

Arıkan, E., Fichtinger, J. & Ries, J.M. (2014). Impact of transportation lead-time variability on the economic and environmental performance of inventory systems. *International Journal of Production Economics*, 157, pp. 279-288. doi: 10.1016/j.ijpe.2013.06.005



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Original citation: Arıkan, E., Fichtinger, J. & Ries, J.M. (2014). Impact of transportation lead-time variability on the economic and environmental performance of inventory systems. *International Journal of Production Economics*, 157, pp. 279-288. doi: 10.1016/j.ijpe.2013.06.005

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Impact of Transportation Lead-Time Variability on the Economic and Environmental Performance of Inventory Systems

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Abstract: Storage and transportation of goods within global supply chains is a major cause of environmental damage in modern value added processes. Thus, in the past, theory and practice developed several approaches in order to decrease these negative environmental impacts that frequently counteract the traditional efficiency-oriented ambitions. However, in many cases the economic and environmental performance can be improved at the same time. As many activities in logistics and inventory management are related to the treatment of potential uncertainties in the system by establishing redundancies, the reduction of uncertainty has equally a positive impact on both performance measures. To investigate the interrelation between uncertainty and the economic and environmental performance of supply chains, a serial inventory system consisting of a manufacturer who works with overseas suppliers and a carrier is considered, whereas the carrier is able to reduce lead time uncertainty. The relationships between uncertainties and the economic and environmental performance of the considered inventory system are highlighted by a simulation study based on empirical data from an international container shipping supply chain.

Keywords: Inventory, Transportation, Lead-time variability, Carbon emission, Simulation

Introduction

In recent years we have seen the necessity of including environmental considerations in business operations, in particular for emission intensive activities such as global transportation of goods. Although we should be willing to undertake some cost for reducing the environmental impact, identifying opportunities which have positive environmental effect without deteriorating economic performance has become very important. Such efforts would lead to sustainability on both dimensions. As mentioned by Wu and Dunn (1995) and McKinnon (2010) preserving the environment while maintaining economic growth is a priority for many countries and therefore developing and implementing practical and cost-effective carbon mitigation strategies for the logistics sector is a major challenge. Several activities through the supply chain contribute to these challenges.

Goods storage and transportation is a major cause of CO₂ emissions and is cited as the single largest source of environmental hazard in the logistics chain (Wu and Dunn, 1995). It is estimated that 2,800 mega-tonnes of the overall greenhouse gas emissions, which is equivalent to 5,5% of the total emissions are caused by the logistics and transport sector (WEF, 2009). In 2004 transport activities were responsible for 23% of the energy-related greenhouse gas emissions and freight transport was responsible for around 8% (IPCC, 2007). Lengthening of supply lines and the increase in freight transport intensity coupled with high usage of carbon-intensive transport modes are the main drivers of transport related carbon

emissions in global supply chains (McKinnon, 2010). In addition, carbon emissions related to warehousing is a significant factor because of the considerable energy requirements for heating, cooling, materials handling equipment, etc. (Dhooma and Baker, 2012), which is a result of the increasing warehouse capacities due to rising buffers caused by longer lead times in global supply chains as well as due to growing product portfolios.

In order to decrease the negative environmental impact of goods storage and transportation, different entities of the logistics chain can take on actions with immediate implications on the transportation system. Manufacturers and retailers can use more environmentally friendly transportation modes, or reduce the need for transportation by buying from on-shore suppliers as well as centralizing warehouses. On the other hand, logistics providers can work on reducing the carbon intensity of the energy they use and increase the energy efficiency of their operations by freight consolidation or by improving the technical features and the maintenance of their vehicles (McKinnon, 2010). Additionally, there are actions which can help improve the system through the interaction of the overall operations. One example is coordinating production schedules among suppliers to allow joint shipments which results in better vehicle utilization and hence fewer emissions (Bonney and Jaber, 2011).

Similarly, in this paper we analyse the economic and environmental implications of a serial inventory system through such an interaction effect: the indirect effect of transport lead time variability through the replenishment policy on economic and environmental performance of supply chains. In order to develop sustainable operations we need to understand the effect of system parameters on environmental performance. In this study we are interested in the impact of a system parameter, transport lead-time variability, on carbon emissions.

As Fransoo and Lee (2012) put it, although ‘containerised ocean transport has become the lifeline of almost any global supply chain’, there appears to be little or no attention to end-to-end supply chain focus. Similarly, in a recent review, Tang and Zhou (2012) conclude that there is a need to develop and analyze end-to-end supply chain models that incorporate the issue of sustainable operations. Although we do not consider a complete end-to-end supply chain, we still consider the interactions of different parts of the supply chain.

When we consider global supply chains with overseas transportation, air freight and containerized ocean transportation are the two relevant modes of transportation. Decreasing lead-time variability is an operational improvement which can indirectly affect the carbon emissions on the whole supply chain by triggering actions and policies from shippers that lead to lower carbon emissions. It is commonly acknowledged that unanticipated variability in demand and/or lead-time is the major reason for stock-outs or excess inventories in supply chains. As the ocean carrier is able to reduce the lead-time variability under certain conditions, the need for both emergency shipments by air freight as well as safety stocks will decrease, which will also have significant impacts on the environmental performance of the supply chain.

Economic implications of lead-time variability have extensively been studied. Song (1994), He et al. (2005), and Song et al. (2010) analyse the effect of lead-time variability on optimal inventory control policies and the resulting total costs under standard inventory control policies. With a simulation study of a multi echelon supply chain Chaharsooghi and Heydari (2010) show the significant impact of lead-time variability on performance measures such as inventory levels, product availability and bullwhip effect.

The time factor is a critical component in ocean transportation. Shipping lines have developed a strong focus on designing liner services with high frequencies, short transit times, combined with a high degree of schedule reliability. Variability in transportation time and the resulting delays not only decrease the reliability of the liner services, but can also incur additional costs (Notteboom, 2006).

Delays have negative impact not only on economic performance but also on environmental implications. McKinnon (2007) presents a framework where seven sustainability ratios link supply chain activities with the carbon emissions of freight transport operations. Sanchez-Rodrigues et al. (2010) study the negative impact of operational uncertainty on the seven key ratios. They present the perceived economic and environmental risks of transport uncertainty based on focus groups and surveys from different industries including manufacturers, retailers, and logistics providers. Delays are identified as the main source of transport uncertainty which has the highest economic and environmental risk.

Recently, several models and policies have been developed which consider an environmental objective or constraint in addition to the economic objectives. Generally, environmental considerations are included in the models as they are imposed by regulations: either as limits on carbon emissions or as costs derived from carbon taxes or carbon trading.

Benjaafar et al. (2010) study how classical operational models can be modified to include carbon emission concerns in order to address the role of operational decisions on carbon reduction. In a following study, Chen et al. (2011) analyse the classical EOQ model with a carbon constraint and extend the results to the newsvendor model and facility location problems. They provide conditions under which carbon reductions can be achieved without significantly increasing cost using only operational adjustments. Similarly, Hua et al. (2011) and Song and Leng (2012) analyse the EOQ and newsvendor models respectively under carbon cap-and-trade mechanism and show that under some conditions it is possible to reduce carbon emissions and decrease cost or increase profit at the same time. Jaber et al. (2012) model a two echelon supply chain considering emissions trading. Using an EOQ type formulation they consider different legislative systems such as carbon tax, emissions penalty, and a combination of a carbon tax and penalty.

In addition to identifying optimal policies for companies, these studies provide insight about the effectiveness of different regulations on emission reductions. However, this implies that most of the research on operations including carbon emissions ignores market forces including competitors and consumers (Tang and Zhou, 2012). An exception is El Saadany et al. (2011) who study a two-level supply chain under cost optimization objective where demand is assumed to be a function of several product features including its environmental performance. Bouchery et al. (2012) state that the regulation based models poses a restriction with respect to their relevance and applicability. They study a multi-objective model in order to avoid this problem and apply their model for the EOQ problem. They identify the efficient frontier between total cost and total amount of carbon emissions resulting from the inventory system, and further use this to analyze the effectiveness of different regulations.

Hugo and Pistikopoulos (2005) and Frota Neto et al. (2008) address the supply chain network design problem using multi-objective models with environmental and economic criteria. They identify settings where significant improvements in one criterion can be achieved with marginal compromise in the other one. Similarly, Chaabane et al. (2012) show how to achieve environmental objectives in a cost efficient way while designing supply chains under carbon

regulations. On the other hand, Harris et al. (2011) present a network design problem with a classical economic objective of cost minimization in order to study the impact of this approach on environmental performance. They analyse the relation between total logistics cost and their environmental impact in terms of carbon emissions from transportation and warehousing. They highlight that the cost-optimal solution is not necessarily the same as the solution which minimizes environmental impact.

The remainder of the paper is organised as follows: Section 2 presents our model and the modelling assumptions. We present the findings from our model based on a simulation study in Section 3, and Section 4 finally concludes the article.

Problem Description

This paper studies a serial inventory system consisting of a shipper, i.e. a manufacturer or a retailer who works with overseas suppliers and has to decide on replenishments in the presence of uncertain customer demands as well as uncertain lead times associated to ocean freights (see Figure 1). The retailer uses a common continuous review inventory control system to determine the size and timing of orders and issues a regular order whenever the inventory position reaches the reorder point. Lead time for regular sea freight deliveries is assumed to be uncertain and is consists of the average lead time and a lead time delay which is common with regard to containerized shipping (c.f. Drewry, 2010). Besides, the retailer also employs an emergency supply mode via air freight to hedge against shortages and to ensure a 100% customer service level. This setting is observable in many practical scenarios, for example in highly competitive industries in which supply bottlenecks lead to the migration of customers or high contract penalties if the guaranteed service level targets were infringed. Air shipments usually have a short and rather predictable lead time compared to regular deliveries at the expense of higher transport cost and CO₂ emissions per item and are assumed to arrive within the same day (see Moinzadeh and Nahmias 1988, Johansen and Thorstenson 1998, Axsäter 2007 or Huang et al. 2011 for a similar setting). In order to quantify the effect of lead time variability reduction on carbon emissions and supply chain performance, we present and analyse a simulation model based on a standard multi-period inventory control policy in such a dual transportation mode setting.

Figure 1

As there is still a lack of global, integrative performance metrics that combine environmental and operational measures and targets, in practice many organisations treat these concerns separately (El Saadany et al., 2011). Therefore, two different scenarios with respect to the measurement of the global performance of the supply chain and the inducible decision objectives are studied in the remainder of the paper.

Under the first scenario, it is assumed that the replenishment policy is based on cost minimization without consideration of the environmental performance during the decision making process. This scenario can be considered as the one closer to practice as most of the commonly used inventory policies are based on cost minimization. Since with the availability of emergency option all demand is satisfied, a customer service level criterion is not relevant in this setting. Our aim is to identify the impact of consequent transportation performance on CO₂ emissions under such a classical cost based approach.

The second scenario takes the complete opposite approach where the inventory levels are set according to a pure emission minimization objective. Our aim with this scenario is to identify the cost of minimizing environmental impact by comparing the results of the two scenarios. We do not combine the two objectives in a multi-objective model nor we include the environmental performance as a constraint or try to convert the emissions into monetary units and use it in the cost minimization. This way we avoid using a regulation based model as mentioned in the previous section. Rather than developing a prescriptive model we illustrate the interactions among the two distinct objectives and the relation between system parameters under different settings.

Simulation model

The purpose of the following simulation mode that considers the inventory system described above is to find the optimal model parameter based on the given setting and to evaluate the system in different parameter settings for a given policy.

Figure 2

Figure 2 illustrates the decision process. The retailer faces a random daily demand which is satisfied from on-hand stock as long as possible. Whenever the inventory position declines to or below the reorder level, a regular order is issued that is delivered by the carrier via containerized sea freight and whose lead time is affected by uncertain delays in shipping times. Demands that cannot be fulfilled by on-hand stock will be served by emergency orders by air freight within one day at the expense of higher unit transport cost. As there is no fixed ordering cost for emergency replenishments assumed, the manufacturer will satisfy the daily shortages by emergency supplies.

The supply chain model discussed above is simulated using AnyLogic 6.8.1 software and is based on a discrete event simulation model to describe the sequence of operations within the system.

Inventory Control Policy

In the setting described above, the manufacturer decides on the stock levels as well as the reorder behaviour and deploys the carrier for the deliveries from overseas suppliers. Besides these regular replenishment processes, he can also use emergency supplies via air freight, i.e. a second means to deliver with negligible lead times but at the expense of higher transport costs and emissions.

As mentioned in Axsäter (2007) and Huang et al (2011) accomplishing emergency orders usually imposes a direct unit cost which is in or case related to the increase in shipment cost per unit by using air freight instead of container shipping and avoids ordering cost for normal replenishments. Furthermore, as the demand fulfilled by emergency deliveries disappears from the regular replenishment process, the changes of the system state are essentially equivalent to a lost-sales approach.

Since it is difficult to obtain the optimal policy for an inventory system with emergency orders, heuristics and approximations are commonly used. Minner (2003) provides an extensive review on inventory policies with multiple supply modes. There exist several models based on the extensions of (Q,r) policy. For example, Johansen and Thorstenson

(1998), and Axsäter (2007) provide heuristics based on (Q,r) policy for triggering emergency orders. Jain et al. (2010) study a make-to-order system with two transport modes where they assume a (Q,r) policy and derive the optimal policy parameters. Huang et al. (2011) provide a heuristic decision rule for an inventory system with emergency orders and partial backordering where the normal orders are set according to a (Q,r) policy. These models assume a positive lead time for emergency orders while we assume zero lead time for the emergency orders. Furthermore we assume that all demand which cannot be immediately satisfied has to be satisfied through an emergency order. These two assumptions make our model simpler and we do not really need a decision rule for when to put an emergency order and the size of the emergency order. Our decision variables are the size of the regular shipments.

The regular ordering using ocean transportation can be seen as a lost sales system. Sheopuri et al. (2010) presents the connection between the lost sales inventory control problem and the dual sourcing problem. Based on their findings, we can observe that the dual mode system that we consider is identical to a lost sales system where the regular mode is the only supply source and the amount of orders placed from the emergency mode is exactly the amount of lost sales in the regular mode every period.

For lost sales systems, the (Q,r) policy has been studied extensively, but it remains difficult to analyze the model exactly and determine the optimal values for Q and r. Bijvank and Vis (2011) provide a recent review on lost sales inventory models.

In practice, it is common to derive the order quantity Q from a deterministic model using mean demand and lead-time, and stochasticity is considered while determining the reorder point r. This procedure is generally an adequate approximation to the optimal policy (Axsäter 2006). In this study, we determine Q from the economic order quantity (EOQ) model, and find the optimal reorder point by simulation. We have used the default optimization engine in AnyLogic which is based on OptQuest Optimization Engine.

Calculating logistical parameters

To create a rather realistic description of the considered problem setting, the simulation model is based on data from different sources such as reports from public authorities and industry groups as well as internal operating data collected from a UK retailing company. An overview of the considered model parameters is given in Table 1, whereas their derivation is explained in detail in the following paragraph.

Table 1

Demand characteristics are based on the average daily product demand of the considered retailer. To achieve comparability between different product classes, demand is assumed to follow a normal distribution where the daily mean demand is normalized and different levels of the standard deviation are considered within the simulation. We consider products with stationary demand, where seasonality and trend are not significant. Hence, variability of demand refers to the forecast error, which in this setting stems from uncertainty in the demand process.

As the considered products are purchased from overseas suppliers on a make to stock basis,

lead time for regular replenishments is predominantly influenced by transportation lead times (see Tersine and Hummingbird, 1995) and thus, the performance of the oversea carrier which is mainly determined by two key factors, transit time and schedule variability (Notteboom, 2006). Regular shipping time is chosen on the basis of typical transit time between the two considered ports. In addition, variability of these shipping times is included by considering delays appearing within these regular schedules. This schedule variability can be described by difference between the planned arrival date and the actual arrival date and is influenced by different factors such as terminal operations, port access, maritime passages and chance (Notteboom, 2006). Therefore, additionally to the regular fraction of the shipping time, a gamma distributed delay with mean of one day and a standard deviation of 2.05 days is considered, which reflects the average schedule reliability statistics for all types of carriers on this specific route (see Drewry, 2010). The variability appears to be comparatively small, but always depends on the considered route and the individual ocean carrier deployed.

Inventory holding cost include the physical holding cost as well as the cost of capital and are also derived by the internal data provided by the retailer. The fixed element of the ordering cost consists of the fixed cost for ocean freight such as booking and documentation fees as well as the internal documentation and administration expenses and amounts to 195 USD. For the derivation of the variable sea transport cost per item all the cost associated with a FFT container such as hinterland transport cost in Asia and Europe, the ocean freight rates as well as customs and port handling fees are considered on the product level by assuming a full container load and an average product size. It is implied that remaining container space may be used for other products as well. A similar approach is used to derive the air transport cost per item. After considering all air freight cost per kg, such as transport cost, direct air freight cost, security and handling fees, the air transport cost rate is determined by assuming an average product weight. Table 2 summarizes all the relevant cost factors and the derivation of the variable transport cost per item for the employed transportation alternatives.

 Table 2

Calculating CO₂ emissions

The presented approach considers the overall carbon emissions of the inventory system on an end-to-end supply chain focus as the sum of transport related and warehouse related emissions which can be identified as the main drivers of environmental pollution in global supply chains (see WEF, 2009).

As the presented study is based on a retailer that works with different carriers and doesn't have in-house transport operations that provide direct access to energy data, the transport related CO₂ emissions are estimated on the level of transport activity. Thus, to calculate the emissions from transportation, the average product weight, the distances for ocean and air freight and the respective ocean and air freight emission factors are considered as follows:

$$\text{kgCO}_2 / \text{item} = \text{average item weight} * \text{distance} * \text{CO}_2 / \text{tonne-km}$$

where an average emission factor of 8 gCO₂/tonne-km is assumed for container vessels and 602 gCO₂/tonne-km for airfreight (cf. McKinnon and Piecyk, 2010).

For the calculation of CO₂ emissions from the distribution warehouse, we estimated the

average daily emissions per product based on the energy consumption (kWh) of fuels and electricity spent on lighting and air conditioning. Note that in the considered inventory system, the products don't require a specialized storage environment, i.e. extensive cooling or heating. Consequently, the warehouse emissions per item within a year are calculated by using energy consumption benchmarks for retail warehouses and respective conversion factors as well as the provided warehouse capacity and average stock size:

$$\text{kgCO}_2/\text{item} = (\text{warehouse capacity}/\text{average stock size}) * \text{energy benchmark} * \text{conversion factor}$$

where an energy benchmark for electricity of 67 kWh/m² and for fossil fuels of 169 kWh/m² is used (CIBSE, 2004). The respective conversion factors for electricity of 0.54 kgCO₂/kWh and for fossil fuels of 0.27 kgCO₂/kWh are used to derive the appropriate emissions (DEFRA, 2012), which leads to overall warehouse emissions of 81,81 kgCO₂/m². Considering the average stock size of 250,000 products and the area of the warehouse of 5,500m², this leads to a daily emission of 0,005 kg CO₂/item. In this case, it is implicitly assumed that a reduction of the amount of products stored leads to reduced emissions as the warehouse space may also be used for other products.

Results

Effect of lead time variability on cost and emissions

With the given parameters we can observe that cost optimal re-order points r_c^* is always smaller than the emission optimal re-order point r_e^* . This is a result of the relation between two ratios: the sea-air freight cost ratio and the sea-air freight emission ratio. Because of the large air freight emissions, optimisation on emissions results in higher safety stocks and hence lower emergency shipments.

The direct effect of lead time variability on total cost and total emissions is illustrated in Figures 3 and 4.

Figure 3 + 4

Figure 3 shows the increase of mean total cost and their 95% confidence intervals in δ_L . As expected, total cost increase in δ_L , which is perfectly in line with the literature and validate our model. Figure 4 shows the corresponding effect of δ_L on mean total emissions and their 95% confidence intervals. Intuitively total emissions are also increasing in δ_L , since both safety stocks and the amount of air shipments increase.

Table 3: Optimality gap between cost and emission optimization, sea:air cost ratio 1:10.5, emission ratio 1:32

σ_L	$\Delta TC \%$	$\Delta TE \%$
1.00	0.08%	0.03%
2.00	0.16%	0.52%
3.00	0.13%	1.17%
4.00	0.25%	1.42%

Table 4: Optimality gap for an alternative product with sea:air cost ratio 1:6 and emission ratio 1:50

σ_L	ΔTC %	ΔTE %
1.00	0.39%	0.88%
2.00	0.65%	4.82%
3.00	0.60%	10.92%
4.00	0.57%	15.71%

Tables 3 and 4, and Figures 5 and 6 show how a change in the objective from minimizing total cost to minimizing total emissions affects the shipper. Let $\Delta TC = (TC(r_e^*) - TC(r_c^*)) / TC(r_c^*)$ be the relative cost difference: The increase in cost if the shipper decides based on emission minimisation instead of cost minimisation. Similarly, $\Delta TE = (TE(r_c^*) - TE(r_e^*)) / TE(r_c^*)$ is the decrease in total emissions when the shipper minimizes total emissions instead of total cost.

As can be observed this optimality gap depends mainly on the relation between the cost and emission ratios. The more different these two ratios become the larger the optimality gap is.

In the base case in Figure 5, we observe a cost ratio of 1/10.5 (3.84/40.90) together with an emission ratio of 1/32 (1.76/56.80). Under this relation, the optimality gap both on cost and emissions are very small. This implies that the pricing is able to regulate the system such that cost optimal policy and the emission optimal policy are very close to each other.

For products with different characteristics which can lead to a more divergent cost and emission ratios would cause the optimality gap to grow. In Figure 6 with a cost ratio of 1/6 and emission ratio of 1/50, especially for high levels of δ_L , a change in the policy has a strong effect on the environmental performance (here around 15% savings in emissions for the highest lead time variability), which comes with a small increase in total cost (below 1% for all values of lead time variability).

While we can observe that the optimality gap on total emissions can be quite considerable, especially for large δ_L , the gap on total cost is typically rather low independent of the cost and emission ratios. This can be explained with the fact that cost functions are typically steep left of the cost optimal re-order point where high cost of air freight are relevant. Right of the cost optimal re-order point the cost function is rather flat as holding cost are typically much lower than air-freight cost. Since $r_c^* < r_e^*$ changing the objective from cost to emission minimisation does not harm the economic performance but improves the environmental performance considerably.

 Figures 5 + 6

Impact of ratio air:sea freight emissions

Figure 7 shows how a change in the emission rate of air freight from a basis value of 23 impacts total cost, when the objective is to minimize emissions. For low levels of demand variability ($c_{VD} = 0.2$ and $c_{VD} = 0.4$), total cost are almost unchanged in a change of air

emissions. This again confirms the finding that emission optimisation has little impact on the total cost. Only for high levels of demand variability ($cv_D = 0.6$), increasing air freight emission rates impact the order policy strong enough that a significant decrease in total cost can be seen, which is caused by increased safety stocks and hence decreased air shipments.

Figure 8 shows the impact of increasing air freight emissions from a basis value on total emissions, again with the objective to minimise emissions. Higher levels of demand uncertainty ($cv_D = 0.6$) have a stronger impact on the change in total emissions.

Figure 7 + 8

Impact of ratio air:sea freight cost

In order to analyze the effects for a cost minimizing shipper, Figure 9 shows the impact of air freight cost on total cost. This is again perfectly in line with the literature. Figure 9 shows the effect of air freight cost on total emissions of the shipper. Clearly an increase in air freight cost reduces the percentage of air freight necessary and hence also emissions. Note that as $r_c^* < r_e^*$, the decrease in r_c^* has a significant impact on emissions.

Figure 9 + 10

Detailed cost and emission analysis

In Figures 11 to 14 we illustrate the distribution of costs and emissions between warehousing and air freight. The reason for choosing these two is that both warehousing and air freight are measures to deal with uncertainties in the system. Uncertainties can be either covered by safety stocks or by emergency shipments. Since by far the largest part of quantity shipped through ocean shipping is independent of variabilities, cost and emission related to ocean shipment are almost fixed for all levels of lead time and demand variability.

Figure 11 shows the emissions from warehousing and airfreight for different levels of σ_L under emission minimization. On the other hand Figure 12 shows the same under cost minimization. It can be observed that under emission minimization it is mainly additional safety stocks that cover the increase in uncertainty of lead time as typically warehousing related emissions are considerably smaller than emissions of air shipment. Under the cost minimization criterion mainly air freight covers additional lead time variability.

Figures 11 + 12

In Figure 13 and 14 we show warehousing and air shipment cost under emission and cost minimization, respectively. Under emission minimization we can again observe that additional lead time variability is covered by safety stocks, air shipments remain almost constant. Under cost minimization, both additional safety stocks and air shipments are used to cover uncertainty. The main cost implication is on air shipments.

As discussed previously cost is rather insensitive to the level of re-order points within these ranges, while emissions can change considerably. As a result, the (emission) values in Figures 11 and 12 become very different for high lead time variability, while the (cost) values in Figures 13 and 14 are relatively similar.

Conclusion

In this study we quantified the effects of variability in deep sea container shipping on emissions and total cost for a retailer or manufacturer with high service level requirements. An important finding is that a change in the optimal policy from cost to emission minimization has a low impact on cost, but can have a considerably high impact on emissions. We showed this based on the optimality gap between cost and emission optimization.

As this study is based on data from the case of a typical UK retailer and real-world cost and emission data, an additional value of this work is to provide estimates on the absolute cost and emission implications of typical ocean freight lead time variabilities. This is particularly relevant as recently ocean carriers have begun to offer ‘perfect reliability’ (i.e. aiming zero lead time variability) in containerized ocean shipping on major routes from Far East to Europe. In this sense our paper provides an illustrative case how such a change in shipping lead time variability affects a typical retailer’s cost and emission performance through inventory policies.

An immediate extension of this work is to consider more levels of the supply chain and including the potential variability on different echelons. Production lead time on the supplier site and the transportation time on road/rail from the supplier to the port and from the central warehouse to further stocking points and customers are potential causes of variability and inefficiency in the supply chain. Moreover, the consideration of different transportation modes as well as the combination in intermodal logistics networks may lead to further interesting results.

There exists a large body of literature on supply chain network design considering the environmental impact. Combining the strategic and tactical levels of supply chain planning with an eye on the environmental performance would be another challenging research topic. A plethora of works exist on the simultaneous analysis of the strategic network design and the interaction with tactical and operational level problems such as inventory control and transportation decisions. However, the environmental performance of such an integrated model has not been covered yet. It is worthwhile to look at the interaction of the two levels of problems from the environmental sustainability aspect.

In this study we did not consider holding cost for pipeline inventory, which is a result of cost of capital and depreciation, and is very common and significant for products with a short life cycle. For example, in the electrical machinery industry depreciation rate per day accounts for around 1% of the product’s value (see Hummels 2000). In such a setting we would expect to see an even higher proportion of air shipment if the objective is cost minimization. This would increase the gap between emission and cost optima even further.

Moreover, in our simulation approach we employed the direct carbon emissions caused by transportation and storage of goods as an indicator for the environmental performance of the inventory system. More sophisticated environmental performance metrics that include a variety of qualitative and quantitative measures (c.f. El Saadany et al., 2011) could be used to illustrate the different environmental impacts of such a system and the ensuing customer behaviour.

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Tables and Figures

				Table 1: Default model parameter used for simulation study, if not mentioned otherwise
Parameter	Value	Description		
d	= 100.00	Mean demand per day		
cv_D	= 20%	Coefficient of demand variation		
L	= 30.00	Mean lead time		
σ_L	= 2.05	Standard deviation of lead time		
c_h	= 0.01	Holding cost rate per item		
c_s	= 3.84	Sea transport cost rate per item		
c_a	= 40.80	Air transport cost rate per item		
c_o	= 195.00	Fixed cost per regular order and delivery		
e_h	= 0.005	CO2-emission storage per item and day		
e_s	= 1.76	CO2-emission sea transport per item		
e_a	= 56.80	CO2-emission air transport per item		

Table 2: Calculation of transport related cost factors

Cost factors sea transport	per FFTC	Cost factors air transport	per kg
Hinterland transportation to Yangshan terminal	357 USD	Transportation from vendor to Pudong airport	0.30 USD
Yangshan port terminal handling	120 USD	Air Freight	0.97 USD
Customs brokerage	50 USD	Security fee	0.18 USD
Ocean freight rate and security fee (including cost of fuel)	3510 USD	Handling cost	0.14 USD
Import customs clearance to UK	90 USD	Fuel surcharge	1.82 USD
Felixstowe port terminal handling	270 USD	War risk charge	0.13 USD
Delivery from Felixstowe terminal to customer	750 USD	Heathrow airport handling	0.24 USD
		Delivery from Heathrow airport to customer	0.30 USD
Total sea transport cost per FFT container	5147 USD	Total air transport cost per kg	4.08 USD
Sea transport cost per item*	3.84 USD	Air transport cost per item**	40.80 USD

* with 1340 products of average size per FFT container

** with an average product weight of 10 kg

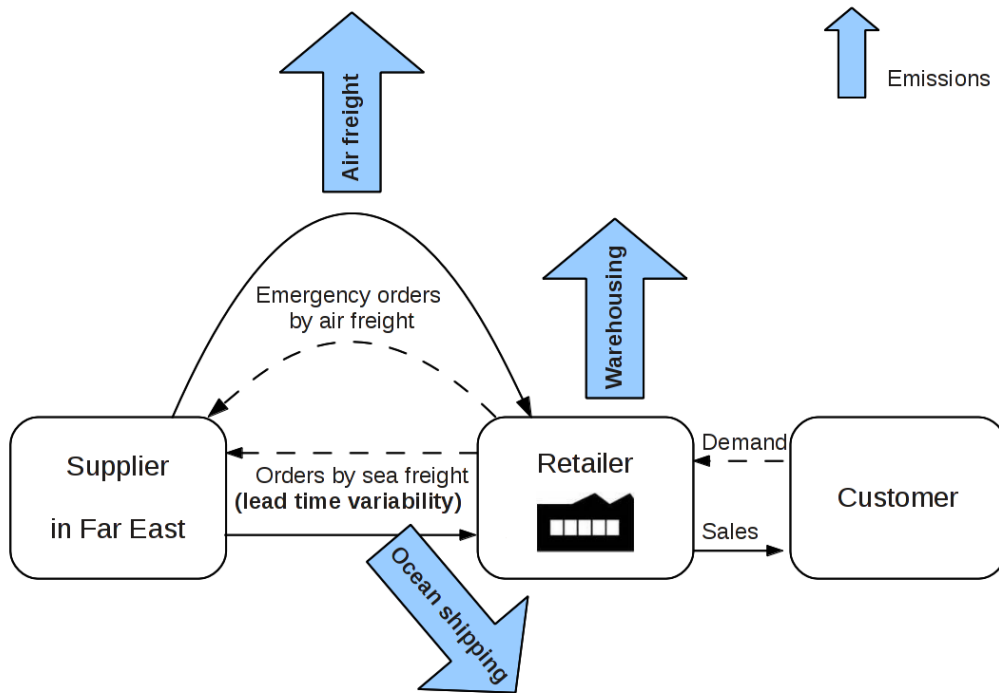


Figure 1: Schematic diagram of the two stage supply chain with air freight, ocean shipping and warehousing emissions

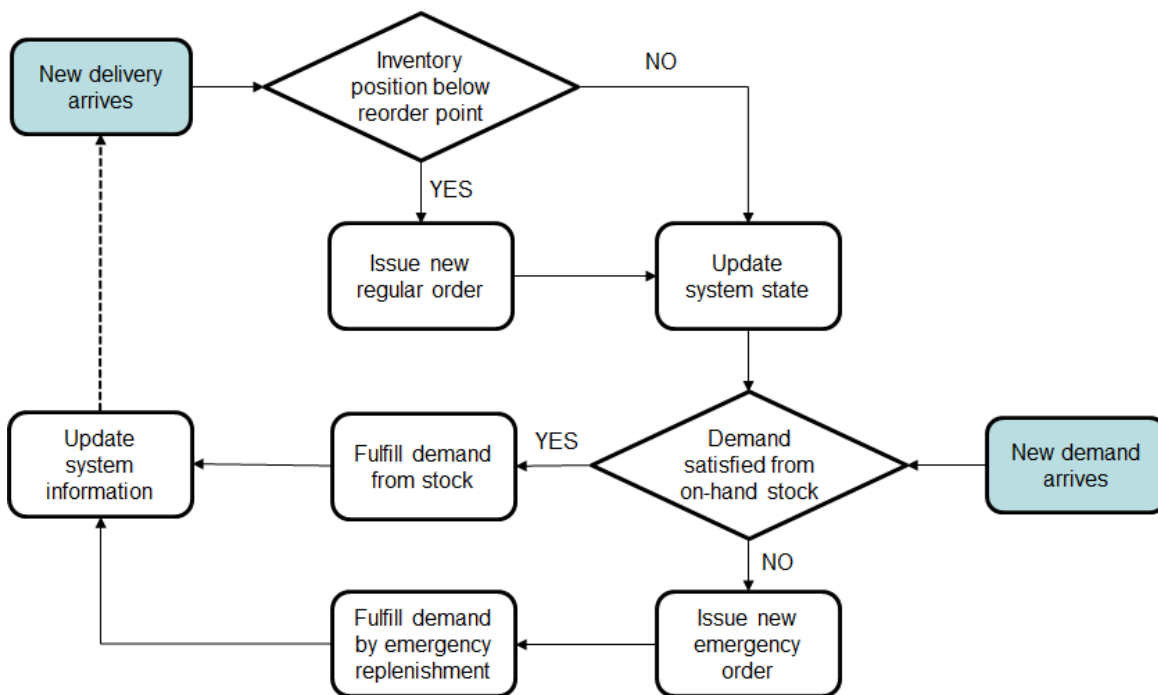


Figure 2: Decision flow chart of the inventory control and re-ordering subsystem of the simulation model

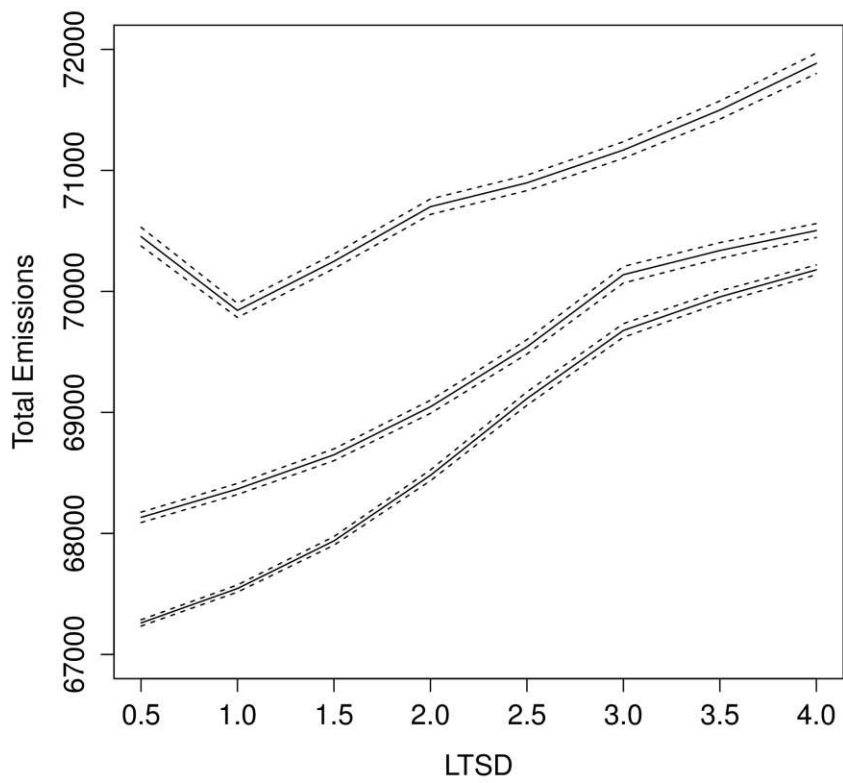


Figure 3: Total emissions over σ_L for different levels of demand uncertainty: $cv_D = \{0.40, 0.20, 0.01\}$ for top, middle and bottom plot, with 95% confidence intervals.

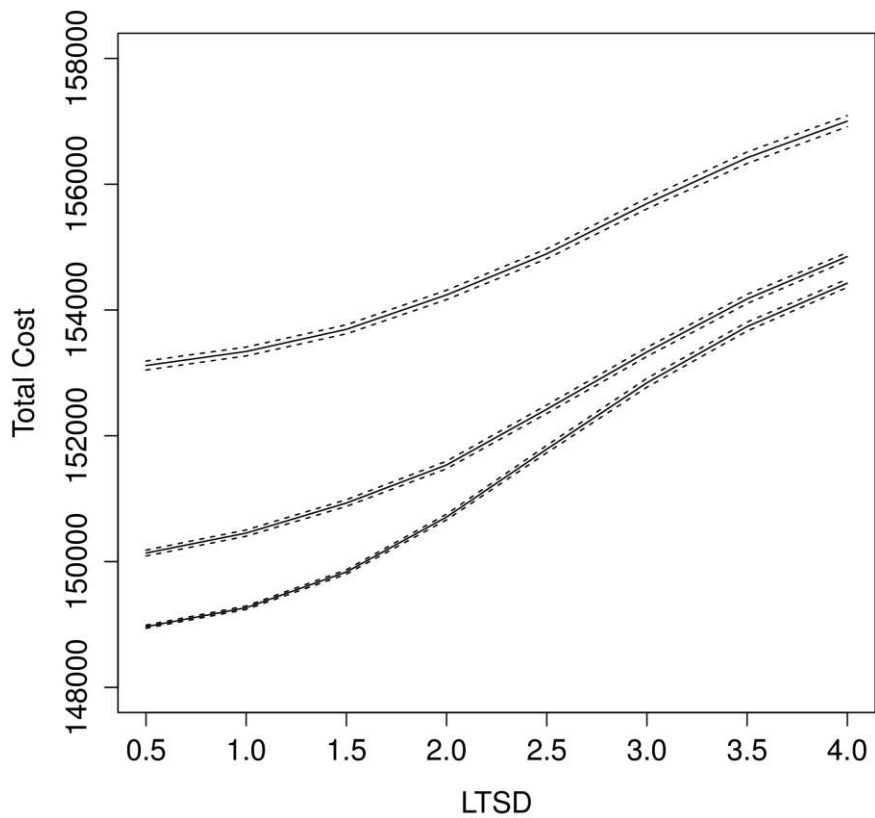


Figure 4: Total cost over σL for different levels of demand variability: $cv_D = \{0.40, 0.20, 0.01\}$ for top, middle and bottom plot, with 95% confidence intervals.

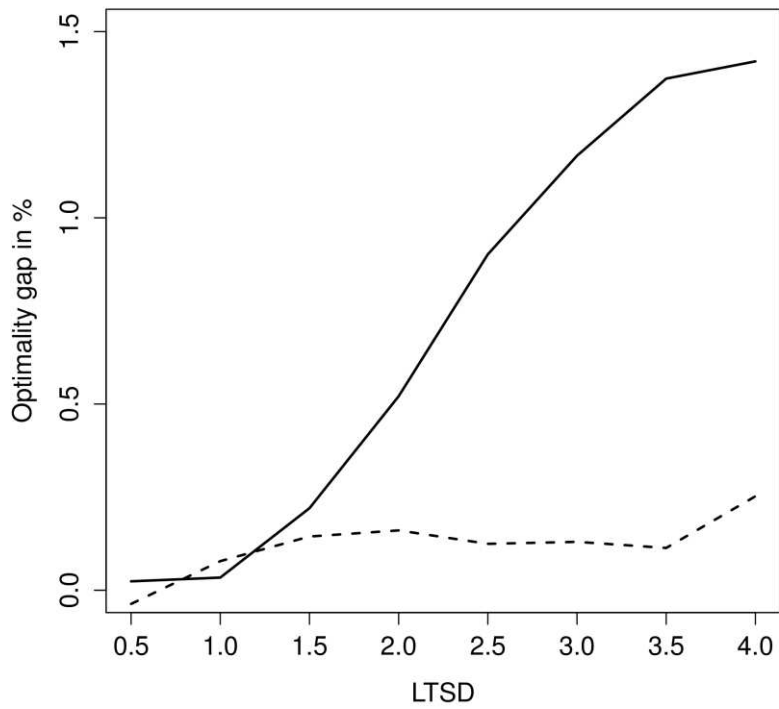


Figure 5: Optimality gap in % of emissions (solid line) and cost (dashed line) for a product with sea:air cost ratio 1:10.5 and sea:air emission ratio 1:32, $cv_D = 0.20$.

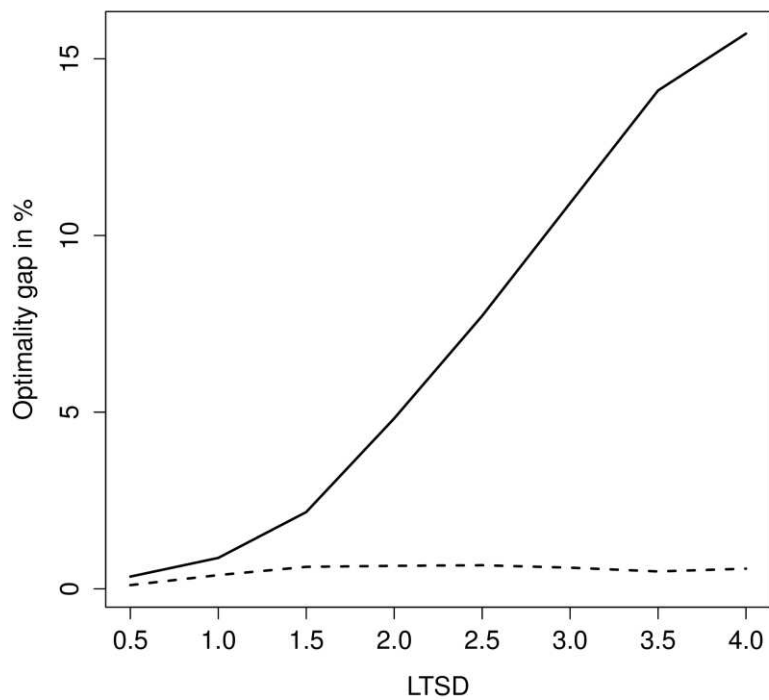


Figure 6: Optimality gap in % of emissions (solid line) and cost (dashed line) for an alternative product with more diverge sea:air ratios: a cost ratio of 1:6 and an emission ratio of 1:50, $cv_D = 0.20$.

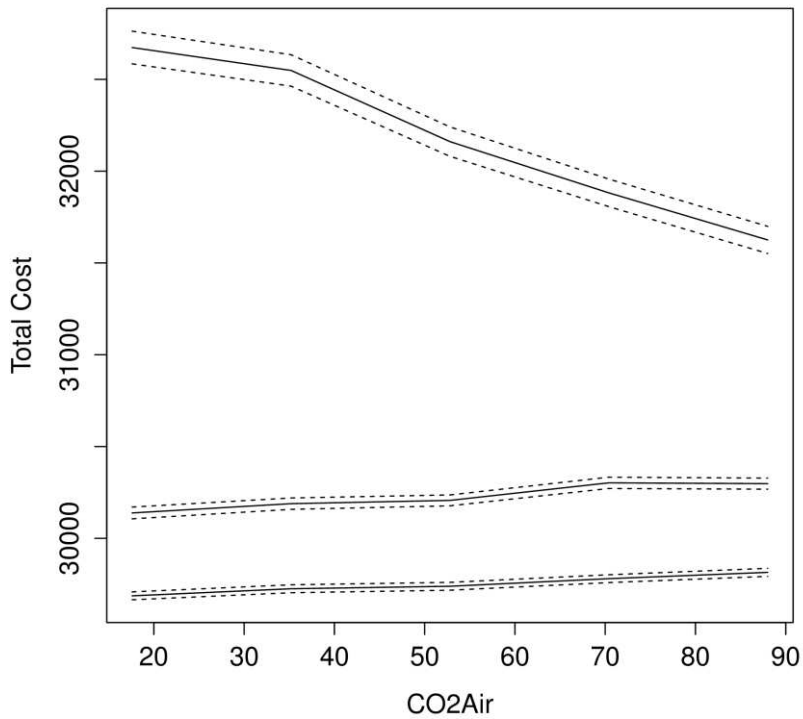


Figure 7: Sensitivity analysis of total cost with respect to emissions of air freight with an emission minimization objective, $cv_D = \{0.60 \text{ (top)}, 0.40 \text{ (mid)}, 0.20 \text{ (bottom)}\}$, and 95% confidence intervals.

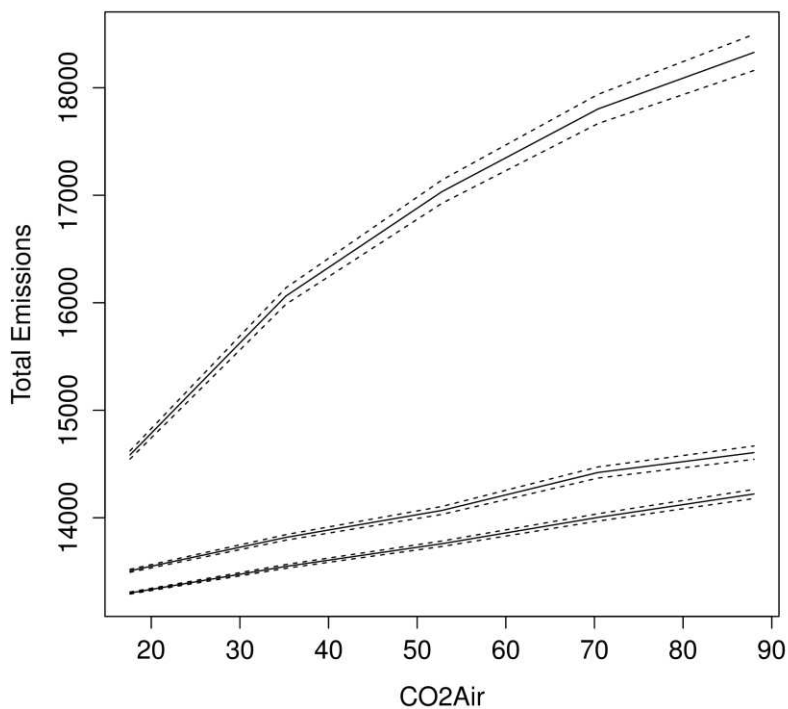


Figure 8: Sensitivity analysis of total emissions with respect to emissions of air freight with an emission minimization objective, $c_{VD} = \{0.60 \text{ (top)}, 0.40 \text{ (mid)}, 0.20 \text{ (bottom)}\}$, and 95% confidence intervals.

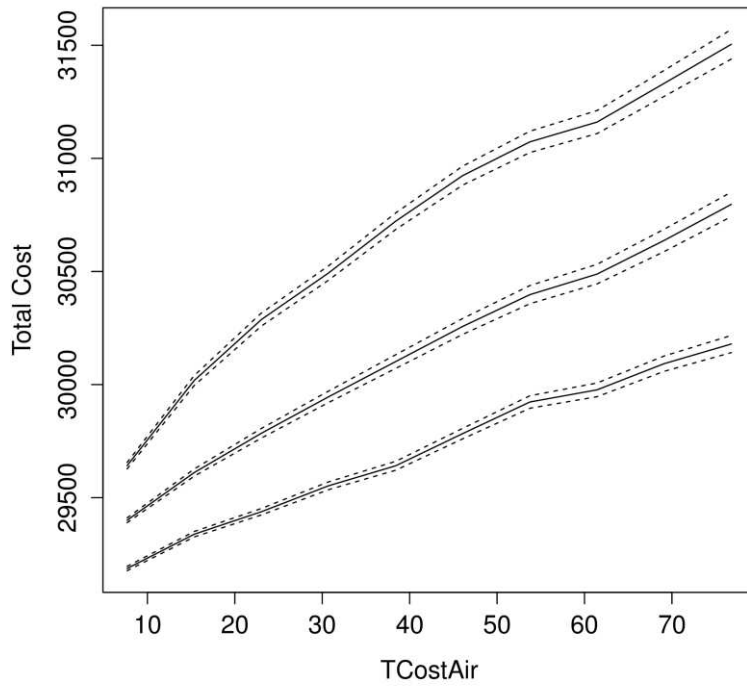


Figure 9: Sensitivity analysis of total cost with respect to cost of air freight with a cost minimization objective, $c_{VD} = \{0.60 \text{ (top)}, 0.40 \text{ (mid)}, 0.20 \text{ (bottom)}\}$, and 95% confidence intervals.

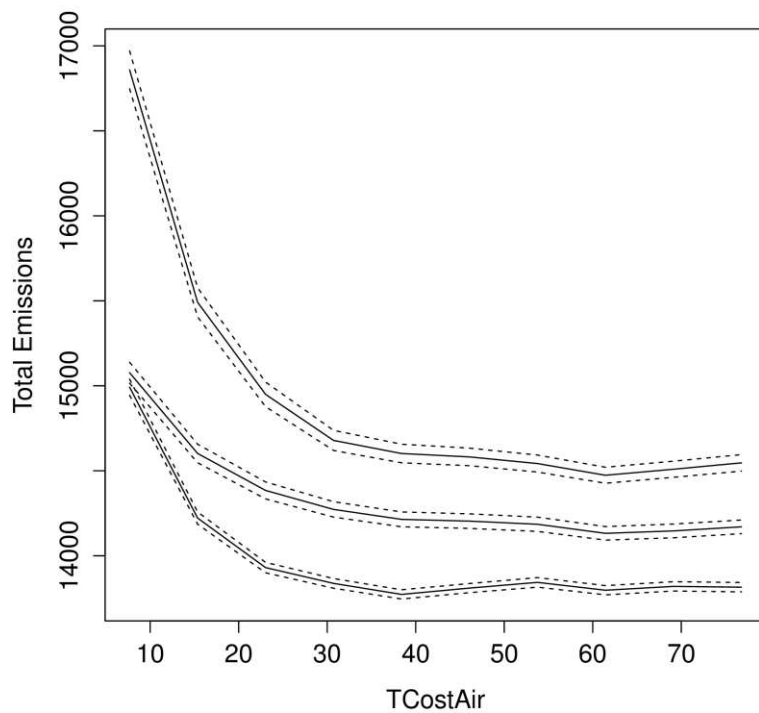


Figure 10: Sensitivity analysis of total emissions with respect to cost of air freight with a cost minimization objective, $cv_D = \{0.60 \text{ (top)}, 0.40 \text{ (mid)}, 0.20 \text{ (bottom)}\}$, and 95% confidence intervals.

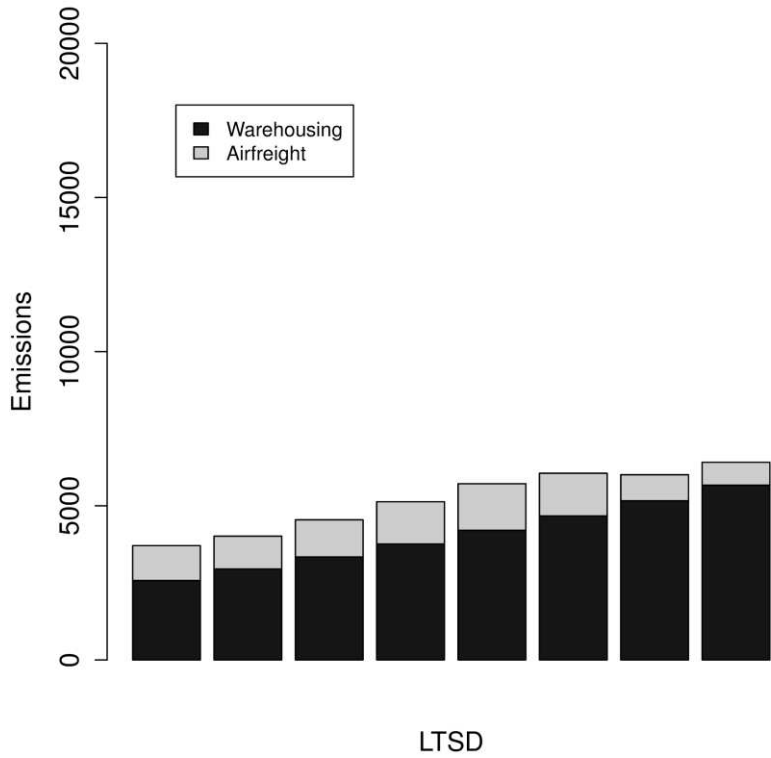


Figure 11: Detailed emissions of warehousing and air freight using r_e (emission optimal re-order point), $cv_D = 0.20$.

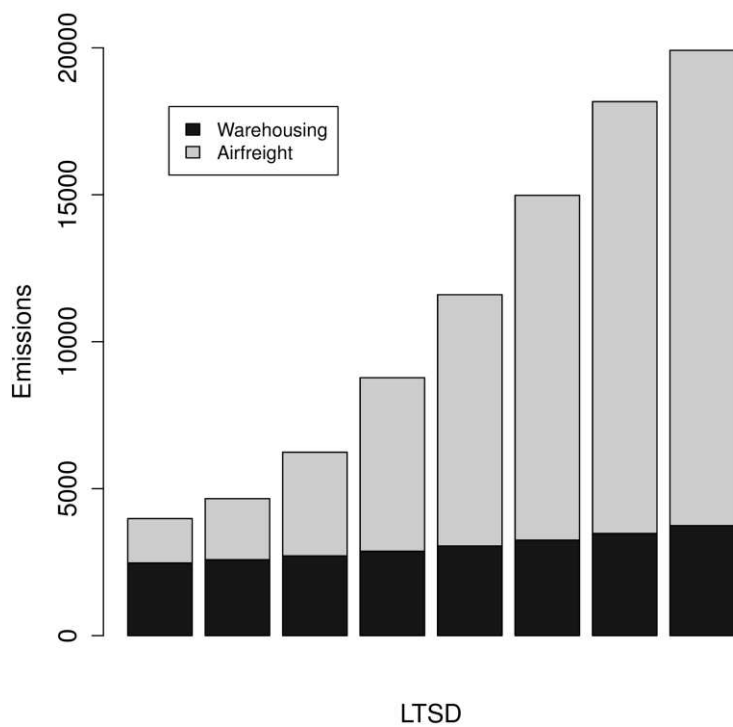


Figure 12: Detailed emissions of warehousing and air freight using r_c (cost optimal re-order point), $cv_D = 0.20$.

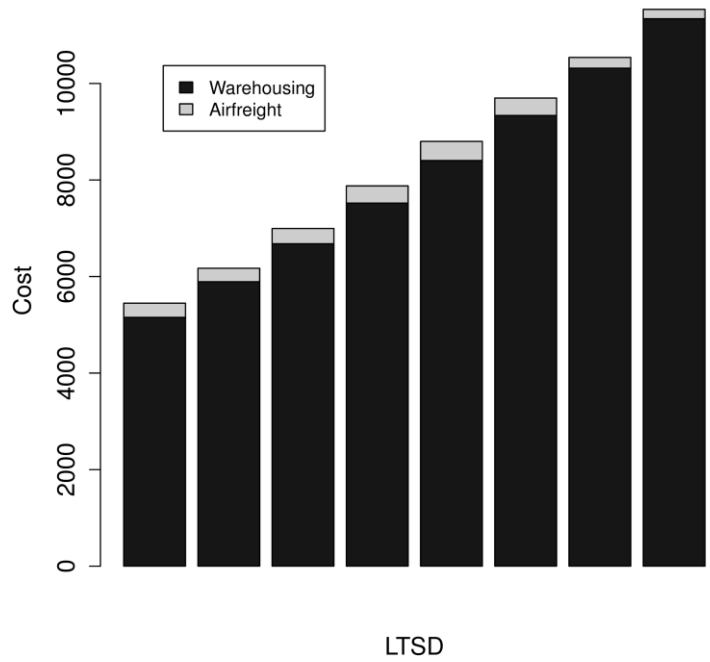


Figure 13: Detailed cost of warehousing and air freight using r_e (emission optimal re-order point), $cv_D = 0.20$.

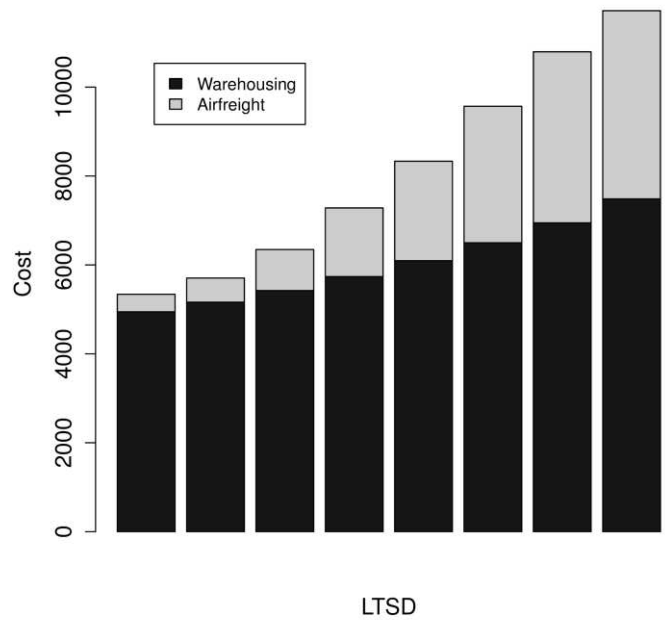


Figure 14: Detailed cost of warehousing and air freight using r_c (cost optimal re-order point), $cv_D = 0.20$.