Star method	2057	1576	44.4	0.766
	Shapley	2853	2864	94.4	1,004
	nucleolus	3925	2660	100.0	0.678
	Lorenz+	3116	3129	100.0	1.004
	Equal Profit+	3585	2683	100.0	0.748
Type III	Star method	5070	4048	33.3	0.798
	Shapley	5836	4716	100.0	0.808
	nucleolus	7390	4703	100.0	0.636
	Lorenz+	6422	5210	100.0	0.811
	Equal Profit+	6986	4575	100.0	0.655

could lead to different results. There are also some similarities between our results and the results of Naber et al. (2018) on robustness: we both obtain high values for the CoV in all cases and we both conclude that the nucleolus is the best method in terms of robustness.

5.1.4 Computation time

When we consider the definitions of the allocation methods, we see that the Star method executes a polynomial number of computations to come to a solution. The other methods require an exponential number of computations depending on the number of costumers. The nucleolus even requires an exponential number of computations for each iteration. This is consistent with the average computation times over all instances that we determined for the allocation methods, which can be found in Table 4. In these average computation times, solving the travelling salesman problem with the Christofides (1976) heuristic is included. The Star method clearly has the shortest average computation time. For the Shapley Value, the Lorenz+ Allocation and the Equal Profit+ method the average computation times are higher than for the Star method, but are still relatively low. However the average computation time of the nucleolus seems to have exploded a bit, which deviates from the results of Naber et al. (2018). This is caused by the generated data instances with 15 costumers, as can be concluded from Table 4. The data instances of Naber et al. (2018) contain no more than 11 costumers.

Now that we have finished the evaluation of the allocation methods, we want to choose the allocation method(s) to compute emissions of companies. Based on stability, consistency and robustness, the nucleolus and the Equal Profit+ method outperform the other methods. However, the nucleolus has a relatively long average computation time, especially for data instances with 15 costumers. Since our multi-depot data instances can contain more than 15 costumers it is inconvenient to use this method. Therefore we decide to use the Equal Profit+ method.

Table 4: For each allocation method the average computation time over all instances, and over the instances with 5, 10 and 15 costumers.

Allocation method	Average time (s)	Average time (s) 5 cost.	Average time (s) 10 cost.	Average time (s) 15 cost.
Star method	0.013	0.010	0.013	0.017
Shapley value	3.958	0.039	0.252	11.584
nucleolus	80.798	0.032	1.940	240.423
Lorenz+	4.063	0.012	0.238	11.939
Equal Profit+	3.669	0.015	0.240	10.752

5.2 Comparison emissions cooperative case and non-cooperative case

In this section we show our results on the comparisons between emissions of companies in the cooperative and non-cooperative case. As mentioned before, we consider the case in which two or three companies can cooperate. For both cases, all the multi-depot instances have a non-empty core. We first focus on the results on the case with two companies. We then do the same for the case with three companies. Finally, we briefly compare the results on the cases with two and three companies.

The results on the case with two companies can be found in Table 5 in the Appendix. For every company duo the emissions of both companies decrease when they plan their transport together. The emission decrease of a company ranges from 5.7% to 85.9%, and is on average equal to 48.2%. The wide range might be caused by the location configurations that we have combined when creating the multi-depot data instances. For instance, we see that the emissions of both companies decrease heavily when the companies have location configurations 3 and 10 or 10 and 10. In these two location configuration combinations the depot of each company is two clusters apart from its other costumers, whilst the depot of the other company is in the same cluster as these costumers. For such companies we see that they almost completely switch costumers when they cooperate, leading to a significantly lower travelled distance for each company. That might explain the large emission decrease for both companies. This explanation is visualized in Figure 1 and Figure 2 for location configuration combination 3 and 7. Based on location configuration combinations we can also explain why some companies observe a relatively small emission decrease when they cooperate. We see that Company 1 observes a slight emission decrease for the location configuration combination 2 and 7. For this combination, the depot of Company 2 is not located nearer Company 1's other costumers than the depot of Company 1 itself. Thus Company 1 has to serve most of its own costumers, which could lead to a relatively small emission decrease.

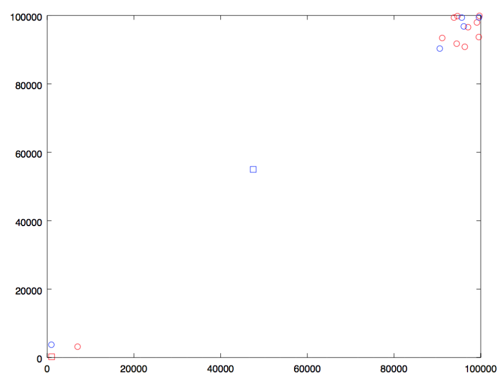

Figure 1: Two companies with location configurations 3 and 7 that don't cooperate. The squares are the depots, the circles are the costumers, and the color indicates which depot serves which costumer.

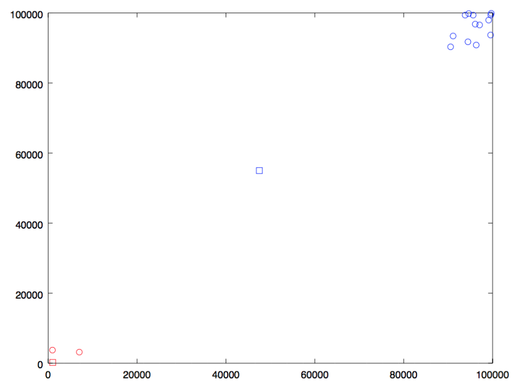

Figure 2: Two companies with location configurations 3 and 7 that cooperate. The squares are the depots, the circles are the costumers, and the color indicates which depot serves which costumer.

In Table 6 in the Appendix the same results are shown for the case with three companies. For 13 out of 21 generated company trio's, emission decreases for every company. For the remaining 8 company trio's the emission decreases for two companies and increases for one company. The emission increases range from 5.1% to 270.2%. Large increases are for instance observed for the location configuration combination 7, 9 and 1. In this combination, there is one depot in every cluster. Most costumers (25 out of 30) are located in the bottom left cluster, in which the depot of Company 3 is located as well. Thus Company 3 serves the majority of the costumers, which increases its emission dramatically. The emission increases for other location configuration combinations can have an explanation of the same sort.

From the table we conclude that the emission decrease of a company that cooperates has a wide range from 3.7% to 100.0%, and is on average equal to 56.3%. The wide range could have the same explanation as for the case with two companies.

Finally we compare the results on the cases with two companies and three companies. A benefit of the case with two companies is that every company benefits from collaboration. This is not true for the case with three companies. However, for the case with two companies the average emission decrease is smaller than for the case with three companies.

6 Conclusion

We end our research with some concluding remarks. We first evaluated five different emission allocation methods on stability, consistency, robustness and computation time. For this we performed a case study with generated data. The nucleolus and the Equal Profit+ method performed best during this evaluation. Since the nucleolus has a relatively long and inconvenient average computation time, we concluded that the Equal Profit+ method performs best.

Using this method we computed emissions of companies for the cooperative and non-cooperative case, and compares these emissions. We did this for the cases in which two or three companies have the opportunity to plan their freight transport together. When two companies cooperate the emission of both companies decreases. The average decrease in emission of a company is 48.2%. For three companies this average is higher, equal to 56.3%. However, when three companies cooperate it can happen that the emission of one company increases. This all depends on the locations of their depots and costumers. When a company takes this in consideration, it can greatly benefit from collaborative transport planning in terms of emission.

We have three recommendations on future research. First, for our algorithm that constructs routes for the cooperative case we make two assumptions; the first assumption is that each company has the same products in stock, and the second assumption is that each company owns only one truck. However, both assumptions are not very realistic. It would be interesting to drop one assumption or both, recreate the research and compare the results with the results of our research.

Second, when we create the multi-depot instances, we choose the single-depot instances to combine randomly and don't create every possible combination of single-depot instances. However, the combinations that we didn't make might give us different results than we have obtained now. Thus it might be interesting to create all possible multi-depot instances and see if this leads to different conclusions. With this it should be kept in mind that the amount of results is enormous.

Third, using an exact method instead of the Christofides (1976) heuristic to construct routes might also be worth investigating. We think that this would improve our results since the Christofides (1976) heuristic has an approximation factor of 0.5. When this indeed improves results and the results show the same benefits in terms of emission, companies will have more incentives to plan their freight transport collaboratively.

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8 Appendix

8.1 Calculating e(S)

As mentioned before, we use the emission function introduced by Ligterink et al. (2012) to calculate $e(S)$. This function computes the emission per kilometer by taking into account the load weight, distance and driving speed between two consecutive costumers. Put differently, the inputs of the function are d, which is equal to the load of the transport vehicle expressed in order units, and V, which is the driving speed of the transport vehicle expressed in kilometers per hour. With d, we first calculate $KWt = \frac{131.25}{5+0.01d}$. Then we can calculate the emission per kilometer e_{km} with the following equation:

$$e_{km} = \frac{465.390 + 48143KWt}{V} + 32.389 + 0.8931KWt - (0.4771 + 0.02559KWt)V + (0.0008889 + 0.0004055KWt)V^2. \quad (17)$$

Using $\sigma(S)$, we first compute the emission of transport between each pair of consecutive costumers. For this we determine e_{km} for each pair of consecutive costumers and multiply this with the distance between the two costumers, defined as the two-dimensional Euclidian distance. To calculate $e(S)$, we sum over these emissions of transport.

8.2 The Christofides heuristic

This heuristic is developed using graph theory. In our case the vertices in the graph G are the costumers and the depot, and the edges are the roads between any pair of vertices. In the first step the heuristic finds the minimum-cost spanning tree over the vertices, which we call T. Next, it computes the least-cost perfect matching M over the vertices in T with odd degree. The heuristic takes the union of edges in T and M. This union, which we name H, is the Eulerian subgraph of G. In the final step, the heuristic makes sure that no vertex in H has a degree greater than two. If a vertex does not meet this requirement, it deletes two edges indicent to this vertex and to two other vertices, which we call i and j. Also, it adds an edge between i and j. The heuristic repeats this procedure until each vertex meets the degree requirement. Overall, this heuristic performs well: it has an approximation factor of 0.5, which means that the heuristic finds a route of which the costs are at most 50% higher than the costs of the optimal route.

Table 5: This table shows the characteristics of the two companies that can decide whether or not to cooperate[a] *with order size in order units, the emission of each company in the non-cooperative and cooperative case in grams, and the difference between these emissions for each company in percent. In this table we refer to location configurations using Table 1.*

Company 1						Company 2					
Number of cost.	Order size (unit)	Location config.	Emission non-coop. (g)	Emission coop. (g)	Diff. (%)	Number of cost.	Order size (unit)	Location config.	Emission non-coop. (g)	Emission coop. (g)	Diff. (%)
15	35	2	8824	6365	-27.9	10	35	3	14886	11767	-21.0
10	7	2	8360	6044	-27.7	5	7	6	15094	9992	-33.8
15	35	2	8824	8319	-5.7	15	35	7	13730	8319	-39.4
15	7	2	10183	6763	-33.6	10	1	10	15848	10525	-33.6
15	35	3	13409	2728	-79.7	15	1	3	16878	2728	-83.8
5	1	3	14932	10562	-29.3	15	1	5	10236	7235	-29.3
10	1	3	16857	4329	-74.3	10	35	6	14247	5329	-62.6
10	35	3	14886	4388	-70.5	5	1	7	16022	4718	-70.6
15	35	3	13409	8476	-36.8	5	7	9	14532	9203	-36.7
10	1	3	16857	2543	-84.9	5	1	10	16241	2450	-84.9
5	7	5	8233	5607	-31.9	10	1	6	16344	11149	-31.8
5	35	5	7639	5480	-28.3	15	7	7	16372	11437	-30.1
15	7	5	9113	6944	-23.8	10	35	10	14877	10682	-28.2
10	7	6	16209	8899	-45.1	5	35	6	15069	8260	-45.2
5	7	6	15094	4431	-70.6	10	1	7	21921	6422	-70.7
10	35	6	14247	11568	-18.8	15	7	9	15181	12324	-18.8
15	1	6	16670	6510	-60.9	10	35	10	14877	5810	-60.9
15	7	7	16372	5503	-66.4	5	7	9	14532	4894	-66.3
5	1	7	16022	4446	-72.3	10	35	10	14877	4132	-72.2
10	35	9	12849	10451	-18.7	15	1	10	16604	12165	-26.7
5	7	10	15497	2189	-85.9	10	7	10	16515	2333	-85.9

[a]The number of costumers and order size are shown in this table such that others are able to replicate it.

Table 6: This table shows the characteristics of the three companies that can decide whether or not to cooperate[a] *with order size in order units, the emission of each company in the non-cooperative and cooperative case in grams, and the difference between these emissions for each company in percent. In this table we refer to location configurations using Table 1.*

Company 1						Company 2						Company 3					
Number of cost.	Order size (unit)	Location config.	Emission non-coop. (g)	Emission coop. (g)	Diff. (%)	Number of cost.	Order size (unit)	Location config.	Emission non-coop. (g)	Emission coop. (g)	Diff. (%)	Number of cost.	Order size (unit)	Location config.	Emission non-coop. (g)	Emission coop. (g)	Diff. (%)
10	1	2	9755	9003	-7.7	5	1	3	14932	2402	-83.9	10	35	1	2934	6050	106.2
5	35	2	8416	5611	-33.3	10	7	6	16209	9148	-43.6	10	1	9	16072	10715	-33.3
15	7	2	10183	4519	-55.6	10	1	7	21921	8211	-62.5	15	35	6	13224	6775	-48.7
5	1	2	8886	5978	-32.7	15	7	10	16145	2788	-82.7	10	1	10	15848	10662	-32.7
5	7	3	16068	0	-100.0	5	7	3	16068	3284	-79.6	10	35	9	12849	22412	74.4
15	35	3	13409	2671	-80.1	5	35	5	7639	7148	-6.4	15	7	2	10183	16318	60.2
5	7	3	16068	2758	-82.8	10	35	6	14247	7441	-47.8	10	1	4	8436	7363	-12.7
5	35	3	14322	2655	-81.5	10	7	7	14742	2659	-82.0	10	1	8	16528	12385	-25.1
15	1	3	16878	5976	-64.6	10	35	9	12849	5035	-60.8	10	1	7	21921	9622	-56.1
10	35	3	14886	2384	-84.0	15	7	10	16145	3315	-79.5	5	35	10	14718	27144	84.4
5	35	5	7639	3394	-55.6	10	1	6	16344	7263	-55.6	5	1	9	15890	7061	-55.6
10	7	5	9100	5757	-36.7	10	35	7	14105	4158	-70.5	5	7	5	8233	7928	-3.7
15	35	5	8179	7767	-5.0	15	7	10	16145	8796	-45.5	5	7	2	8737	10454	19.7
10	7	6	16209	5583	-65.6	5	1	6	15632	5399	-65.5	10	1	7	21921	7550	-65.6
10	7	6	16209	5524	-65.9	5	1	7	16022	5456	-65.9	10	7	6	16209	5524	-65.9
15	35	6	13224	5620	-57.5	10	7	9	15118	6433	-57.4	5	1	6	15632	6652	-57.4
15	1	6	16670	8336	-50.0	10	1	10	15848	3558	-77.5	10	1	2	10149	7892	-22.2
10	35	7	14105	4966	-64.8	5	1	9	15890	5320	-66.5	15	1	1	3521	7209	104.7
5	35	7	14480	1733	-88.0	10	1	10	15848	6391	-59.7	15	7	6	16292	17121	5.1
5	35	9	14381	8186	-43.1	15	7	10	16145	2442	-84.9	10	7	1	2318	8582	270.2
10	35	10	14877	2667	-82.1	10	1	10	15848	2699	-83.0	5	7	3	16068	12754	-20.6

[a] The number of costumers and order size are shown in this table such that others are able to replicate it.