The trade-off between costs and carbon emissions from lot-sizing decisions

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Abstract

Logistics decisions can have a significant impact on carbon emissions, a driver of global warming. One possible way to reduce emissions is by adapting a lower delivery frequency, which enables better vehicle utilization or the usage of relatively efficient large vehicles. We study the situation in which a decision maker decides on the amount to be shipped in each period, where he/she can order items in each period and keep items on inventory. If the shipped quantity is large, vehicle capacity is well utilized, but many products have to be stored. Existing studies in this field of research, called lot-sizing, have introduced models for incorporating carbon emissions in the decision making, but do not focus on realistic values of the emission parameters.

Therefore, we conduct a survey of empirical studies in order to establish the possible marginal emissions from holding inventory and performing a shipment with a truck. We consider a case study based on real-life considerations and on the findings of the survey study, and introduce a novel bi-objective lot-sizing model to find the Pareto optimal solutions with respect to costs and emissions. In our initial experiments, we consider various demand scenarios and other relevant factors, such as product properties and driven distances. We find that it is often costly to reduce carbon emissions from the cost optimal solution, compared to carbon prices in the market. The cases in which carbon emissions can be reduced most cost-efficiently are those in which carbon emissions are large relative to costs, typically because costs are the results of past investments and can be considered sunk.

1 Introduction

Recently, there has been much attention in Operations research on the minimization of carbon emissions of logistics decisions (Dekker et al., 2012). Road freight transportation is an important source of these emissions. As of 2016, road freight transportation contributes to 4.95% of greenhouse gas emissions in the European Union and warehouses 0.55% (Rüdiger et al., 2016). One way to reduce the transport emissions is to improve the utilization of a vehicle, since fully loaded vehicles emit much less carbon per item or per ton than an empty one. However, if one wishes to use well utilized vehicles, this may cause low shipment frequencies and high inventory costs (and possibly high emissions from holding inventory). For a logistics provider, it would be relevant to know the shape of the trade-off between the potentially low carbon emissions from infrequent shipments versus the high inventory holding costs.

Existing studies have tried to model this trade-off. Some studies use a version of the Economic Order Quantity (EOQ) model, which minimizes the costs related to a shipment, called a set-up, and costs related to inventory levels. It presumes constant demand over an infinite time horizon and a continuous review setting, i.e., orders can be placed at any point in time. Bouchery et al. (2012) consider a version of these models with environmental objectives. In Economic Lot-Sizing (ELS) models order decisions are taken periodically and demand varies between periods (but it is known and deterministic). The studies by Retel Helmrich (2013), Romeijn et al. (2014), and Retel Helmrich et al. (2015) consider the carbon emissions of lot-sizing decisions, and focus on developing efficient solution methods for these problems. Benjaafar et al. (2013) use lot-sizing models to measure the impact of measures such as carbon caps, taxes, and trading schemes on the decision how much to order and how much to put on inventory using lot-sizing models. Section 2 describes the studies in more detail.

One shortcoming is that the mentioned studies only introduce generic emission parameters related to transport (per shipment and sometimes per item transported), and to inventory (per item stored at the end given period, a fixed emission for having any inventory at all). However, little effort is made to determine realistic values of these parameters. If a concrete case is constructed, as in Bouchery et al. (2012) and Benjaafar et al. (2013), the chosen parameter values are fictional, but computational results and insights are presented nevertheless. A conclusion in Bouchery et al. (2012) is that carbon emissions can be reduced by 22% for a 5% cost increase in the case study. The risk is that such results are used to draw conclusions, such as that "emission caps could be (achieved) more cost-effectively by adjusting operational decisions than by investing in costly more energy-efficient technology" (Benjaafar et al., 2013), which may be hard to assess without actual information on cost and emission parameters.

The aim and contribution of this paper is to conduct a realistic assessment of the trade-off between carbon emissions and costs in lot-sizing decisions. This requires an assessment of the carbon emissions from transporting a given amount of items and from holding inventory, for which, to the best of our knowledge, no tools are available. The contribution is relevant, as it enables practitioners and researchers to perform such assessment based on realistic parameter values and to identify situations where carbon emissions can be reduced at low cost.

To achieve our goal, we construct a concrete benchmark case, and we identify and vary factors, such as product attributes, that affect the carbon emissions and/or costs and thereby the trade-off between these objectives. The setting we consider is as follows. Shipments are performed with dedicated Full Truck Load vehicles, namely a medium truck and a large truck. We assume that demand over the horizon is known and deterministic, and do not consider inventory models with random demand, as has been done in Hoen et al. (2010); Tang et al. (2015). Emissions and set-up costs of production, e.g., starting a machine, are not considered in this paper (most studies use transport in their motivation for studying emissions from lot-sizing).

Our paper is organized as follows. In Section 2 we discuss lot-sizing models for minimizing carbon emissions. Section 3 describes current relevant results on emissions from transport and from keeping inventory. We formulate a mathematical model that includes the relevant costs and emissions related to transport and inventory decisions in Section 4. Section 5 describes exploratory experiments, in which we determine which factors affect the trade-off between cost and carbon emissions, while Section 6 presents the extensive analysis in which we aim to determine when emissions reduction can be achieved against reasonable cost. The conclusions and directions for future research are given in Section 7.

2 Literature on green lot-sizing

In this section, we summarize existing lot-sizing studies and the application to carbon emissions. The key question is how much to order and ship in each period to satisfy demand over a given time horizon T. Economic lot-sizing (ELS) models have been developed for the situation where demand fluctuates and decisions are taken periodically (Wagner and Whitin, 1958). In its most basic form, there is a trade-off between the fixed costs related to the placement of an order in a period, the so-called set-up costs, and the amount of inventory held at the end of a period, the inventory holding costs. Jans and Degraeve (2008) list practical applications of ELS models, which include the process industry, the chemical industry, car production, the glass industry, consumer products in general, and pharmaceutics. ELS models are mainly at the operational level, though extensions to the tactical and strategic levels exist through e.g. aggregate planning and supply chain optimization; see Jans and Degraeve (2008). This is important, as it limits the time horizon of decisions in ELS models.

Recently, the objective of minimizing carbon emissions has been introduced to ELS models. The studies by Absi et al. (2013) and Absi et al. (2016) consider the imposition of carbon emission constraints, both over single periods and multiple (possibly overlapping) intervals of periods. Carbon emissions are related to the choice of transportation mode, which depends on the size of the order. Romeijn et al. (2014) introduce bi-objective models for minimizing carbon emissions as well as costs in an ELS setting, where emissions are related to the number of items on inventory and to the number of shipments. The thesis by Retel Helmrich (2013) contains two applications of green lot-sizing: lot-sizing with remanufacturing (Retel Helmrich et al., 2014), where it is argued that the usage of used products or components is green, and determining cost optimal schedules under emission constraints Retel Helmrich et al. (2015). They put a limit (cap) on the emissions, which are related to inventory levels and the transport needed at each set-up; there are also fixed set-up emissions for transport. Note that caps or limitations occur in practice in combination with a possibility to purchase additional emission allowances or to sell remaining quantities in cap-and-trade emission schemes, such as the European Trading Scheme (ETS) (`https://ec.europa.eu/clima/policies/ets_en`).

Benjaafar et al. (2013) present a study that uses lot-sizing models to mimic the decisions of a firm in order to determine the environmental consequences of measures. This firm faces situations with 1) carbon caps (a limit on the amount of carbon to be emitted), 2) a carbon tax, or 3) a cap-and-trade emission scheme. The emission caps apply to individual periods, so if emissions in a given solution in a given period are higher than the cap, the solution is infeasible or the firm has to buy emission rights elsewhere. There are fixed and variable emissions due to ordering, and emissions per unit held on inventory, but emissions are not based on empirical measurements. The study then determines how the emission reduction measures would affect the decisions of the firm.

ELS models can be considered an extension of the Economic Order Quantity (EOQ) model, in which demand occurs at a constant rate and decisions can be taken continuously. Bouchery et al. (2012) have developed a variant of the EOQ model, called the sustainable order quantity, which minimizes in addition to costs, carbon emissions and a social objective (injuries). The main purpose of the study is to present a multi-criteria methodology, not to present a realistic assessment of carbon and injury effects.

The size of emissions in the aforementioned studies are related to two factors: 1) to the number of items held on inventory at the end of the period, and 2) to the set-up, where the typically given example is transport. However, as mentioned earlier, these values are not based on actual research into the sources of emissions. However, the next section determines how carbon emissions do relate to transport and inventory decisions.

3 Emissions from transport and inventory decisions

In this section we determine the carbon emissions resulting from a shipment ordering policy, which we use later in our mathematical model and case study. We distinguish between the emissions from transport by truck and from holding inventory. There are several greenhouse gases and the impact of the gases is normalized to kilogram (kg) of carbon emissions. The measurement unit is a carbon emission equivalent, denoted by CO_2e. Before determining carbon emissions, however, we address some relevant issues regarding the measurement of carbon emissions.

It is important to distinguish between *average* and *marginal* emissions and use them appropriately. Carbon emission measurements generally require average measurements, meaning that the total emissions should be divided between the number of products or items. For example, if a package travels by truck, it is not allowed to use the additional emissions of the truck with the item as opposed to the emissions without the item (the marginal emissions); see e.g. the CEN16258 norm.[1] Many of the available emission estimates are averages.

However, the problem with average emissions is that they may not reflect the consequences of our decisions. For example, if there are 1000 items in a warehouse and the average emissions are 2 kg of CO_2 per item, it is by no means the case that total emissions are 4000 kg of CO_2 when 2000 items are stored (as fixed emissions do not increase with the number of items stored). For our purpose, it is necessary to know the marginal emissions of adding these 1000 items, for example from additional operations or cooling, or from renting additional warehouse space. This issue is also relevant if a warehouse is used for multiple products. If we store 2000 items of a given product instead of 1000, a larger share of the warehouse emissions is allocated to the product. However, if this increase does not change the total emissions of the warehouse, there should not be an emission increase in our model. In fact, we plan to construct a multi-product version of our approach in order to capture the sharing of emission sources between different products as a direction of future research.

Moreover, the so-called *scope* of emissions is relevant (Piecyk, 2015). A complete evaluation of carbon emissions from, e.g., a warehouse could include the power needed to operate the warehouse, both from our own power source (scope 1 in Piecyk (2015)) and from purchased power (scope 2)[2], but also the emissions from building the warehouse, from the travel of the people operating there, and so on. It is important to limit the emissions to the most relevant sources that are related to the decisions that we take. In this study we limit ourselves to scope 2 emissions. For example, we consider the construction of the warehouse as a strategic decisions that does not follow from our tactical or operational model and exclude the emissions from construction in our analysis.

Another assumption is that we do not consider the emissions throughout the *supply chain*, even though the emissions from storage at and transport to the supplier could well be affected by our ordering decisions, but this would complicate the modeling to a large degree.

3.1 Transportation emissions

The emissions from transportation are both due to the combustion of the fuel and the emissions from extraction and production of fuel (the well-to-wheels emissions). The fuel consumption of a vehicle is due to several factors: the distance driven, characteristics of the vehicles, such as the Gross Vehicle Weight (GVW: the weight of the vehicle including the payload), the distance driven, and the speed of the vehicle or the driving conditions; see Barth et al. (2005).

The shipment size in lot-sizing decisions determines the number and size of the vehicle

[1]See, e.g., `https://standards.globalspec.com/std/1562222/cen-en-16258`
[2]Note that scope 1 emissions are included in scope 2 emissions

to be used as well as the load on the used vehicles. Transport emission models tend to have that the emissions of a vehicle increase linearly with the weight of the load on the vehicle (Barth et al., 2005). Therefore, we compute the emissions of the empty vehicle $\hat{e}$ (the fixed emissions per shipment) and the fully loaded vehicles $\hat{f}$ in our study. Given the maximum payload capacity of the vehicle, we can compute the carbon emissions due to the load (the variable emissions related to the size of the shipment). For example, if the vehicle is loaded to up to 60% of its payload capacity, emissions are $\hat{e} + 0.6(\hat{f} - \hat{e})$.

Broadly speaking, existing optimization studies compute carbon emissions for vehicles with different load factors in two ways. Some studies use *observations* obtained for specific vehicles, as in e.g., Ubeda et al. (2011). Many other studies use so-called *engine emission models* to compute carbon emissions, through inserting a number of input parameters, typically the vehicle weight, the load, vehicle characteristics, and the driving conditions. An overview of the usage of engine emissions in route planning (green routing) is given in Lin et al. (2014). Both computation methods have the disadvantage that they apply to a specific vehicle, either because observations are taken for it or because parameter values are given for it. We wish to use simpler, more general computation methods for generic vehicles.

The emission computations by the Finnish road transport ministry (LIPASTO, 2015), which we denote by 'LIPASTO', contain the values of $\hat{e}$ and $\hat{f}$ for different vehicles and driving conditions. The vehicles have GVWs of 6, 15, 40, 60 and 76 t, and the driving conditions are typical Highway, Urban, and Delivery driving conditions, where the latter one refers to a combination of different driving conditions. In our experiments, we use the emissions of a medium vehicle (with a GVW of 15 and a payload capacity of 9 ton) and a large vehicle (with a GVW of 40 ton and a capacity of 25 ton) for Highway and Urban driving conditions; see Table 1.

Table 1: Computed carbon emissions in grams per km for urban and highway stretches of selected vehicles

		LIPASTO	
Truck (GVW)	Road type	Empty	Full
Large (40 t)	Urban	1034.8	1518.4
	Highway	668.2	907.4
Medium (15 t)	Urban	408.2	605.8
	Highway	395.2	483.6

We have compared the results to a similar study in the Netherlands (Ligterink et al., 2012), and find that results are roughly similar. It is, however, not our intention to provide a comparison of different emission levels, but to provide realistic emissions per kilometer, which will serve as input for the model to be presented in Section 4.

3.2 Inventory emissions

The question is how inventory levels have an influence on carbon emissions. Some studies have measured the carbon emissions as a result of the size of the warehouse (which could follow from the amount of inventory to be stored). The size of the warehouse is given in terms floor area (m^2 or square feet) but also in terms of volume (m^3).

Some studies base their results on the energy usage in KWh. Harris et al. (2011) set the energy usage of 2 KWh per m^2 per year. Interestingly, the source that is cited in that paper (Brander, 2005) uses a figure of 33.19 KWh per m^2. The energy usage can be multiplied by a country specific conversion factor from KWh usage to kg carbon emissions, e.g., the Dutch electricity conversion factor is 0.413 kg per KWh.

A different approach is followed by Mallidis et al. (2014), who relate carbon emissions to the size of the warehouse in cubic meters. In their regression study, the authors find a loglinear relationship. A large warehouse size ('L') of 200,000 m^3 has emissions of 0.36 ton of CO_2 per day and a small warehouse ('S') of 2000 m^3 generates 0.05 ton (based on the conversion factor in Greece of 0.761 kg CO_2/KWh). Per m^3, this gives emissions of between 6.57 and 9.13 kg/m^3 per year.

Rüdiger et al. (2016) report emissions for three types of warehouses for different products, namely a cross-docking warehouse for palletized products (77.1 g CO_2 per ton of freight handled), warehouse for sanitary equipment (20.67 kg CO_2e per m^2 per year for inventory), and a spare part warehouse (206.63 kg per m^2 per year).

In studies from 2012 by the Environmental Protection Agency (EPA) called CBCES[3], the emissions from several types of buildings are reported, including 'warehouse and storage', namely 32.38 kg CO_2e per m^2. The results are reported in BTUs (British thermal unit; a unit of energy), which are then transformed into kg CO_2e through a reported conversion factor of 5.32 kg CO_2/BTU.[4] The study also identifies a decreasing trend compared to previous observations from 2003. A Corporate Responsibility Report from the British Land PLC (2003) reports emissions of 73 kg per m^2.[5]

Table 2: Computed carbon emissions in kg per year from inventory

Source	Carbon emissions	Unit	Country
Harris	1.08	m^2	UK
CBCES	32.38	m^2	
Brander	33.19	m^2	
British Land	73	m^2	
Mallidis L	6.57	m^3	Greece
Mallidis S	9.13	m^3	Greece
Rüdiger, sanitary	20.67	m^2	
Rüdiger, spare part	206.63	m^2	

We summarize the results in Table 2. The median emission appears to be around 33 kg per m^2 per year. The results from Mallidis et al. (2014) are at a similar level when the warehouse is 3 to 5 meter high. The emissions from storing spare parts from Rüdiger et al. (2016) are much higher than the other estimates, presumably because so few spare parts are stored.

[3] https://www.eia.gov/consumption/commercial/

[4] https://www.epa.gov/energy/greenhouse-gases-equivalencies-calculator-calculations-and-references

[5] http://www.britishland.com/~/media/Files/B/British-Land-V4/reports-and-presentations/reports-archive/2003_cr_report.pdf

There are two related factors that we choose not to take into account in our analysis. If products on inventory need *freezing*, this significantly increases the amount of energy needed and thereby carbon emissions. A report from the Energy Efficiency and Renewable Energy (EERE) office[6] provides standards for the energy usage in KWh for several types of freezers per m^3. For instance, a refrigerator of 10 m^3 may use at most 3.04 KWh per day, which, depending on the conversion factor, gives emissions of 0.3 to 2 kg per day (100 to 700 kg per year), which is much more than the emissions for operating a warehouse listed above. The second factor is wastage of items on inventory (which implies that one needs emissions to produce once more). This is typically beyond the scope of lot-sizing, because of the stochastic nature of wastage processes.

The emissions so far report the direct emissions from operating warehouses (the scope 2 emissions), but do not consider the emissions from building the warehouse. The study by Rai et al. (2011) provides a life cycle analysis of carbon emissions from building a warehouse with a floor space of 8,000 m^2 in Sheffield, UK. It is found that the emissions from the 'material burden' are about a third of the emissions from operating the warehouse, assuming a lifetime of 25 years.

Interestingly, we have not found any studies explicitly considering the number of items on inventory as a key driver of carbon emissions. We choose therefore to relate emissions to the size of the warehouse that is needed to store items. Moreover, it appears unlikely that the amount of warehouse space varies precisely with the amount that is kept on inventory at the end of each period. Instead, we presume that the logistics provider reserves a given amount of warehouse space s for a particular item at the beginning of the entire period. In fact, the available warehouse space may be a discrete function and only certain warehouse sizes may be available, but that is beyond the scope of this study.

4 Mathematical model

In the previous section we have shown how emissions depend on transport and inventory decisions, i.e., on the usage of road transport vehicles and on the warehouse space needed. In Section 4.1 we present the mathematical model that relates these emissions as well as the costs to lot-sizing decisions (the costs are relatively well-defined). The aim is to minimize both costs and emissions. As it is not clear how to transform emissions into costs (and vice versa), the model is a bi-objective optimization model. The purpose of the model is to present the trade-off between costs and carbon emissions for different transport and inventory decisions, that is, to determine how much a reduction in carbon emissions would cost. To quantify the latter, we use several characteristics of the efficient frontier, as will be explained in Section 4.2.

4.1 Mathematical formulation

In order to describe the model, we first present the necessary notation and definitions.

[6]https://www.regulations.gov/document?D=EERE-2010-BT-STD-0003-0052

Parameters/functions:

T	number of periods in planning horizon (with t as associated index)
K	number of vehicle types (with k as associated index)
M	number of items (with i as associated index)
d_{it}	demand of item i in period t
C_k	vehicle capacity of type k
f_k	fixed cost for a trip of vehicle type k
h_{it}	holding cost for carrying one item i in period t to the next period
$\hat{e}_k$	emissions for a trip of an empty vehicle of type k
$\hat{f}_k$	emissions for a trip of a fully loaded vehicle of type k
$\hat{h}_{it}$	emissions for carrying one item i in period t to the next period
$\hat{E}(s)$	emissions for occupying a warehouse space of size s

Variables:

q_{it}	order quantity of item type i in period t
x_{kt}	quantity transported by vehicle k in period t
I_{it}	ending inventory of item type i in period t
y_{kt}	number of full vehicle loads of type k needed in period t
δ_{kt}	share of unused capacity of the non-full vehicle load of type k in period t
s	reserved warehouse space for the items

Model:

$$
\begin{aligned}
\min \quad & (z_1, z_2) && && (1)\\
\text{s.t.} \quad & z_1 = \sum_{t=1}^{T}\left(\sum_{k=1}^{K} f_k y_{kt} + \sum_{i=1}^{M} h_{it} I_{it}\right) && && (2)\\
& z_2 = \sum_{t=1}^{T}\left(\left(\sum_{k=1}^{K}(\hat{f}_k y_{kt}) - (\hat{f}_k - \hat{e}_k)\delta_{kt}\right) + \sum_{i=1}^{M} \hat{h}_{it} I_t\right) + \hat{E}(s) && && (3)\\
& I_{it} = I_{i,t-1} + q_{it} - d_{it} && t = 1, \dots, T; i = 1, \dots, M && (4)\\
& \sum_{i=1}^{M} q_{it} = \sum_{k=1}^{K} x_{kt} && t = 1, \dots, T && (5)\\
& x_{kt} + C_k \delta_{kt} = C_k y_{kt} && t = 1, \dots, T; k = 1, \dots, K && (6)\\
& s \geq \sum_{i=1}^{M} I_{it} && t = 1, \dots, T, && (7)\\
& q_{it}, x_{kt}, I_{it}, s \geq 0 && t = 1, \dots, T; i = 1, \dots, M && (8)\\
& \delta_{kt} \in [0, 1] && t = 1, \dots, T; k = 1, \dots, K && (9)\\
& y_{kt} \in \mathbb{N} && t = 1, \dots, T; k = 1, \dots, K. && (10)
\end{aligned}
$$

The first objective (2) models the monetary costs, while the second objective (3) models the emissions. Constraints (4) are the well-known flow balance constraints and model the balance between production, inventory and demand in period t. Constraints (5) model how the items to be transported are distributed over the different vehicles, while constraints (6) model the amount of vehicles needed as well as the unused capacity of the non-fully loaded vehicles. Finally, constraints (7) model the needed inventory space used by the items.

The warehouse emissions $\hat{E}(s)$ are related to the size of the warehouse, and not to the actual inventory levels in the warehouse. In our model the decision to reserve warehouse space s is taken over the entire time horizon, i.e., the reserved warehouse space $s \geq I_t$ for all periods $t = 1, \ldots, T$. The motivation is that warehouse capacity may be difficult to adjust on a daily or weekly basis. Furthermore, inequality can hold when the available warehouse space is discrete. We assume that the function $\hat{E}(s)$ is non-decreasing in s.

In comparison to the existing lot-sizing models (see Section 2) we add: 1) a general emission function $\hat{E}(s)$ related to the necessary warehouse space s; and 2) a transport-related emission function that distinguishes between different payloads. The functional form of $\hat{E}(s)$ determines how easily the model can be solved. For example, if we can approximate $\hat{E}(s)$ by a piecewise linear function, then it can be solved as a MIP. Alternatively, if $\hat{E}(s)$ is concave, we could use a constraint generation approach, where $\hat{E}(s)$ is approximated by linear functions 'on the fly'.

Since the model is used for experimental purposes, we solve it as a regular MIP and are not concerned with determining whether some variants are solvable in polynomial time with a suitable decomposition solution approach based on dynamic programming, or can be solved fast using smart cuts. This is left as a direction for future research, as this paper focuses on determining the trade-off between carbon emissions and costs.

Finally, we limit ourselves to a single product and drop the subscript i from the model parameters. However, for the sake of completeness and the potential for future use of the model to the multi-product case, we have included it here.

4.2 The efficient frontier and measuring its shape

In order to evaluate the trade-off between the two objectives z_1 and z_2, we generate the set of solutions that dominate all other solutions, the Pareto optimal solutions. Some of these solutions are *supported* (or *extreme*), meaning that there exists a unique weight α such that these solutions are optimal with respect to the objective $z = \alpha z_1 + (1 - \alpha) z_2$. Such solutions can be obtained with the *weighted method*. Other efficient solutions are *non-supported*, meaning that no such value of α exists. The whole Pareto or efficient frontier can be obtained to any desired precision by the so-called ε-constraint method, i.e., by bounding one of the objectives and adding it as a constraint. For an overview of these concept and solution methods, we refer to Ehrgott and Gandibleux (2000). In particular, all supported solutions, say n in total, can be found by solving $2n - 1$ times model (1)–(10) with the objective replaced by $z = \alpha z_1 + (1 - \alpha) z_2$ for suitably chosen values of α (Przybylski et al., 2010).

For a given instance, we would like to describe the trade-off between costs and carbon emissions. We report the costs of reducing a given amount of carbon emissions along the efficient frontier, which can be regarded as a dynamic shadow price. The alternative would

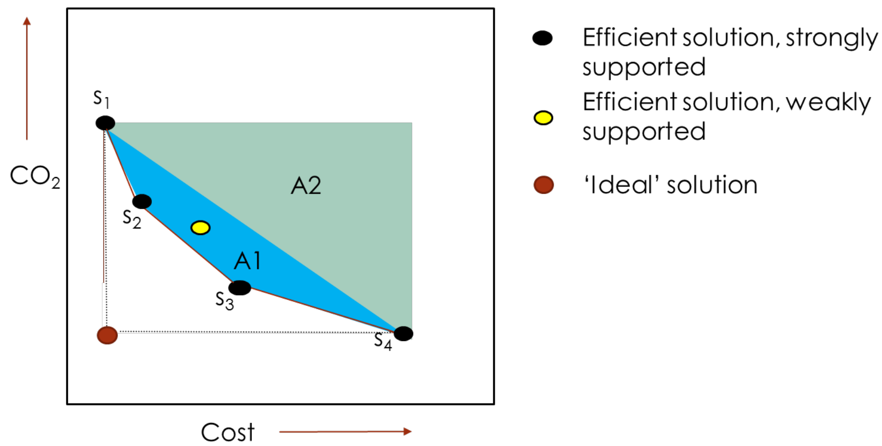

Figure 1: Illustration of an efficient frontier with 4 supported efficient solutions (black dots) and a weakly supported one (yellow dot)

be to present the results as relative decreases, e.g., "a 5% reduction in carbon emissions can be obtained at the expense of 2% higher costs", but this obscures the actual cost increase incurred for this carbon emission reduction. To that end, we determine the efficient frontier of Pareto optimal solutions where we cannot improve one objective without deteriorating the other using the bi-objective model given in Section 4.

We use Figure 1 to illustrate the two types of Pareto optimal solutions: supported solutions (the black dots in Figure 1) and non-supported ones (the yellow dots). We create an efficient frontier with only supported solutions with the weighted method. Non-supported solutions would be relevant if a company were to put a cap on emissions and pledge a certain reduction, but that is not considered here. Note that the cost of carbon reductions is non-increasing when only supported solutions are included. If the frontier includes non-supported solutions, such as the yellow dot as in the visualization in Figure 1, we have that the shadow price of emission reductions from solution S_2 to the non-supported solution is higher than to the supported solution S_3. Thus, it would be possible to remove more emissions against a lower price by going from S_2 to S_3 than from S_2 to the yellow dot. As we consider this as undesirable behavior, we do not consider non-supported solutions.

It is impractical to present all efficient frontiers of all instances: If there are n supported efficient solutions, there would be $n-1$ different shadow prices that are difficult to aggregate across multiple instances. Instead, we present four characteristics of each efficient frontier:

- The *relative emission reductions*;
- The (initial) *shadow price* of carbon emissions at the cost optimal solution;
- The number of strongly *supported efficient solutions*;
- The curvature of the efficient frontier, measured with the *hypervolume*: the higher the hypervolume, the stronger the curvature is.

These characteristics are computed as follows. Consider a problem instance with $n \geq 1$ (supported) efficient solutions, denoted by $s_1, \ldots, s_n$. We order the solutions in increasing order of costs, i.e., s_1 is cost optimal and s_n is carbon optimal. We obtain for each $i = 1, \ldots, n$ the costs and carbon emissions of s_i, denoted by $z_1(s_i)$ and $z_2(s_i)$, respectively. The relative emission reductions are computed as $[z_2(s_1) - z_2(s_n)]/z_2(s_1)$, and the initial shadow price is computed as $(z_1(s_2)-z_1(s_1))/(z_2(s_1)-z_2(s_2))$. Informally, the hypervolume is the area between the diagonal and the efficient solutions, represented by A_1 in Figure 1, divided by the surface of the triangle spanned by the diagonal and the 'ideal point', corresponding to A_2. For a formal definition, we refer to Cao et al. (2015). Note that the hypervolume and shadow price are not defined for an efficient frontier with a single supported point and the hypervolume equals 0 if the frontier consists of two supported points.

We only report the shadow price at the cost optimal solution, the most relevant one, and not the shadow price at other efficient solutions, as this constitutes a large amount of information. When the Pareto frontier is strongly curved and the hypervolume is high, this indicates that the shadow price can increase strongly.

5 Exploratory experiments

As specified in the introduction, we address the following question: How much does it cost to reduce carbon emissions through the choice of shipment size? To answer this question, we apply the proposed methodology of Section 4 to several problem instances. Each instance is characterized by a different set of cost and emission parameters as well as a demand pattern. We construct a set of representative instances by taking a benchmark case of shipments between two Dutch cities. In our exploratory experiments, we vary key parameters in order to determine how they influence the trade-off between costs and carbon emissions. These results form the basis for further experiments in Section 6 on a large set of instances with randomly generated demand.

5.1 The benchmark case

In our benchmark case, a company located in Groningen in the north of the Netherlands orders items from a supplier located near the harbor of Rotterdam, also in the Netherlands. The location of the cities as well as the route followed are presented in Figure 2. The ordered items are shipped with a large or medium truck. The transported items are either processed to satisfy demand in the same period or put on inventory to be used in a later period. In this section, we specify the values of the parameters in the mathematical model from Section 4.

The transportation route between Rotterdam and Groningen is 246 kilometer, consisting of 3.2 km (Rotterdam) plus 5.5 km (Groningen) of urban road, and 238 km of motorway, according to Google Maps. In our model, the large (resp. medium) truck (GVW 40 t) is denoted by $k = 1$ (resp. $k = 2$). Based on the LIPASTO results from Table 1 we set

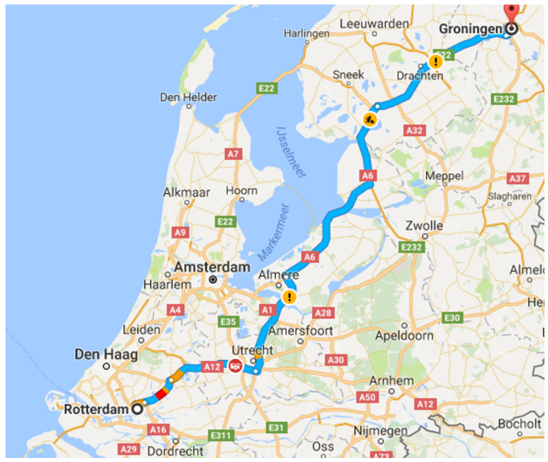

Figure 2: Example route from Rotterdam to Groningen in the Netherlands (obtained with Google Maps)

$\hat{e}_1 = 168.0$ kg and $\hat{f}_1 = 229.2$ kg. We set the weight of the product to 11.11 kg, so that there are 90 units per ton. For a maximum load of 25 ton, that gives a capacity of $C_1 = 2250$ and $C_2 = 810$ items, assuming that the weight of the items limits the capacity of the vehicle. In our case study, we distinguish between the transportation costs and the inventory holding costs. For the transportation costs we set the shipment cost for a large vehicle to €500, in accordance with observed freight tariffs. One can observe that the load on the vehicle does not affect the trip price.

We find that the standard practice for determining inventory holding costs is to take a fixed percentage of the sales price of between 20 and 30%. In the benchmark case the price is set to €20 and the holding cost percentage to 25%. Furthermore, inventory holding cost per month per item are assumed to be constant over time and across different items, so $h_t = 0.25 \cdot 20/12 \approx$ €0.42 for any time period t. We use that the number of units per m^2 are 100 (this would make that the full load of a large vehicle would cover 22.5 m^2, which does not appear unreasonable) and that the emissions are 33 kg per m^2 (based on Table 2). If any warehouse size can be rented, emissions per item per month would be $33/100 = 0.33$ kg per capacity item s per year, meaning that $E(s) = 0.33 \cdot s$. According to the discussion of Section 3 we set the emissions per item per time period $\hat{h}_t = 0$ for each period t in all our cases. An overview of all parameters is given in Table 3.

Table 3: Overview of the parameter settings

	Parameter	C_k	f_k	$\hat{e}_k$	$\hat{f}_k$	h_t	$\hat{h}_t$	$\hat{E}(s)$
truck $k = 1$	Value	2250	500	168.0	229.2	0.42	0	$0.33 \cdot s$

5.2 Parameter variations: considered cases

We conduct two sets of experiments: an exploratory experiment on instances where we wish to determine the effect of predetermined demand scenarios and parameter values in order to determine the factors that strongly influence the efficient frontier, and a second set of experiments where we test the influence of these factors on many randomly generated demand scenarios. We describe the parameter values here and introduce the demand scenarios in the next Section 6.

In our exploratory experiment, we take a horizon of $T = 12$ months and determine how the parameters in our model affect the trade-off between costs and carbon emissions from lot-sizing decisions. We consider six different demand scenarios over a 12 month period, denoted by $D_0, \ldots, D_5$ and given in Table 12 in the appendix. These scenarios include a default case (D0), a case with constant demand (D1), and the reverse (period wise) of the default case (D4). Furthermore, we have a case with constant demand half the size of that under D1 (D5), as well as cases with increasing (D2) and decreasing (D3) demand. In the benchmark case C0, the parameter values are as previously specified and only the large vehicle is used for transportation. In order to measure the impact of the following factors, we add the cases C1,...,C9 as in Table 4.

Table 4: Cases considered in experiments

Case	Effected parameter	Change w.r.t. default C0
C1	Item value €200	$h_t := 10h_t$
C2	Item weight times 10	$C_1 := 0.1C_1$
C3	Twice as many periods	$T := 2T$
C4	Large and medium vehicles	$K := 2$ (see below)
C5	Distance divided by 10	$\hat{e}_k := 0.1\hat{e}_k$, $\hat{f}_k := 0.1\hat{f}_k$
C6	As C4, but rate medium vehicle €350	$f_2 := f_2 + 50$
C7	Sunk warehouse emissions	$\hat{E}(s) := 0$
C8	Inclusion rental cost of warehouse	$\hat{h}_t := 50/T$
C9	Combining two vehicles (C4) with the charge on inventory space (C8)	$K := 2$, $\hat{h}_t := 50/T$

We add the possibility of using a second, smaller vehicle, namely a medium the medium size truck (GVW 15 t and capacity 9 t), denoted by $k = 2$. The charge per shipment is €300 in case C4 and €350 in case C6 to determine the effect of variations in vehicle costs relative to each other. Emissions are $\hat{f}_2 = 120.4$ kg and $\hat{e}_2 = 97.61$ kg per shipment. The choice of the other factors can be explained as follows. The value of the product determines the inventory holding costs (C1), and the product weight and volume how many can be taken on the truck (C2), though the high volume items have lower emissions and require more storage space. The addition of periods (C3) could increase the number of options and thereby the number of efficient solutions. The choice between vehicle types (C4) gives the decision maker additional options and could increase the number of efficient solutions. We also include cases with a short distance (C5) and a rent of €50 per m^2 warehouse space (C8). We consider the case where warehouse emissions are set to 0 (C7), which applies if the warehouse space has already been reserved and our inventory decisions have no impact on total carbon emissions, and a combination of case C4 and C8 to assess the joint effect of a warehouse space charge and multiple vehicles (C9).

5.3 Results of the exploratory experiments

In the initial experiments, the purpose is to derive insights and formulate hypotheses for more extensive experiments in the next section. In particular, we try to determine cases where CO_2 reduction makes sense from a cost point of view.

Example 1: We illustrate the results of the case (C0,D0), i.e., default parameters and default demand. There are three supported solutions with, in increasing order of costs, $(z_1, z_2) = (5541.67; 2055.16)$, $(5666.67; 1920.16)$, $(6645.83; 1851.16)$, respectively. In these solutions, we use 8, 7, and 6 shipments, respectively, and reduce carbon emissions while obtaining higher inventory costs and slightly higher inventory-based emissions. It costs €$5666.67 - 5441.67 =$ €125 to reduce $2055.16 - 1920.16 = 135$ kg carbon emissions, giving a shadow price of €925.95 per ton. The reader can check that the hypervolume equals 0.55 and the carbon emission reduction potential is 9.93%. The relatively high hypervolume indicates that the shadow price of carbon increases strongly (in fact, to €14,191 per ton) from solution 2 to 3.

The transport and inventory quantities are shown in Table 5. Each reduction in shipments is at the cost of additional inventory: The share of emissions due to transportation decrease from 82% for solution 1 to 79% for solution 2, and 73% for solution 3.

Table 5: Transport (x_t) and inventory (I_t) quantities in case (C0,D0)

		Solution 1		Solution 2		Solution 3	
Period	Demand	T	I	T	I	T	I
1	1000	1900	900	1900	900	2050	1050
2	900	0	0	0	0	0	0
3	1000	2100	1100	2150	1150	2250	1250
4	1100	0	0	0	0	0	0
5	1200	1200	0	2250	1050	2250	1050
6	1100	2100	1000	0	0	0	0
7	1000	0	0	1800	800	2250	1250
8	800	1500	700	0	0	0	0
9	700	0	0	1900	1200	0	0
10	1200	1200	0	0	0	1750	550
11	1300	1300	0	1300	0	2250	1500
12	1500	1500	0	1500	0	0	0

We present the shadow prices for each demand scenario and each case in Table 6. Subsequently, we present the other characteristics of the efficient frontiers in a condensed form by reporting averages, and determine why the frontiers have these characteristics.

The shadow prices in Table 6 are in the hundreds or thousands of euros per ton of carbon emissions saved. These prices are relatively high: The lowest value of around €113 is an order of magnitude larger than the current price in the ETS of €20.60.[7] These initial results suggest that reducing emissions through adjusting the shipment in a lot-sizing setting is quite expensive and it would be far less costly to purchase emission rights, if necessary. If the company is planning to reduce its own emissions, there may be more

[7]Taken March 26, 2019 from `http://markets.businessinsider.com/commodities/co2-emissionsrechte`

Table 6: Shadow price in euro for considered cases and demand scenarios

	D0	D1	D2	D3	D4	D5
C0	925.93		1406.47	617.28	408.50	2167.06
C1	43168.25	36547.97	50142.52	43168.25	46031.82	12565.83
C2	429.04		447.82	428.35	353.77	
C3	925.93		617.28	617.28	408.50	2167.06
C4	113.64	697.22	681.85	1018.84	113.64	645.36
C5	2004.96	2040.48	1359.99	1822.69	1274.21	
C6	777.53		156.74	179.43	777.53	
C7	744.05		992.06	496.03	248.02	1023.07
C8	296.66	344.43	826.21	431.50	966.18	3861.31
C9	1363.70	1952.22	909.13	909.13	2892.80	1906.73

cost-effective solutions, such as investments in energy efficient vehicles or in insulation of warehouses.

Table 7: Efficient frontier properties: averages for demand scenarios

Demand scenario	D0	D1	D2	D3	D4	D5
Nr Pareto	3.60	1.50	4.80	3.60	4.90	1.90
Hypervolume	0.38	0.00	0.46	0.41	0.53	0.10
Reduction %	15.43%	11.13%	14.26%	14.12%	14.27%	15.42%

Table 8: Efficient frontier properties: averages for cases

Case	C0	C1	C2	C3	C4	C5	C6	C7	C8	C9
Nr Pareto	2.67	3.33	2.17	3.00	4.67	2.00	5.00	2.83	3.50	4.67
Hypervolume	0.58	0.32	0.10	0.39	0.35	0.02	0.59	0.40	0.51	0.28
Reduction %	7.78%	24.95%	3.03%	8.40%	11.19%	26.05%	7.42%	21.52%	18.73%	12.00%

In order to further analyze the potential CO_2 emission reduction, we report the average number of supported efficient solutions, the hypervolume, and the percentage reduction of carbon emissions over the demand scenarios and cases in Tables 7 and 8, respectively. Note that the cases with relatively many efficient solutions appear to correspond to the cases with relatively high hypervolumes and relatively low shadow prices.

Firstly, the relative emission savings in the carbon optimal solution are only about 10 to 20%. A larger emission savings potential can occur when inventory costs are high compared to transportation costs, resulting in many shipments, as in cases C1 (high holding costs) and C8 (charge for renting warehouse space), but it is not always cheap to reduce the number of shipments.

Secondly, the number of efficient solutions is relatively small, around two or three. In all cases (except for case C5), emission reductions involve larger inventory quantities and fewer shipments. Often, the scope for reducing the number of shipments is low, e.g., from 8 shipments to 6 in Example 1. In the cases with two vehicles, C4 and C6, we observe a relatively large number of supported solutions, as the number of shipment options increases, and we observe relatively low shadow prices. The demand scenarios D0 and D2 to D4, with demand fluctuations show a similar pattern.

We generally find that transportation emissions are around 70% for the emission minimizing solution and between 80 and 100% for the cost minimizing solution. Inventory-based emissions can increase shadow prices, as they reduce the emission savings that can be achieved by scheduling fewer shipments, as can be seen from a comparison between case C7 (no warehouse emissions) with the default case C0. In the case (C0,D0) in Example 1, emission savings of only 9.93% can be achieved, but when warehouse emissions are considered to be sunk in the case (C7,D0), emission savings are twice as high, showing that inventory emissions can play a role.

5.4 Discussion

This raises the question in how far the observed results, in particular the high shadow prices, are due to properties of our experimental set-up, and whether realistic instances with low shadow prices can be constructed. We observe the following:

- Total costs are high in comparison to carbon emissions: As in Example 1, carbon emissions are often around 2000 kg and costs around €5000 to €6000. This could be a main cause of the high shadow prices. The question is whether cost parameters can be reduced compared to their carbon emission counterparts.
- There are relatively few shipments options. For instance, there are only three efficient solutions in Example 1, with 8, 7, and 6 shipments. One potential reason is that our choice of an average demand of 1075, forms a large share of the vehicle capacity of 2250. In demand scenario D5, where demand is twice as small, we indeed observe a higher number of efficient solutions than in D1.

One way to reduce costs is by having shorter periods: It would reduce both the absolute cost levels and make it cheaper to reduce the number of shipments (because of lower inventory costs). We have considered an additional case with 12 periods of one week each (where warehouse emission and holding cost parameters are multiplied by 12/52), similar to the other 12 period cases. However, the resulting Pareto frontier consists of a single point for all but one demand scenario, possibly because of *alignment* between objectives (see later).

6 Extensive experiments with randomly generated demand

For managerial purposes, it would be interesting to determine for which demand scenarios and cases low shadow prices are likely and carbon emission reductions are inexpensive by just changing transportation decisions. The current experimental design has not covered these yet, but indicate that: 1) shadow prices become lower when we take shorter period lengths (as this reduces inventory holding costs); and 2) the number of shipment options is increased, by using two vehicles and by making the cost optimal solution use many shipments, and by decreasing demand relative to the vehicle capacity.

In our further experiments, we extend the numerical experiments from Section 5 in two ways. Firstly, we generate demand scenarios randomly to measure the variation within each instance type. The demand scenarios are taken from a uniform distribution with averages of 350 (low) and 1075 (high) and with a range of 200 (low) and 500 (high). Demand is abbreviated such that the first letter denotes the average demand level and the second one the degree of variation, e.g., 'LH' is the case with low average demand and high variation. For each of these, we generate 20 demand scenarios.

Secondly, the exploratory experiments identify possible causes of the observed high cost of reducing carbon emissions, namely 1) the high cost levels in absolute terms compared to emissions, and 2) the relatively few efficient solutions. This is addressed in our further experiments as follows. We consider instances with 12 months and 26 fortnights (instances with 52 weeks could often not be solved within our limit of half an hour). We decrease costs relative to emissions by adding case C3b (case C3 no longer applies) with the emissions of the return haul included, and we generate instances in which transportation costs to €150 for the large vehicle and in case C4, to €100 for the medium vehicle (case C6 is dropped here).

6.1 Results of the extensive experiments

We report the average and minimum shadow prices of each case and of each demand scenario (LL,...,HH) as our summarizing statistic. We have also determined median shadow prices in order to avoid a strong effect from extreme values, but the difference between average and median are not large. We report the number of efficient solutions, the hypervolume, and the size of emission reductions briefly.

Table 9: Average shadow prices in euro for the 12 and 26 period case (total of one year), missing data implies single efficient solution

	12 periods				26 periods			
	LL	LH	HL	HH	LL	LH	HL	HH
C0	5298	6200		1283	1194	1813		5761
C1	5062	1950	38428	42319	124	411	11073	10370
C2	284	589	122	122	332	131	2294	908
C3b	1014	1583	6219	542	373	522	48736	2381
C4	27775	4375	700	821	25324	2838	214540	87278
C5	2837	5888	1218	1221	3322	1311	22939	9080
C6	146241	1725	321	983	794	445	214540	38397
C7	1257	2146	646	1423	584	939	5212	1939
C8	6533	8653	420	1144	1981	2965		5745
C9	27560	4849	2007	1594	27530	3508	214540	76449

Table 9 shows the average shadow prices for the 12 and the 26 period cases. The results indicate that the average shadow prices for the 26 period case are often lower than for the 12 period case, with notable exceptions of C2, C4, and C6. Moreover, shadow prices appear to be lowest in case of low average demand and in case of high variation, so for the demand scenario LH.

The observations can be explained as follows: The shorter period length in the 26 period case makes the holding costs in case C1 less costly and shadow prices become

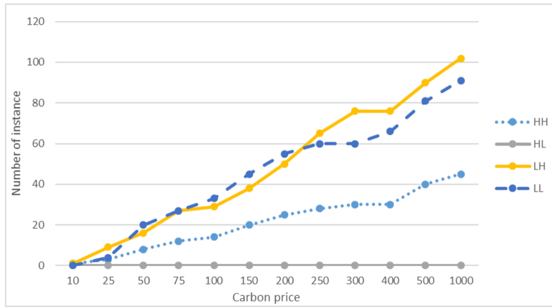

Figure 3: Number of instances out of 200 for which the shadow price is lower than a particular carbon price

lower. The opposite, namely large increases in shadow prices, occurs for the cases with two vehicles, C4 and C6. The lower inventory holding costs make it more attractive to increase the utilization of the vehicle. However, instead of making it cheaper to shift from a cost-minimizing to a greener solution, it makes that the cost-optimizing solution is very green to start with, and that switching to the second solution becomes expensive, i.e., the objectives become aligned. Indeed, the average emission savings in these cases are only 3 to 10%; see Table 10.

These averages do not show the range of shadow prices. In order to present the progression of shadow prices, Figure 3 has the carbon price on the horizontal axis and the number of instances such that the shadow price is lower than that value, aggregated over all cases. We find that the minimum shadow prices lie between €10 and €20 for the 26 period case. These aggregate results do not show that these low shadow prices mainly occur for the case C1 and C2, and for the scenarios LL and in particular LH. In a similar experiment, we find that even lower shadow prices are attained for the 12 period case (in the cases C2 and C3b).

Table 10 presents the carbon emission reduction potential, the hypervolume, and the number of efficient solutions for the 26 period instances. We only report these for the extreme demand scenarios LH (with small shadow prices) and HL (high shadow prices). It can be seen that the emission savings potential, the hypervolume, and the number of Pareto optimal solutions are clearly higher in case of LH, which appears to be consistent with the lower shadow prices observed for this case. A striking result is the large number of efficient solutions ('Nr. Pareto') for the case C1, in particular for the scenario LH, which coincides with the low shadow prices for this case.

We argue that low shadow prices may occur if costs are low compared to carbon emissions. Lower inventory costs occur when we increase the number of periods within the horizon. A reduction in the transportation costs occurs when we consider part of these costs as sunk, such as the driver wages and the vehicle maintenance. To explore whether our claim holds true, we conduct more experiments, where transportation costs are set to €150 for the large vehicle and in case C4, to €100 for the medium vehicle (case C6 is dropped here). Table 11 shows the shadow prices, both the average and minimum over 20

Table 10: Properties of efficient frontier in euro for 26 period case (total of one year)

	% Reduction		Hypervolume		Nr Pareto	
	LH	HL	LH	HL	LH	HL
C0	9.40%	0.00%	0.40	0.00	4.10	1.00
C1	63.65%	34.98%	0.69	0.02	13.75	3.30
C2	25.65%	24.33%	0.61	0.00	4.70	2.05
C3b	18.76%	0.68%	0.37	0.00	4.20	1.05
C4	3.15%	0.02%	0.56	0.00	4.05	1.05
C5	25.65%	24.33%	0.61	0.00	4.70	2.05
C6	9.13%	0.02%	0.56	0.00	5.15	1.05
C7	27.77%	5.37%	0.25	0.00	3.00	1.05
C8	11.25%	0.00%	0.35	0.00	3.90	1.00
C9	4.20%	0.02%	0.52	0.00	4.20	1.05

instances, for this situation.

Table 11: Minimum and average shadow prices in € for 26 period case (total of one year) with low transportation costs

	Minimum				Average			
	LL	LH	HL	HH	LL	LH	HL	HH
C0	27	21		113	164	274		187
C1	2260	312	13115	11981	2482	509	13645	13151
C2	6	7			471	115		
C3b	9	9	140	40	78	116	152	62
C4	4	4	3	7	1823	236	65	104
C5	61	65			4710	1149		
C7	14	15	223	53	141	187	230	71
C8	11	4		602	320	274	722	730
C9	2	2	0	14	261	419	105	225

The results show that shadow prices are indeed generally low compared to Table 9. In addition to the fact that the absolute size of the costs is reduced compared to the size of the carbon emissions, the cost-optimal solution uses more shipments and the scope for reducing emissions is larger, most notably in case C4. In isolated cases (C1 and C5), the changing balance between inventory holding and transportation costs can make emission reductions more expensive.

6.2 Discussion

In our computational experiments, we have constructed the efficient frontiers of a set of cases and demand scenarios based on a transport haul in the Netherlands. In the base cases, the cost of reducing emissions is high, because the emissions are relatively small compared to the costs, and because only a small part of the emissions in the cost-minimizing solution can be reduced. However, our results provide some predictions on the cases in which carbon emission reductions are relatively inexpensive – at least, the initial ones from the cost-optimal solutions.

As can be expected, it generally holds that a reduction in the number of shipments in the cost-optimal solution increases the carbon emission reduction potential and possibly the shadow price. To that end, both inventory holding costs and transportation costs should be low. Moreover, inventory-based emissions per period should be low, for example due to a short period length, and transport based emissions per haul should be high to have that the emissions savings from less transport are as high as possible. We find that, in reality, such low cost levels are attained when a large part of the costs are sunk, so investments in the vehicle and in the warehouse have been made and do not form part of the objective in our problem. The emission savings then follow only from short-term operational decisions.

It should be noted, however, that the relation between the shadow price and inventory holding costs per unit and transport costs per haul are not linear. If one reduces inventory holding costs, it may *align* the objectives of costs and carbon emissions and make that the cost-optimal solution contains few shipments. The remaining carbon emission reductions are then more expensive per unit, as can be seen in the cases C4 and C6 with 26 periods (see Table 9). Likewise, low transport costs per haul makes keeping inventory relatively expensive and could increase the costs of reducing the number of shipments and thereby carbon emissions.

7 Conclusions and directions for future research

In this paper, we address the trade-off between costs and carbon emissions in an economic lot-sizing setting. Such decisions can determine the frequency with which transport hauls are conducted and as a consequence, whether transport can be conducted with large and/or well-filled vehicles. Current studies in this field have not been based on realistic estimations of carbon emissions. This has adverse consequences: We do not know which emission sources are relevant, and we do not know whether decreasing the shipment frequency is a cost-effective way to reduce emissions. In this study, we determine how inventory and transport decisions influence carbon emissions, we establish a model with realistic parameter values for a concrete case study, our benchmark, and perform experiments to determine how key factors influence the results.

In our initial experiments, we find that carbon emission reductions, even small ones, are relatively expensive. One reason is that the ratio between absolute cost and carbon emission levels is large compared to the current price for carbon emissions in trading schemes (an indicator of the real price of carbon emissions). Another reason is that the scope for emission reductions from the cost optimal solution is often quite small (around 10 to 20%).

In our subsequent experiments, we determine the cases in which emission reductions would be reasonable. This is most likely to occur when the costs are small and the cost-optimal solution performs badly on the carbon objective, which may hold if much of the transport and warehouse costs are the result of past investments and therefore sunk, and when demand is relatively low compared to the vehicle capacity. Moreover, the presence of demand fluctuations and multiple vehicle types makes that there are many shipment options between the cost optimal and carbon emission optimal one. For these cases, we observe that the cost of reducing a given amount of carbon emissions can increase strongly, but tends to be low for the initial reductions. Finally, we would like to note that different cost, demand, and emission parameters interact. For example, in some cases with low inventory costs, it is cost optimal to have few well-loaded shipments and further emission reductions can be expensive or even unattainable.

There are several directions for future research. First of all, from a modeling perspective, the question is which variants of the model from Section 4 can be solved in polynomial time. If so, it would allow us to analyze decisions on a longer time horizon with shorter periods, say a weekly or daily basis. Secondly, our study isolates the impact of our firms operations of transport and holding inventory. A future study could consider the impact of our decisions throughout the supply chain, such as on inventory levels and shipment quantities at the supplier. Thirdly, we consider the choice between different types of trucks; A future study could consider different transportation modes. Fourth, freezing of items could have relevant impact on the trade-off.

Finally, we have not considered the multi-product case. In reality, it could well be that multiple products share common resources, such as vehicle and/or warehouse capacity. To reflect that reality, one can construct a model that allows for joint decision making on multiple products. A direction for future research is to consider the multi-product case and observe the impact of demand, emissions, and cost parameters.

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Appendix: Demand scenarios

Table 12: Demand scenarios

	scenario					
Period	D0	D1	D2	D3	D4	D5
1	1000	1075	800	1350	1500	537.5
2	900	1075	850	1300	1300	537.5
3	1000	1075	900	1250	1200	537.5
4	1100	1075	950	1200	700	537.5
5	1200	1075	1000	1150	800	537.5
6	1100	1075	1050	1100	1000	537.5
7	1000	1075	1100	1050	1100	537.5
8	800	1075	1150	1000	1200	537.5
9	700	1075	1200	950	1100	537.5
10	1200	1075	1250	900	1000	537.5
11	1300	1075	1300	850	900	537.5
12	1500	1075	1350	800	1000	537.5