

International Journal of Production Economics

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Article information:

Post-Print version

To cite this document:

Guido J.L. Micheli, Fabio Mantella, (2018) "Modelling an environmentally-extended inventory routing problem with demand uncertainty and a heterogeneous fleet under carbon control policies", International Journal of Production Economics, Vol. 204, pp.316-327.

Permanent link to this document: <https://doi.org/10.1016/j.ijpe.2018.08.018>

Modelling an environmentally-extended inventory routing problem with demand uncertainty and a heterogeneous fleet under carbon control policies

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Abstract

Carbon emissions produced by supply chain activities, and in particular by transportation, contribute substantially to global warming. In order to tackle this problem, many governments and regulatory authorities have started to implement carbon control policies, which may directly impact on the decisions of a company. In a traditional inventory routing problem, a supplier determines the optimal vehicle routing and scheduling of deliveries, based on the observed inventory levels of the customers, to minimise the costs of the entire system. This research contributes by modelling the problem simultaneously taking into account the uncertainty in customer demand, a comprehensive emissions model, and a heterogeneous fleet of vehicles. The proposed model is further deployed to address four different policies, namely the cap, the carbon tax, the cap-and-trade and the cap-and-offset. Based on a case study, the economic and environmental implications of each different policy are discussed, focusing on the operational decisions of the models.

Keywords: inventory routing problem; carbon emissions; carbon control policies; heterogeneous fleet; comprehensive emissions model; demand uncertainty.

Highlights

1. An environmentally-extended formulation of the inventory routing problem is developed.
2. Insights on the economic implications of carbon control policies are provided.
3. A comparison between the results of a heterogeneous and homogeneous fleet is provided.
4. Cap policy is effective in achieving high emissions reduction at low cost.
5. A comprehensive emission model is necessary for contexts with highly-variable demand.

Paper type Research Paper

1. Introduction

Climate change is one of the most serious threats that mankind must face in this century. As shown by Cook et al. (2013), the scientific community has reached a wide consensus in establishing that the causes of global warming are anthropogenic. Greenhouse gas emissions (GHGs), driven by economic and population growth, have increased exponentially since the pre-industrial era, reaching unprecedented levels (IPCC, 2014). In Europe, the energy supply sector is the most important emitter of greenhouse gases, followed by the transport sector, which accounts for 23% of the total emissions (Eurostat Statistics Explained, 2017). Emissions from light-duty (LDVs) and heavy-duty vehicles (HDVs) represent 37.6% of the total road transportation sector, which in turn accounts for 72.9% of total emissions from transportation.

In this context, it emerges how supply chain activities, which include production, transportation and inventory management, contribute substantially to GHG emissions, representing one of the main sectors where researchers have focused their efforts to find ways to curb emissions. Besides the academic world, companies have also started to focus on this aspect (Dekker et al., 2012). As indicated by Treitl et al. (2014), there are three main reasons that push companies to address environmental considerations in their decision-making processes: *(i)* the growing concern of consumers for “green” products; *(ii)* governments and policymakers have started to regulate the environmental impacts of companies; *(iii)* high emissions generated by the operations of a company are often a symptom of inefficiencies.

With respect to the second point, Kossoy et al. (2015) show the increasing number of national, regional and sub-national carbon control policies implemented or scheduled for implementation worldwide. However, even if only a fraction of the implemented policies addresses the emissions from transportation, the inclusion of this sector under existing policies is widely debated (Achtnicht et al., 2015; Mahler and Runkel, 2016). In this sense, it is therefore important to analyse the effects of different emissions reduction measures on the same economic activity, to provide both companies and policymakers with insights into the problem.

Concerning the third aspect pointed out by Treitl et al., Benjafaar et al. (2013) highlight how the tendency of focusing on process-based emissions may lead to the overlooking of significant fields of emissions reduction, represented by the operational practices of a company. In this sense, Ugarte et al. (2016), focusing on supply chain activities, analyse the environmental impact of the best practices of lean logistics (just-in-time, postponement, vendor-managed inventory (VMI)), showing how VMI can reduce transportation-related emissions. Under a VMI agreement, the supplier takes on the responsibility of managing the customers' inventories, determining the scheduling of deliveries based on the observed levels of inventory, but has to assure that the customers do not incur stock-outs. Thus, the supplier can better coordinate deliveries and customers do not have to allocate resources to inventory management (Soysal et al., 2015). The logistics problem that describes the VMI is the Inventory Routing Problem (IRP), which is a variant of the vehicle routing problem (VRP). In the IRP the decision maker determines at the same time: (i) when to deliver the products to the customers; (ii) how much to deliver to each customer; (iii) the routing of vehicles. These decisions

should minimise the overall total cost for the planned period (Soysal et al., 2015). The inclusion of environmental considerations into inventory routing is relatively recent (Treitl et al., 2014; Mirzapour Al-e-hashem and Rekik, 2014). Benjafaar et al. (2013) stress the need for quantitative-based models, fundamental to understanding how considerations of carbon emissions could affect the operational decisions of a company, highlighting the lack of studies that focus on the effect of carbon control policies on the operational sphere. Given these assumptions, this research addresses the effects of different carbon control policies on an environmentally-extended IRP, from an operational perspective. First, a literature review is conducted of those papers that have already tackled this problem, and based on the highlighted literature gaps, a partially new formulation of the environmentally-extended IRP is developed. Then, different carbon control policies are applied to this formulation, and insights into the economic and environmental implications of the policies are provided.

2. Literature review

The Scopus online database was used, to find those articles that have already tackled the environmental extension of the IRP. The choice of only relying on papers indexed on Scopus has of course one major upward and one major downward; specifically, it ensures a “controlled” quality of the papers, while it might lead to a set of papers which is not “complete”, if compared to other online databases such as Google Scholar. As a matter of fact, this is the commonest choice in recent papers, in order to be rather prudential in terms of result. The keyword “inventory routing problem” was combined

with the keywords “emissions”, “green”, “environmental”, “sustainable” “pollution”, and the following selection criteria were considered: (i) time frame of publication up to 2017; (ii) articles written in English; (iii) exclusion of document types other than academic papers and conference proceedings. Then, the abstract and content analysis allowed the exclusion of those articles which do not explicitly consider IRPs and the related carbon emissions. This choice depends on the willingness of the authors to focus only on papers directly connected to scope of the research, disregarding potentially interesting (still, indirectly related) papers such as, as an example, Franco et al. (2017), about IRP and fuel consumption. The resulting set, composed of twelve papers, is reported in **Table 1**. Although the IRP makes its first appearance in 1983 (Bell et al., 1983), its integration with environmental considerations appears only in 2014, in the pioneering works of Treitl et al. (2014) and Mirzapour Al-e-hashem and Rekik (2014), which were the first to consider the concepts of green logistics in IRPs. According to Mirzapour Al-e-hashem and Rekik (2014), the traditional criteria used to classify the different variants of the IRP are the following: finite or infinite planning horizon, single or multi-period, single or multi-customer, single or multi-product, homogeneous or heterogeneous fleet, deterministic or stochastic demand. This classification is integrated with the following criteria: single or multi-objective, topology of the network, typology of emissions model, whether shortage is ignored or considered, modelling of environmental concerns, and whether a carbon control policy is applied or not.

2.1. Descriptive analysis

All the analysed papers consider multi-periods and finite-planning horizon IRPs.

Concerning the type of logistic network, Soysal et al. (2016) individuate three main cases: (1) one-to-one, (2) one-to-many and (3) many-to-many networks. In the one-to-one network, one supplier serves one customer. None of the analysed articles adopts this solution. In the one-to-many case, one supplier serves a set of customers. This is so far the commonest approach to set the IRP, and it is employed by two-thirds of the papers analysed. The outbound logistics problem of a one-to-many network is equivalent to the inbound logistics problem of a many-to-one network (Cheng et al., 2016). In this case, a set of vehicles collects products from a set of suppliers and delivers it to a customer. Finally, in the many-to-many distribution network, a set of suppliers serve a set of customers. Only Soysal et al. (2016) consider this case. Concerning the fleet of vehicles, all the articles consider a multi-vehicle problem; half of the papers consider a heterogeneous fleet, while the rest consider a homogeneous fleet.

Concerning the modelling of the demand that represents the consumption rate of the downstream stage of the distribution network, half of the analysed papers adopt a deterministic approach, while the other half employ non-deterministic approaches. Among the first, Treitl et al. (2014) consider a static demand pattern over the periods of the planning horizon, while the rest consider a variable, deterministic pattern. Concerning the papers that adopt non-deterministic approaches, Soysal et al. (2016) and Soysal et al. (2015) model the demand with normal distributions, determining a priori the customer service level to assure at the downstream stage, and modelling it as a constraint of the problem; Rahimi et al., (2017) and Niakan and Rahimi (2015) employ a fuzzy distribution and, using multi-objective models, maximise the customer service level or minimise the stock-out occurrences; Mirzapour et al. (2017) and Soysal (2016)

consider a multi-scenario framework with deterministic data of demand for each scenario and use proper shortage costs associated with the stock-out occurrences.

The majority of the analysed papers adopt an economic single-objective function, thus maximise profit or minimise costs, while the rest adopt multi-objective models, where the traditional economic objective function is integrated with different types of objective functions, such as minimising GHG emissions (Rahimi et al. (2017); Franco et al. (2016)), maximising social concerns (Rahimi et al. (2016)), or both minimising GHG emissions and maximising customer service level (Rahimi et al. (2017); Niakan and Rahimi (2015)).

Concerning emissions generated by transportation, half of the papers use constant linear functions depending on vehicle type and travelled distance, while the rest use more complex formulations: four papers adopt a comprehensive emissions model (Cheng et al. (2017); Soysal et al. (2016); Soysal et al. (2015); Treitl et al. (2014)), and two papers adopt a simplified emissions model based on travelled distance, vehicle type and vehicle payload (Cheng et al. (2016); Soysal (2016)).

Lastly, regarding environmental concerns, the analysed papers show three main approaches. One third of the papers, adopting multi-objective models, use one of the objective functions to minimise GHG emissions (Mirzapour A. et al. (2017); Rahimi et al. (2017); Franco et al. (2016); Niakan and Rahimi (2015)). The second approach consists in the indirect minimisation of carbon emissions by including the explicit fuel cost in the cost-minimising objective function, and it is adopted by Soysal (2016), Soysal et al. (2016), and Soysal et al. (2015). The rest of the papers deal with the environmental concerns applying different carbon control policies. In particular Rahimi et al. (2016),

Mirzapour A. and Rekik (2014) impose a constraint, called a “carbon cap”, on the maximum allowed amount of emissions; Cheng et al. (2017) apply a carbon tax proportional to the volume of emissions produced; Treitl et al. (2014) consider the combination of the carbon cap and the carbon tax; Cheng et al. (2016) analyse the same model under four different carbon control policies, namely the cap, the cap-and-trade, the cap-and-offset and the carbon tax. **Table 1** summarises the descriptive analysis of the reviewed papers.

Table 1

Descriptive analysis of the reviewed papers in chronological order.

Article – Authors	Network topology	Fleet type	CO₂ emissions model	Demand	Environmental concerns	Model
Mirzapour A. et al., 2017	many-to- one	heterogeneous	constant	stochastic	minimising objective function	multi- objective
Rahimi et al., 2017	one-to- many	heterogeneous	constant	stochastic	minimising objective function	multi- objective
Cheng et al., 2017	one-to- many	heterogeneous	comprehensive	deterministic	carbon control policy	single- objective
Cheng et al., 2016	many-to- one	homogeneous	simplified	deterministic	carbon control policy	single- objective
Soysal, 2016	one-to- many	homogeneous	simplified	stochastic	explicit fuel consumption	single- objective
Franco et al., 2016	one-to- many	homogeneous	constant	deterministic	minimising objective function	multi- objective
Rahimi et al., 2016	one-to- many	heterogeneous	constant	deterministic	carbon control policy	multi- objective
Soysal et al., 2016	many-to- many	homogeneous	comprehensive	stochastic	explicit fuel consumption	single- objective

Niakan and Rahimi, 2016	one-to-many	heterogeneous	constant	stochastic	minimising objective function	multi-objective
Soysal et al., 2015	one-to-many	homogeneous	comprehensive	stochastic	explicit fuel consumption	single-objective
Treitl et al., 2014	one-to-many	homogeneous	comprehensive	deterministic	carbon control policy	single-objective
Mirzapour A. and Rezik, 2014	many-to-one	heterogeneous	constant	deterministic	carbon control policy	single-objective

2.2. Content analysis

The aim of the content analysis consists in highlighting the contribution of each paper to the analysed body of literature and identifying those aspects that have not been already exhaustively investigated, to properly contribute to the development of the topic.

Treitl et al. (2014) show how shifting from a retailer-managed inventory policy to a vendor-managed inventory policy can lead to a win-win situation, both reducing total cost and carbon emissions from logistics operations. They further illustrate that the application of a carbon price regime on the emissions does not affect the operational decisions if the price is too low. Mirzapour Al-e-hashem and Rezik (2014) consider an IRP with transshipment. They illustrate the “greenness” of the transshipment option showing how it reduces the number of trips, thus reducing emissions, but increasing inventory holding costs at suppliers. Soysal et al. (2015) develop a chance-constrained programming model to investigate an environmentally-extended IRP considering uncertainty of demand, perishability of products and an explicit fuel consumption formulation. Niakan and Rahimi (2015) develop a multi-objective model to address the

healthcare IRP (HIRP), minimising operational costs, maximising customer service level and minimising vehicles GHG emissions. Soysal et al. (2016) investigate the benefits of horizontal collaboration between the suppliers, which jointly cooperate using the same fleet of vehicles. They illustrate that horizontal collaboration, under some circumstances, can lead to a win-win situation characterised by a reduction of total cost and GHG emissions. Rahimi et al. (2016) address social issues in a reverse logistics IRP, developing a bi-objective mathematical model that considers social and economic criteria, while green criteria are considered as constraints. Franco et al. (2016) integrate the Non-Inferior Set Estimation (NISE) algorithm with a column generation method to create attractive routes and improve the objective function of an environmentally-extended IRP, reducing the computational time of resolution. Soysal (2016) addresses the Closed-loop IRP (CIRP), where products are delivered using Returnable Transport Items (RTIs) that have to be collected by the same fleet of vehicles during the backward routing, showing the economic and environmental benefits of integrating forward and backward logistics. Cheng et al. (2016) develop four different models that address the cap policy, the cap-and-trade policy, the cap-and-offset policy and the carbon taxing policy respectively and propose a hybrid-genetic algorithm to solve them. Analysing the cap policy, they show how in tightening the cap, the model reduces emissions while the total cost increases exponentially, driven by the inventory holding cost. Cheng et al. (2017) consider a comprehensive emissions model in a green IRP with a heterogeneous fleet (GIRP-H), further modelling the vehicle speed as a decision variable. They show how a comprehensive objective function can outperform the traditional objective

function that minimises the distance travelled cost, both in terms of total cost and total emissions.

Rahimi et al. (2017) develop a multi-objective model that simultaneously considers economics, service level, and green criteria, and addresses perishability of products, considering recycling costs and emissions generated by the recycling process. The authors highlight how multi-objective models allow the decision maker to identify those solutions that, with a small profit decrement, achieve a major increase of customer service level. Lastly, Mirzapour Al-e-hashem et al. (2017) study the economic and environmental performance of a transshipment-enabled stochastic IRP (TIRP) in a many-to-one logistics network. They develop a bi-objective stochastic programming model showing that a transshipment strategy can be effective in reducing the total travel distance and GHGs through merging the trips.

2.3. Gap Identification and Research positioning

With respect to the descriptive analysis, it emerges that none of the analysed single-objective models simultaneously address a heterogeneous fleet, a comprehensive emissions model and uncertainty of demand. Keeping into account these three features, as shown by the reviewed literature, leads to better results in terms of economic and environmental performances (Cheng et al., 2017) and of course to a closer description of reality (Soysal et al., 2016). Moreover, despite the growing concerns about the introduction of emissions restrictive measures, and the highlighted need of quantitative-based models able to properly address them, among the analysed papers, only Cheng et al. (2016) specifically focus on the implications of different carbon control policies.

However, the authors analyse a many-to-one logistics network with a homogeneous fleet and deterministic demand, concentrating on the development of a heuristics algorithm to solve large instances.

Given these assumptions, the purpose of this research is to analyse how different carbon control policies affect the operational decisions of an environmentally-extended IRP with a heterogeneous fleet, stochastic demand, and a comprehensive emissions model.

Before analysing how different carbon control policies affect the operational decisions of an IRP, a proposal of an all-inclusive model based on the coded characteristics within the literature is reported, so as not to lose any advancement on the topic, with the unique goal of potentially better grasp the impact of the different carbon policies on an IRP. Thus, a chance-constrained programming model is developed that simultaneously addresses these three features. The developed model is further modified to consider four carbon control policies, namely the carbon cap, the carbon tax, the cap-and-trade and the cap-and-offset, based on the works of Cheng et al. (2016) and He et al. (2016). In addition, an emissions-minimising model is presented in order to provide insights into the modifications of the operational decisions in a solely environmentally-concerned context.

The proposed models are applied to a real logistics problem described by a supplier and a set of customers and, for each policy, a sensitivity analysis is performed on the characterising parameters, highlighting the economic and environmental implications with respect to the base case model where no policy is applied.

3. Problem description

The model proposed in this research is based on the one developed by Soysal et al. (2016), which addresses a homogeneous fleet. The mathematical formulation is modified to consider a heterogeneous fleet. The reference model of Soysal et al. (2016) considers a multi-product, many-to-many network with product perishability. Since the focus of this research is on the implications of different carbon control policies on a general IRP, considerations on waste are neglected, assuming an infinite expiration date. Concerning the distribution network, the proposed model keeps the multi-supplier multi-product notation, properly introducing the data for the single-supplier single-product case, in the computational analysis section. As shown by Soysal et al. (2016), the model's syntax of a multi-product, many-to-many network is still valid for the single-product, one-to-many framework. In both cases, the distribution network comprises a third-party logistics (3PL), which serves as a rental vehicle company.

The analysed problem is defined on a complete graph $G = \{V, A\}$, where V is the set of nodes that consists of a set of customers $V_C = \{1, 2 \dots, |V_C|\}$, a set of suppliers $V_S = \{1, 2 \dots, |V_S|\}$, a 3PL located at the node 0, and $A = \{(i, j): i, j \in V, i \neq j\}$ is the set of arcs. The distance between the nodes is denoted by $a_{i,j}$. Planning horizon is finite, each period is indicated by $t \in T = \{1, 2 \dots, |T|\}$ and the set of products is given by $P = \{1, 2 \dots, |P|\}$. The set of vehicles is given as $K = \{1, 2 \dots, |K|\}$, where the k -index does not refer to the vehicle type, but to the specific vehicle. The model features the following assumptions:

- Values of demand of customer i , of product type $p \in P$, at time $t \in T$, are indicated by $d_{i,p,t}$ and they are assumed to be normally distributed with mean $\mu_{i,p,t}$ and standard deviation $\sigma_{i,p,t}$, and pairwise uncorrelated. Demand must be satisfied with a probability of at least α .
- Demand that cannot be fulfilled in one period is backlogged in the next period. No shortages costs are considered.
- A limited, capacitated and heterogeneous fleet is assumed. Maximum payload for each vehicle is indicated by c^k .
- Vehicles routings start and end at 3PL and each vehicle can perform at most one route per period.
- Split deliveries are allowed, so customers can be visited by more than one vehicle per period.
- Inventory holding costs are denoted by $h_{i,p}$, and depend on customer and product type. Inventory levels of customers are assumed null at the beginning of the planning horizon period.
- A limited quantity of product $q_{i,p,t}$ is available for each period at the supplier's site, and it is assumed high enough to satisfy the customers' demand. No inventory holding cost is considered at the supplier's site.
- Customers are characterised by unlimited capacity warehouses.

Concerning the routing cost, w denotes the wage for drivers expressed in €/s, while l denotes the fuel price expressed in €/litre. The objective of this problem is to determine the routing of vehicles and scheduling of deliveries that minimise the expected total

cost, given by the sum of routing and inventory holding costs. The decision variables are the following:

- $X_{i,j,k,t}$: Boolean decision variable equal to 1 if vehicle $k \in K$ goes from node $i \in V$ to node $j \in V$ in period $t \in T$, and 0 otherwise.
- $B_{i,k,p,t}$: quantity of product $p \in P$ picked up from supplier $i \in V_S$ by vehicle $k \in K$ at the beginning of period $t \in T$, expressed in [kg].
- $Q_{i,k,p,t}$: amount of product $p \in P$ delivered by vehicle $k \in K$ to customer $i \in V_C$ during period $t \in T$, expressed in [kg].
- $I_{i,p,t}$: inventory level of product $p \in P$ at customer $i \in V_C$ at the end of period $t \in T \cup \{0\}$, expressed in [kg], where $I_{i,p,0} = 0, \forall i \in V_C, p \in P$.
- $I_{i,p,t}^+$: positive inventory levels of product $p \in P$ at each customer $i \in V_C$ at the end of period $t \in T$, expressed in [kg].
- $F_{i,j,k,p,t}$: load of product $p \in P$ on vehicle $k \in K$ travelling from node $i \in V$ to node $j \in V$ in period $t \in T$, expressed in [kg].
- $U_{i,k,t}$: position of node $i \in V \setminus \{0\}$ in route $k \in K$ in period $t \in T$.

3.1. Comprehensive emissions model

Fuel consumption and related carbon emissions are computed using the comprehensive emissions model developed by Barth et al. (2005), Scora and Barth (2006), and Barth and Boriboonsomsin (2009). This model was successfully applied to many environmentally-extended VRPs, known as pollution-routing problems (Bektaş and

Laporte, 2011; Demir et al., 2012; Demir et al., 2014b). As reported by Demir et al. (2014a), who reviewed 25 different emissions models, the comprehensive emissions model is the best in terms of robustness, reliability and applicability in optimisation. Given a vehicle speed f (m/s), a travelled distance $a_{i,j}$ (m), a kerb weight μ^k , and a payload $F_{i,j,k,p,t}$ (kg), the fuel consumption in litres, is given by:

$$FC^k = \lambda \left(y \left(\frac{a_{i,j}}{f} \right) + \gamma^k \beta^k a_{i,j} f^2 + \gamma^k s (\mu^k + F_{i,j,k,p,t}) a_{i,j} \right) \quad (1)$$

where $\lambda = \xi / (\kappa \psi)$, and $s = \tau + g \sin \phi + g C_r \cos \phi$. The vehicle type-dependent parameters are $\gamma^k = 1 / (1000 \varpi \varepsilon^k)$, $\beta^k = 0.5 C_d^k \rho A^k$, and $y^k = k_e^k N_e^k V_e^k$. Parameters' definitions are reported in **Table 7** (in Annex). This notation allows to distinguish the three different components of the fuel consumption function, which are respectively: (i) the engine module, expressed as $\lambda y (a_{i,j} / f)$ and linear in the travel time; (ii) the speed module, expressed as $\lambda \gamma^k \beta^k a_{i,j} f^2$ and quadratic in speed; (iii) the weight module, expressed as $\lambda \gamma^k s (\mu^k + F_{i,j,k,p,t}) a_{i,j}$ and independent of the vehicle speed. The last component, embedding the decision variable $F_{i,j,k,p,t}$ related to the weight carried by the vehicle, links together the routing part and the inventory management part of the problem since a heavier vehicle tends to consume more fuel and thus to produce more carbon emissions. These carbon emissions, expressed in kgCO_{2e}, are obtained by multiplying the fuel consumption by the fuel-dependent conversion factor u , expressed in kgCO_{2e}/litre.

3.2. Base case model

The following model, denoted by Z_{BC} , represents the base case where no carbon control policy is applied, and it is described by the following objective function that minimises the sum of the operational costs:

$$\begin{aligned}
 Z_{BC} = \text{Minimise } & \sum_{i \in V_C} \sum_{p \in P} \sum_{t \in T} I_{i,p,t}^+ h_{i,p} \quad (2. i) \\
 & + \sum_{(i,j) \in A} \sum_{k \in K} \sum_{t \in T} \lambda \left(y \left(\frac{a_{i,j}}{f} \right) X_{i,j,k,t} + \gamma^k \beta^k a_{i,j} f^2 X_{i,j,k,t} \right. \\
 & \quad \left. + \gamma^k s \left(\mu^k X_{i,j,k,t} + \sum_{p \in P} F_{i,j,k,p,t} \right) a_{i,j} \right) l \quad (2. ii) \\
 & + \sum_{(i,j) \in A} \sum_{k \in K} \sum_{t \in T} \left(\frac{a_{i,j}}{f} \right) X_{i,j,k,t} w. \quad (2. iii)
 \end{aligned}$$

The term (2. i) calculates the expected inventory holding cost, the term (2. ii) calculates fuel cost adopting the comprehensive emissions model, and the term (2. iii) calculates drivers cost. The model is constrained as follows:

$$E[I_{i,p,t}] = \sum_{s=1}^t \sum_{k \in K} Q_{i,k,p,s} - \sum_{s=1}^t E[d_{i,p,s}], \quad \forall i \in V_C, p \in P, t \in T \quad (3)$$

$$I_{i,p,t}^+ \geq E[I_{i,p,t}], \quad \forall i \in V_C, p \in P, t \in T \quad (4)$$

$$\Pr(I_{i,p,t} \geq 0) \geq \alpha, \quad \forall i \in V_C, p \in P, t \in T \quad (5)$$

Constraints (3) – (5) concern inventory decisions. Constraint (3) calculates the expected inventory levels at each customer for each period of the planning horizon, based on the difference between the cumulated value of deliveries and the cumulated value of expected demand. Constraint (4) calculates the positive level of inventory stored in the warehouse. Constraint (5) is the service-level constraint on the stock-out probability at the end of each period. It states that the inventory level for each product at the end of each period must be positive with a probability of service level at least equal to α . The non-linearity of constraint (5) is solved following the procedure proposed by Bookbinder and Tan (1988) and adopted by Soysal et al. (2016), therefore substituting it with the following linear constraint:

$$\sum_{s=1}^t \sum_{k \in K} Q_{i,k,p,s} \geq \sum_{s=1}^t E[d_{i,p,s}] + C_p Z_\alpha \left(\sum_{s=1}^t E^2[d_{i,p,s}] \right)^{1/2} \quad \forall i \in V_C, p \in P, t \in T \quad (5^*)$$

where C_p is the coefficient of variation and Z_α is the standard normal random variate with cumulative probability α . The coefficient of variation C_p can be estimated plotting corresponding pairs of points $(E[d_{i,p,t}], \sigma_{i,p,t})$ on a diagram and calculating the slope of the obtained straight line. Therefore, this approach implies a deterministic approximation of the chance-constrained programming model, where the risk associated with the uncertainty of the demand is only tackled by delivering an additional quantity of product, represented by the last term of constraint (5*), and corresponding to a safety stock to hold in each period of the planning horizon, for each customer considered. The choice of considering the uncertainty of the demand only by delivering

an additional quantity of product, certainly is a simplification of the problem, basically due to the willingness of the authors to stick whenever possible to the models presented in the selected literature.

In addition, the model is subjected to the following routing-related constraints:

$$\sum_{i \in V, i \neq j} X_{i,j,k,t} = \sum_{i \in V, i \neq j} X_{j,i,k,t}, \quad \forall j \in V \setminus \{0\}, k \in K, t \in T \quad (6)$$

$$\sum_{i \in V, i \neq j} X_{j,i,k,t} \leq 1, \quad \forall i \in V, k \in K, t \in T \quad (7)$$

$$X_{i,0,k,t} = 0, \quad \forall i \in V_S, k \in K, t \in T \quad (8)$$

$$X_{0,j,k,t} = 0, \quad \forall j \in V_C, k \in K, t \in T \quad (9)$$

$$F_{0,j,k,p,t} = 0, \quad \forall j \in V_S, k \in K, p \in P, t \in T \quad (10)$$

$$\sum_{j \in V, i \neq j} F_{i,j,k,p,t} = \sum_{j \in V, i \neq j} F_{j,i,k,p,t} + B_{i,k,p,t}, \quad \forall i \in V_S, k \in K, p \in P, t \in T \quad (11)$$

$$\sum_{j \in V, i \neq j} F_{i,j,k,p,t} = \sum_{j \in V, i \neq j} F_{j,i,k,p,t} - Q_{i,k,p,t}, \quad \forall i \in V_C, k \in K, p \in P, t \in T \quad (12)$$

$$\sum_{p \in P} F_{i,j,k,p,t} \leq c^k X_{i,j,k,t}, \quad \forall (i,j) \in A, k \in K, p \in P, t \in T \quad (13)$$

$$\sum_{k \in K} B_{i,k,p,t} \leq q_{i,p,t}, \quad \forall i \in V_S, p \in P, t \in T \quad (14)$$

$$U_{i,k,t} + 1 \leq U_{j,k,t} + |V|(1 - X_{i,j,k,t}), \quad \forall (i,j) \in A(V \setminus \{0\}), k \in K, t \in T \quad (15)$$

Constraint (6) concerns the conservation of the flow of vehicles. Constraint (7) assures that each vehicle performs at most one route per time period. Constraint (8) assures that no vehicle comes back to the depot without visiting any customer. Similarly, constraint (9) assures that no vehicle, after leaving the depot, goes directly to the

customers without visiting the supplier to pick up the products. Constraint (10) states vehicles starting the routing must be empty. Constraints (11) and (12) concern the conservation of flow of products. Constraint (13) concerns the vehicle capacity and constraint (14) ensures that the sum of product quantities picked up at supplier i in period t does not exceed the total available quantity of the supplier. Lastly, constraint (15) eliminates sub-tours. The following constraints represent the restrictions imposed on the decision variables:

$$X_{i,j,k,t} \in \{0,1\}, \quad \forall (i,j) \in A, k \in K, t \in T \quad (16)$$

$$F_{i,j,k,p,t} \geq 0, \quad \forall (i,j) \in A, k \in K, p \in P, t \in T \quad (17)$$

$$-\infty < I_{i,p,t} < +\infty, \quad \forall i \in V_C, p \in P, t \in T \quad (18)$$

$$I_{i,p,t}^+ \geq 0, \quad \forall i \in V_C, p \in P, t \in T \quad (19)$$

$$U_{i,k,t} \geq 0, \quad \forall i \in V \setminus \{0\}, k \in K, t \in T \quad (20)$$

$$Q_{i,k,p,t}, B_{i,k,p,t} \geq 0, \quad \forall i \in V_C, k \in K, p \in P, t \in T \quad (21)$$

3.3. Emissions-minimising model

The emissions-minimising model, indicated by Z_{env} , is needed to compute the maximum feasible emissions reduction that the base case model can achieve, without the application of any carbon control policy. It reflects the solely environmental concern and it consists in the minimisation of the produced carbon emissions.

$$\begin{aligned}
\min Z_{env} = & \sum_{(i,j) \in A} \sum_{k \in K} \sum_{t \in T} \lambda \left(y \left(\frac{a_{i,j}}{f} \right) X_{i,j,k,t} + \gamma^k \beta^k a_{i,j} f^2 X_{i,j,k,t} \right. \\
& \left. + \gamma^k s \left(\mu^k X_{i,j,k,t} + \sum_{p \in P} F_{i,j,k,p,t} \right) a_{i,j} \right) u \quad (22)
\end{aligned}$$

subjected to constraints (3) – (4), (5*), (6) – (15), (16) – (21).

3.4. Cap policy model

Under the cap policy, the carbon emissions generated by the activities of a company over a finite time horizon, cannot mandatorily exceed a given threshold determined by a regulator authority. The non-compliance with this constraint is sanctioned with fines, which can be proportional to the excess of emissions or can be uniform. Having defined the solution of the base case model as Z_{BC} , the cap policy model is described by the following objective function:

$$\text{minimise } Z_{cap} = Z_{BC} \quad (23)$$

subject to constraints (3) – (4), (5*), (6) – (15), (16) – (21), plus the additional constraint that set the maximum allowed level of carbon emissions, denoted as Cap , positive-defined and expressed in kgCO₂e:

$$\sum_{(i,j) \in A} \sum_{k \in K} \sum_{t \in T} \lambda \left(y \left(\frac{a_{i,j}}{f} \right) X_{i,j,k,t} + \gamma^k \beta^k a_{i,j} f^2 X_{i,j,k,t} \right. \\ \left. + \gamma^k s \left(\mu^k X_{i,j,k,t} + \sum_{p \in P} F_{i,j,k,p,t} \right) a_{i,j} \right) u \leq Cap \quad (24)$$

The value of the term Cap is externally determined by a regulator authority, usually starting from the baseline emissions of the company when no carbon control policy is applied, and then applying a desired percentage of emissions reduction.

3.5. Carbon tax policy

Under the carbon tax policy, carbon emissions are priced proportionally to the volume of emissions. The carbon tax is based on the “polluter pays” principle, and should act as an incentive to move towards the most cost-effective low-carbon solution. In most countries where carbon tax regimes are currently implemented the revenues from this tax go to finance low-carbon investments. A carbon pricing approach can be spontaneously adopted by companies that want to incorporate the externality of their activities in their decision-making strategies (Carbon Disclosure Project, 2016). The solution of the carbon tax model is defined as $Z_{carbon\ tax}$ and the price of carbon emissions is denoted as tax , positive-defined and expressed in €/kgCO₂e.

$$Z_{carbon\ tax} = Minimise \sum_{i \in V_c} \sum_{p \in P} \sum_{t \in T} I_{i,p,t}^+ h_{i,p} \quad (25. i)$$

$$\begin{aligned}
& + \sum_{(i,j) \in A} \sum_{k \in K} \sum_{t \in T} \lambda \left(y \left(\frac{a_{i,j}}{f} \right) X_{i,j,k,t} + \gamma^k \beta^k a_{i,j} f^2 X_{i,j,k,t} \right. \\
& \quad \left. + \gamma^k s \left(\mu^k X_{i,j,k,t} + \sum_{p \in P} F_{i,j,k,p,t} \right) a_{i,j} \right) (l + u \cdot tax) \quad (25. ii) \\
& + \sum_{(i,j) \in A} \sum_{k \in K} \sum_{t \in T} \left(\frac{a_{ij}}{f} \right) X_{i,j,k,t} w, \quad (25. iii)
\end{aligned}$$

subjected to constraints (3) – (4), (5*), (6) – (15), (16) – (21).

3.6. Cap-and-trade policy

Under the cap-and-trade policy, emissions allowances are allocated to companies by auctioning or by grandfathering (free allocation based on past emissions baselines). As reported by Zakeri et al. (2015) and by the European Commission (2017), grandfathering is the commonest method. Companies that emit more than the allocated allowances can purchase extra allowances from those companies that emit less than the allocated emissions. From this point of view, the cap-and-trade policy acts as an incentive to move towards low-carbon solutions, since the trading of extra allowances can be an extra source of revenue, while companies are discouraged from emitting more than the allocated amount, because of the extra cost incurred. Companies that are unable to meet the imposed cap, even with the purchasing of extra credits, incur severe fines. The number of purchased allowances is denoted as e^+ , while the number of sold allowances is indicated as e^- , both positive-defined and expressed in kgCO₂e. The price of the bought/sold emission allowances is indicated as χ^{trade} , expressed in €/kgCO₂e.

$$Z_{cap\ and\ trade} = \text{minimise } Z_{BC} + \chi^{trade} \cdot (e^+ - e^-) \quad (26)$$

subjected to constraints (3) – (4), (5*), (6) – (15), (16) – (21), plus the constraint on the total allowed emissions:

$$\sum_{(i,j) \in A} \sum_{k \in K} \sum_{t \in T} \lambda \left(y \left(\frac{a_{i,j}}{f} \right) X_{i,j,k,t} + \gamma^k \beta^k a_{i,j} f^2 X_{i,j,k,t} + \gamma^k s \left(\mu^k X_{i,j,k,t} + \sum_{p \in P} F_{i,j,k,p,t} \right) a_{i,j} \right) u + e^- \leq Cap + e^+. \quad (27)$$

3.7. Cap-and-offset policy

Under the cap-and-offset policy, the overall emissions can exceed the imposed maximum limit only by buying extra credits by investing in emissions-reduction projects (Carbon Tax Center, 2017). In this case, the emissions reduction is not to be achieved at a local level but at a global level, since the effort in decreasing emissions is transferred to those countries where the same net-reduction could be achieved in a more cost-effective way. Carbon offsets are often a feature of emissions trading systems. This configuration provides more flexibility in meeting the set emissions target, since the company can use a mix of measures (emission allowances or credits, carbon offsets, operational domestic reduction) in order to meet the cap. The number of purchased credits is denoted as e^+ , positive-defined and expressed in kgCO₂e. The price of the purchased emission credits is indicated as χ^{offset} , expressed in €/kgCO₂e.

$$Z_{cap\ and\ trade} = \text{minimise } Z_{BC} + \chi^{offset} \cdot e^+ \quad (28)$$

subjected to constraints (3) – (4), (5*), (6) – (15), (16) – (21), plus the constraint on the total allowed emissions:

$$\sum_{(i,j) \in A} \sum_{k \in K} \sum_{t \in T} \lambda \left(y \left(\frac{a_{i,j}}{f} \right) X_{i,j,k,t} + \gamma^k \beta^k a_{i,j} f^2 X_{i,j,k,t} + \gamma^k s \left(\mu^k X_{i,j,k,t} + \sum_{p \in P} F_{i,j,k,p,t} \right) a_{i,j} \right) u \leq Cap + e^+. \quad (29)$$

4. Methods

In this section, the proposed models are applied to a real case study, adapted from the case study analysed by Soysal et al. (2016). The economic and environmental performance of the models are assessed with respect to the following Key Performance Indicators KPIs: (i) driving time, (ii) inventory cost, (iii) routing cost comprised of fuel cost and drivers' cost, (iv) total emissions and (v) total cost. The following fleet-related parameters are considered: (vi) average load factor of the fleet, (vii) total number of vehicles, (viii) fleet mix composition. The average load factor of the fleet is obtained as the average of the load factors of each vehicle, which is given by the ratio between the payload of the vehicle when it leaves the supplier and the vehicle maximum payload capacity. When considering the application of a policy, the related implications on the

operational cost and the emissions are reported. In order to gather insights into the fleet choice, the instances for the proposed models are applied first to a completely heterogeneous fleet, and then to a completely homogeneous fleet of vehicles.

4.1. Description and data

The analysed logistics network comprises one supplier, a 3PL provider of the vehicles and five distinct customers. Three types of vehicles are available, based on the payload capacity: a heavy-duty vehicle (HDV), a medium-duty vehicle (MDV) and a light-duty vehicle (LDV). The heterogeneous fleet instances feature a fleet composed of one vehicle for each type, while the homogeneous fleet instances feature a fleet composed of three identical MDVs. The expected demand of the customers per period is reported in **Table 5** (in Annex), while the distance between the nodes of the network is reported in **Table 6** (in Annex). The numerical data of the vehicle parameters are reported in **Table 7** (in Annex), based on the data of Koç et al. (2014) and Cheng et al. (2017). A fixed vehicle speed equal to 80 km/h is assumed. The coefficients of variation C_p for the product demands are assumed to be constant and equal to 0.1 for all customers in each period. The planning horizon of the problem is set equal to 6 periods, and each period corresponds to one week. Customers incur a holding cost equal to 0.12€/kg-week, which correspond to 10% of the selling price of the product. The drivers of the vehicles are paid hourly, and the wage is 10.8€/h. The fuel price is equal to 1.7€/litre. Lastly, the conversion factor u , needed to convert the litres of fuel consumed into kilograms of emitted CO₂, is set equal to 2.63kg/litre (DEFRA, 2007).

4.2. Description of the analysed cases

First, we present the analysis of the base case, denoted by Z_{BC} , where no carbon control policy is applied. Then, the results of the emissions-minimising model Z_{env} are analysed. Lastly, for the models with carbon control policies, a sensitivity analysis is performed on the characterising parameter of that specific policy. In particular:

- The cap policy is analysed by tightening the cap from 100% of allowed emissions with respect to the base case, to the maximum feasible level, based on the results of the emissions-minimising model.
- The carbon tax policy is analysed by progressively modifying the imposed carbon tax from a null value (equal to the base case) to 500€/tonCO₂e.
- The cap-and-trade is analysed by tightening the cap from 110% to 50% of allowed emissions with respect to the base case and keeping the allowance price fixed and equal to 7€/ tonCO₂e, corresponding to the actual price in the EU ETS (EUA, 2017). In addition, it is analysed by varying the emissions allowance price from a null value (equal to the base case), to 500€/tonCO₂e, keeping the cap fixed and equal to 50%.
- The cap-and-offset is analysed by tightening the cap from 110% to 50% of allowed emissions with respect to the base case and keeping the emissions credit price fixed and equal to 7.27€/tonCO₂e, corresponding to the highest price of certified emissions reductions (CERs), among the available carbon offset projects on the Clean Development Mechanism online platform (UNFCCC, 2017).

4.3. Solution method

The formulations of the proposed problems are developed and solved using the ILOG-OPL Development Studio and CPLEX 12.6 optimisation package. The solutions are obtained on a personal computer with the following characteristics:

- Processor: Intel® Core™ i7 7700hq, CPU 2.80 GHz.
- RAM: 16.0 Gigabyte.

Table 2 summarises the computational time needed to reach the optimal solution for each instance. Concerning instances related to the carbon control policies (cap, carbon tax, cap-and-trade, cap-and-offset) results are obtained as the average of the computational times of the sensitivity analysis described in section 4.2. The overall computational time for the study is not negligible; still, this does not represent a barrier, because this model is not primarily intended for companies to use it as it stands, being the purpose of the research to investigate how different carbon control policies can affect the operational decisions in the IRP.

Table 2

Computational time (in seconds) needed to reach the optimal solution for each instance.

	Instance					
	Base case	Emissions- minimising	Cap	Carbon tax	Cap-and- trade	Cap-and- offset
Heterogeneous fleet	508	90	1440	364	340	438

Homogeneous fleet	1392	30	2377	2184	2320	2051
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5. Results

5.1. Base case model

Results of the base case model are reported in **Table 3**. The comparison shows that the heterogeneous fleet case is better than the homogeneous one, both from an economic and environmental point of view. The reported results are the baseline for the successive comparisons.

Table 3

Base case model: comparison of the heterogeneous fleet and homogeneous fleet instances.

	Heterogeneous fleet	Homogeneous fleet	Difference [%]
Driving time [h]	84.63	81.20	4.22%
Inventory cost [€]	3098.95	3270.39	-5.24%
Driver cost [€]	914.00	876.97	4.22%
Fuel cost [€]	4935.76	5012.03	-1.52%
Routing cost [€]	5849.76	5889.00	-0.67%
Emissions [kgCO₂e]	7635.91	7753.90	-1.52%
Total cost [€]	8948.71	9159.39	-2.30%
Average load factor [%]	86.21%	62.06%	28.01%

Number of vehicles	10	10	0.00%
LDV	4	-	-
MDV	6	-	-
HDV	0	-	-

5.2. Emissions-minimising model

Results of the emissions-minimising model are reported in **Table 4**. The model aims at minimising the number of trips, therefore using fewer vehicles and increasing **the average load factor of the fleet**. Routing costs and emissions decrease but the inventory holding cost exponentially increases. Also in this case, the heterogeneous fleet is better than the homogeneous one, both from an economic and environmental point of view.

Table 4

Emissions-minimising model: percentage differences with respect to the base case results.

	Heterogeneous fleet	Homogeneous fleet
Driving time [h]	-56.24%	-47.32%
Inventory cost [€]	+426.08%	+421.47%
Driver cost [€]	-56.24%	-47.32%
Fuel cost [€]	-47.53%	-45.15%
Routing cost [€]	-48.89%	-45.47%
Emissions [kgCO₂e]	-47.53%	-45.15%
Total cost [€]	+115.59%	+121.25%
Average load factor %	+11.02%	+29.54%

Number of vehicles	-40.00%	-30.00%
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The model aims at minimising the emissions by minimising the number of trips and the number of vehicles used, and maximising the delivered quantity per trip, thus **leading to a considerable increase of** the inventory holding cost. Routing cost decreases following the emissions reduction because of the lower fuel consumption and kilometres driven. **In this case**, the heterogeneous fleet achieves better economic and environmental results because of the employment of HDVs able to deliver the same quantity with less vehicles. These considerations regarding the operational decisions are still valid for the carbon control policy models, that partially reflect the environmental concerns incorporating the emissions cost in the cost-minimising objective function or in the constraints.

5.3. Cap policy

The results, in terms of total cost and emissions, of the sensitivity analysis on the cap value are reported in **Figure 1**. The increase in the total cost is exclusively driven by the inventory holding cost, partially offset by the decrement in fuel and driver cost, while carbon emissions linearly decrease following the imposed emissions reduction. In this case, the heterogeneous fleet case is always the best from an environmental perspective, while in terms of economic performance, the homogeneous case provides better results tightening the cap for values lower than 80%. The results of the cap policy confirm one of the observations by Benjafar et al. (2013): it is possible to achieve considerable emissions reduction without significant impacts on the economic result of

the problem. Considering the heterogeneous fleet case, a 16.97% carbon emissions reduction corresponds to a 1.56% operational costs increase, while for the homogeneous fleet case, a 16.54% reduction in emissions corresponds to a 1.92% cost increase. This is because, in the early tightening of the cap, the total cost increase caused by the inventory cost is offset by the reduction of routing cost (driver cost plus fuel cost), caused by the reduced number of kilometres driven. These results show that a purely cost-minimising approach, represented by the base case model, can hide possible environmental-friendly solutions that can be achieved with almost null cost increases. On the other hand, a purely emissions-minimising approach can hide possible cost-effective solutions. In fact, given the same emissions reduction equal to 45%, the emissions-minimising model leads to a 121.25% total cost increase, while the cap model with a 55% cap only leads to a 77.10% increase.

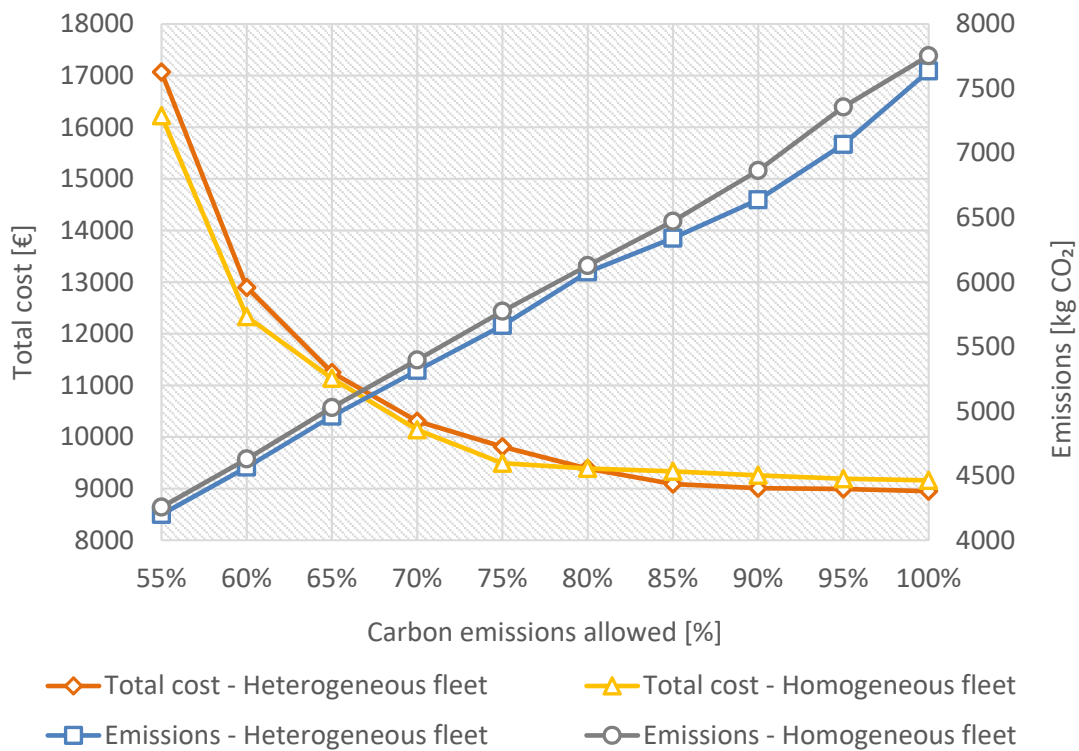


Figure 1 – Cap policy: comparison of the heterogeneous fleet and homogeneous fleet instances

5.4. Carbon tax policy

The results, in terms of total cost and emissions, of the sensitivity analysis on the price of the carbon tax model are reported in **Figure 2**. Here, increasing the severity of the carbon control measures, the homogeneous fleet configuration achieves greater emissions reduction, while, from an economic point of view, the heterogeneous fleet is always the best choice. The emissions reduction shows a staircase pattern, while the total cost increases almost linearly. Therefore, the model is forced to modify the routing and deliveries configuration only when the decrement of emissions cost, due to the achieved emissions reduction, offsets the increase of related operational cost. These considerations lead to two significant insights: (i) given a low value of carbon price (0 ÷

50€/tonCO_{2e}), the carbon tax policy does not provide any operational modifications, thus any emissions reduction; (ii) extended ranges of carbon price provide the same emissions reduction. Therefore, a further increase of the tax will not provide any additional environmental improvements, instead resulting in an additional economic burden for the company. From this point of view, carbon tax policy may not be suitable for static contexts where it is difficult to modify the business-as-usual configuration. The application of the carbon tax on the addressed IRP shows that, for this kind of context, this policy could be an effective incentive to move towards lower-emissions configurations. A tax comprising between 100 ÷ 150€/tonCO_{2e} leads to a 13.07% emissions reduction for the heterogeneous case and to 7.04% for the homogeneous case. According to Korzhenevych et al. (2014), this range of prices reflects the external cost of transport related to climate change, estimated between 48€/tonCO₂ and 168€/tonCO₂.

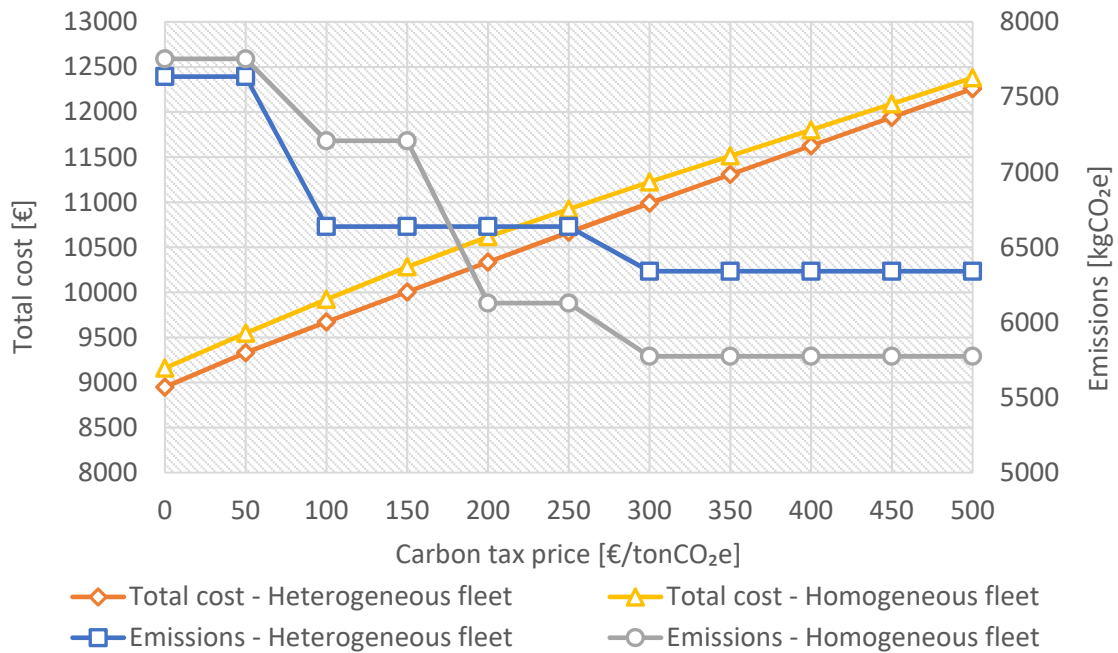


Figure 2 – Carbon tax policy: comparison of the heterogeneous fleet and homogeneous fleet instances

5.5. Cap-and-trade policy

The results, in terms of total cost and emissions, of the sensitivity analysis on the cap value of the cap-and-trade policy model are reported in **Figure 3**. The emissions allowance price is fixed and set equal to 7€/tonCO₂e. Figure 3 highlights that no emissions reduction is achieved, thus the environmental performances exactly correspond to those of the base case model. Therefore, under cap-and-trade, the emissions reduction does not depend on the cap value. However, it is possible to gather two insights from the sensitivity analysis on cap: (i) for cap values higher than 100%, the cap-and-trade model achieves a total cost lower than the base case model by selling the surplus allocated emissions allowances; (ii) it is possible to impose cap values lower than the operational feasible emissions reduction, i.e. a 50% cap. However, this imposed

reduction does not correspond to the real achieved emissions reduction since the cap-and-trade provides other tools to meet the cap, such as the possibility of purchasing extra allowances.

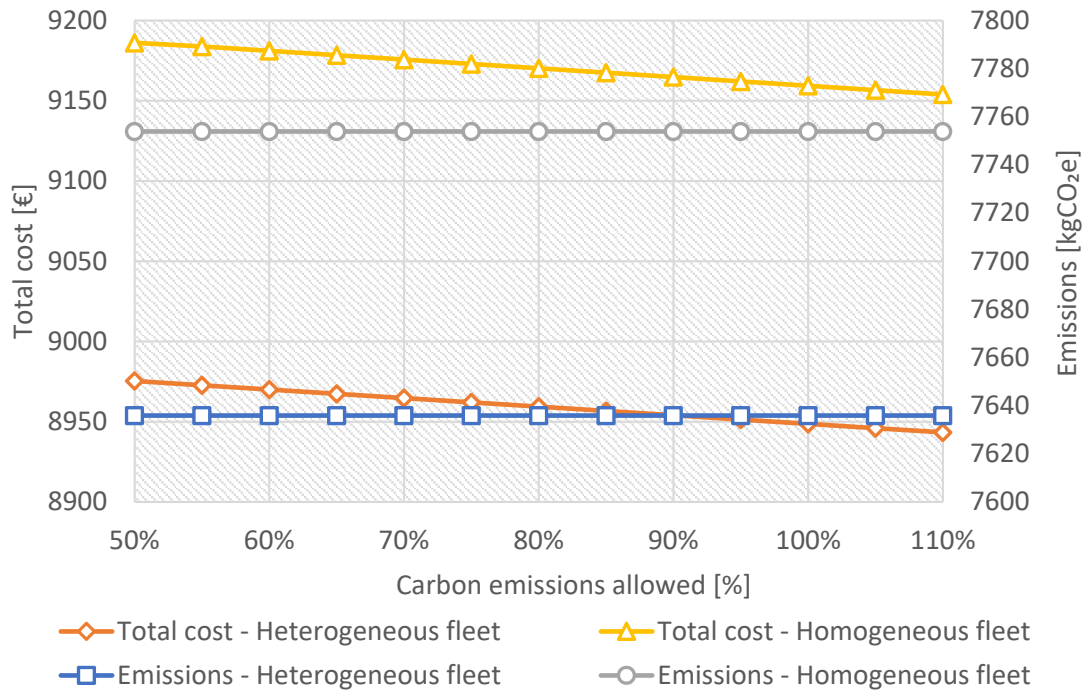


Figure 3 – Cap-and-trade policy with fixed allowance price (7€/tonCO₂e): comparison of the heterogeneous fleet and homogeneous fleet instances.

The results of the sensitivity analysis on the allowance price, given a fixed cap value equal to 50%, are reported in **Figure 4**. In this case, the achieved emissions reduction exactly corresponds to that achieved with the carbon tax policy. These results lead to two considerations on cap-and-trade: (i) achieved emissions reduction does not depend on the cap value but solely on the emissions allowance price; (ii) the carbon tax policy can be considered as a particular case of the cap-and-trade where the allocated allowances are null, and the allowance price corresponds to the price of the carbon tax.

With respect to the first consideration, in reality, the cap-and-trade being a market-based mechanism, the allowance price is dependent on the total number of allowances available on the market, which in turn depends on the value of the cap, and therefore a low value of cap should, in theory, lead to an increase of the emissions allowance price.

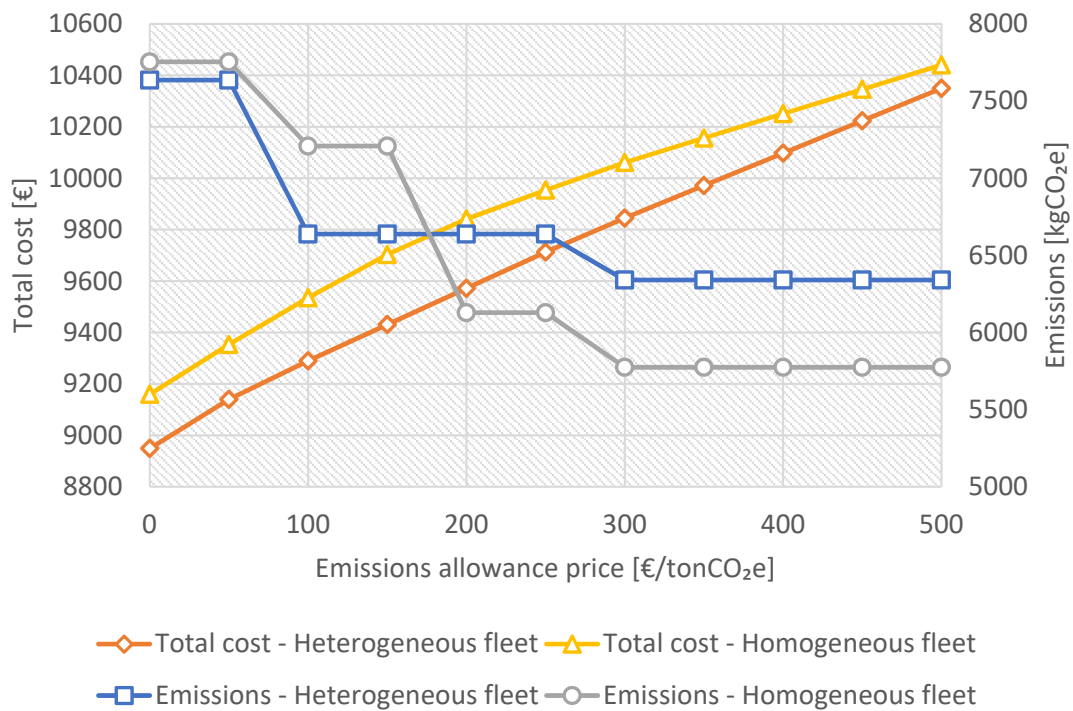


Figure 4 – Cap-and-trade policy with fixed cap value (50%): comparison of the heterogeneous fleet and homogeneous fleet instances

5.6. Cap-and-offset policy

The results, in terms of total cost and emissions, of the sensitivity analysis on the cap value are reported in Figure 5. The emissions credit price is fixed and set equal to 7.27€/tonCO₂e. The results are similar to those obtained under the cap-and-trade, but in this case, given an over-allocation of free allowances (corresponding to values of cap

higher than 100%), there are no economic or environmental improvements, since there is no possibility to sell the extra allocated allowances. The results show that in this case the emissions reduction due to the cap-and-offset is not achieved at a local level, since the model does not modify its initial routing and deliveries configuration, but it is achieved at a global level. In fact, the amount of purchased emissions credits corresponds to the amount of carbon emissions avoided by financing a carbon-free project in a developing country, where the same emissions reduction can be achieved with lower cost (Carbon Tax Center, 2017). From this point of view, the cap-and-offset policy is particularly suitable for those companies that have environmental concerns about their activities but cannot modify their operational arrangement to achieve a local emissions reduction.

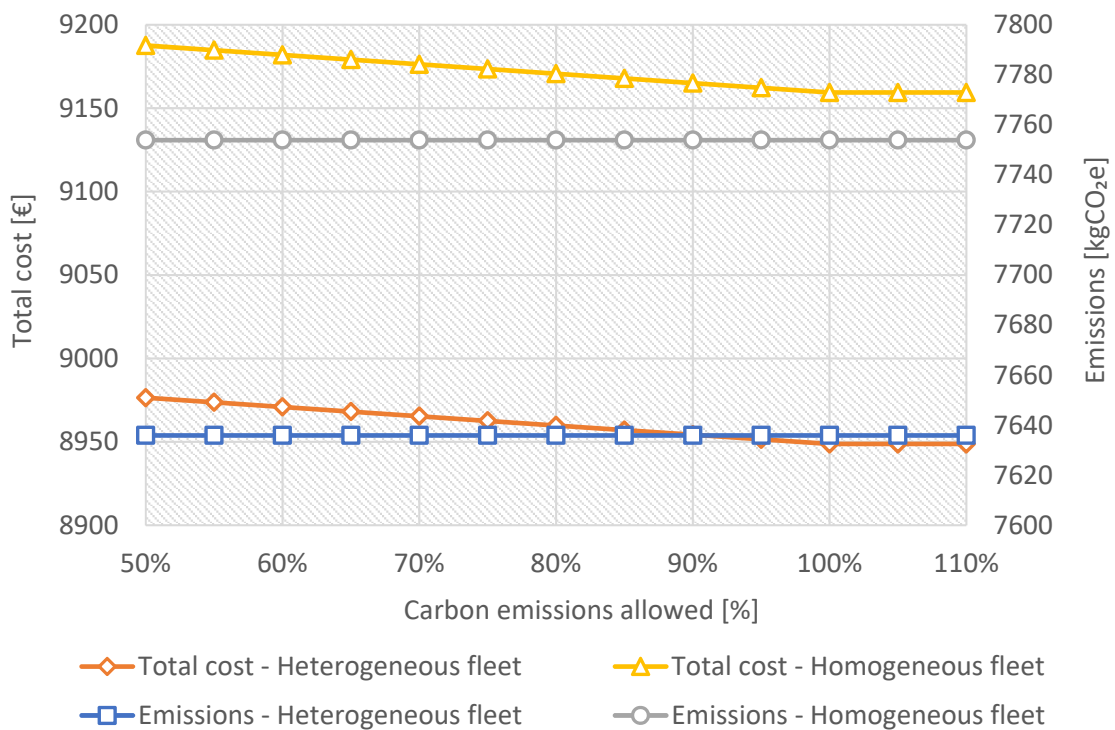


Figure 5 – Cap-and-offset policy with fixed credit price (7.27€/tonCO₂e): comparison of the heterogeneous fleet and homogeneous fleet instances.

6. Analysis and discussion

The above results provide the exemplification of the effects of different carbon control policies on the operational decisions of a short-term logistics problem, where a comprehensive emissions model, a heterogeneous fleet and the uncertainty of the demand are simultaneously taken into account.

On the one hand, the cap policy, simulating a constraint on the total allowed emissions, provide decision makers with alternative solutions based on the specific cap value addressed. For example, for high caps, a significant reduction can be achieved with a small cost increase. This applies more to flexible contexts where there is room for improvement in the short-period decision making.

Differently, the carbon tax scenario incorporates into the decision-making process the external cost of emissions, thus providing decision-makers with different operational configurations, based on the different emissions cost that depends on the context where the business is set.

It is therefore interesting comparing the results obtained with the above mentioned policies, by showing the total cost increase corresponding to the achieved emissions reduction, represented in Figure 6.

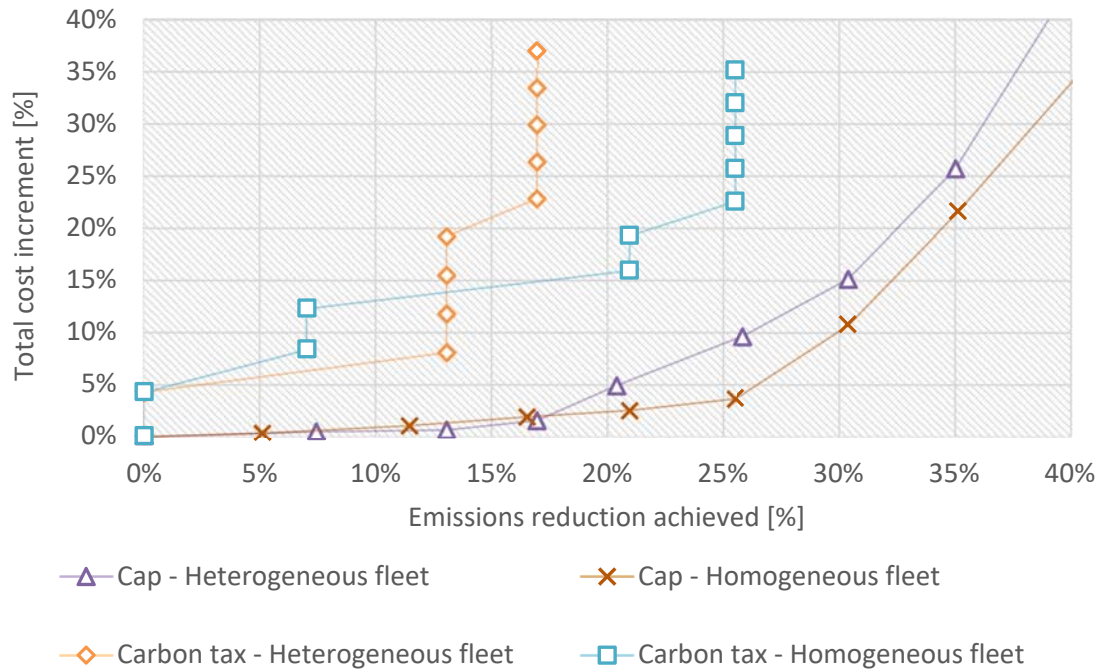


Figure 6 - Comparison between cap policy and carbon tax policy, total cost variation and emissions reduction achieved

Considering the heterogeneous fleet case, a carbon tax equal to 150€/tonCO₂e leads to a 13.07% emissions reduction and a 0.66% increase of operational cost. Since the routing and deliveries configuration is the same as the cap policy with a 90% cap, the results are apparently identical. However, in the carbon tax policy, the operational cost does not correspond to the total cost as in the cap policy, thus the additional emissions cost finally leads to an 11.78% increase in the total cost. Doubling the carbon tax price, from 150€/tonCO₂e to 300€/tonCO₂e, the emissions reduction is slightly improved, from a 13.07% to a 16.97% reduction, but the total cost is doubled from an 11.78% to a 22.82% increase.

On the other hand, when dealing with cap-and-trade, decision makers have to take into account two variables at the same time, respectively the cap value and the emissions

allowance price, but the results in section 5 have shown that the former does not affect the operational decisions. Since the carbon tax policy can be considered as a particular case of the cap-and-trade where there are no free allocation of emissions allowances (cap equal to 0%), it is interesting comparing the results of these two policies in terms of total cost variation (reported in Figure 7), considering two values of emissions cap, respectively equal to 100% and 50%.

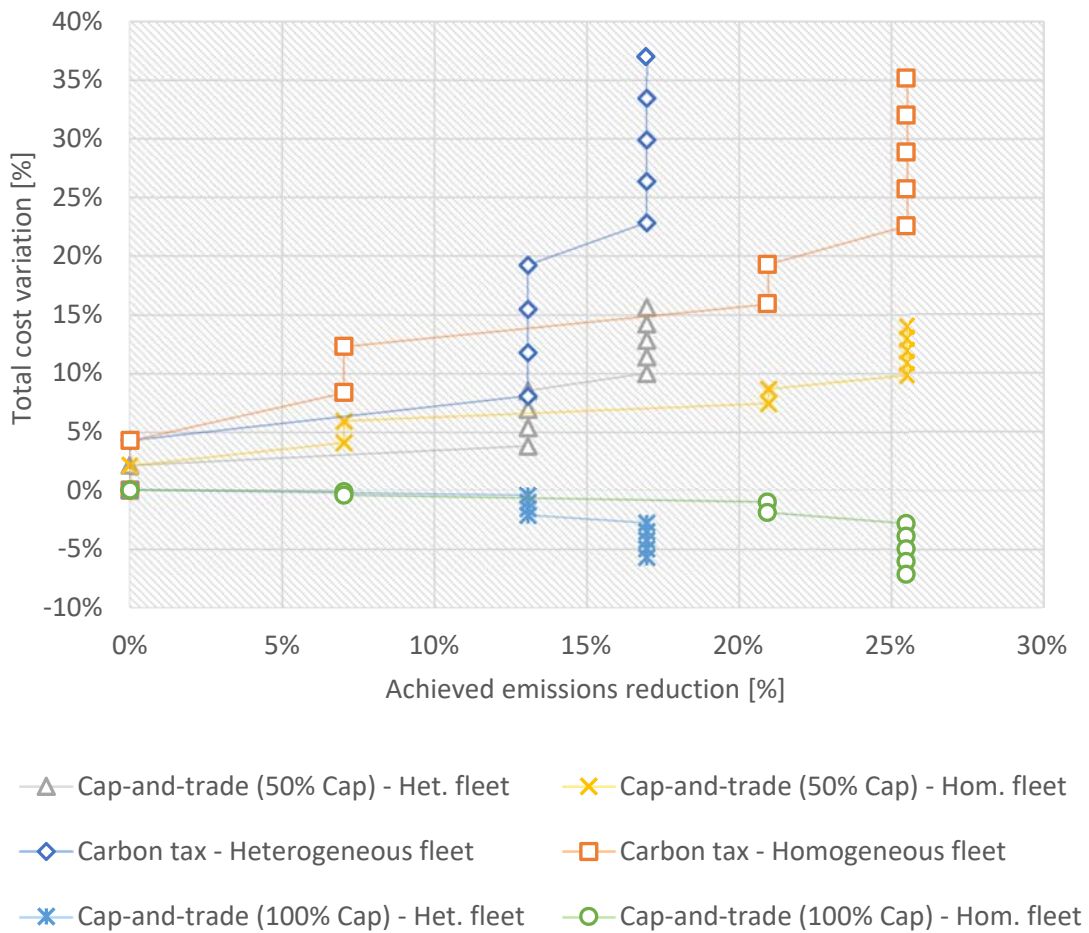


Figure 7 - Comparison between cap-and-trade policy and carbon tax policy, total cost variation and emissions reduction achieved

The comparison shows how the carbon tax policy, given the same achieved emissions reduction, is the policy that implies the highest total cost increase. This because, differently from the cap-and-trade, it does not imply the free allocation of allowances that partially cover part of the total emissions.

The application of these carbon policies on a short-term logistics problem characterised by different costs (driver cost, fuel cost, inventory cost) provide the decision maker with insights on how to modify the strategic decision of his/her business in the medium-long term. For example, in those contexts where emissions constraints get increasingly stricter, the emissions reduction lead to an increase of the inventory holding cost that can be not sustainable if the imposed reduction is too high. At the same time, addressing the additional cost of emissions highlighted by each policy can help to better frame all the hidden aspects of the operational activities. These include external costs when it comes to carbon tax, or the possibility of generating additional revenue from carbon trading, or the cost-convenience of offsetting part of the emissions by purchasing carbon offsets.

7. Conclusions

This research contributes to the topic of the environmentally-extended IRP developing a formulation that simultaneously considers the uncertainty of demand, a comprehensive emissions model and a heterogeneous fleet. In order to reflect the growing concern of companies towards the implementation of curbing emissions regulations, the proposed model is further modified to address four different carbon

control policies, namely the cap, the carbon tax, the cap-and-trade and the cap-and-offset. The results provide companies with insights into the optimal operational configurations under the different policies, highlighting the economic and environmental implications of each policy. The instances tested within this paper confirm the results of other environmentally-extended IRP (Mirzapour A. and Rezik (2014); Treitl et al. (2014); Cheng et al. (2016)), showing that the introduction of a policy leads to an increase of the total cost. This increase can be determined by higher inventory holding costs, the extra emissions costs (tax, allowances or offsets), or by a mix of the two. The results, in terms of total cost and emissions reduction, really depend on the applied policy and on the severity of the policy. Under the cap policy, it is possible to achieve a considerable emissions reduction with a small total cost increase when the cap is relatively large, whereas the carbon tax policy appears to be more expensive and less effective in reducing emissions when the tax is too low. Similar considerations can be made for the cap-and-trade policy where a low allowance price would result in the inefficacy of the policy, while low price carbon offsets would help the company to meet the cap-and-offset more easily.

7.1. Limitations of the study and further research

Given the novelty of the topic, the limitations of the study are numerous, and some of them naturally result in further research avenues.

Mainly in terms limitations, a number can be listed:

- The real logistics problem described includes a supplier and a set of customers; however, specific peculiar relationships and inter-organizational dynamics

potentially linking the supplier and one or more of the customers are not considered, which in turn might imply different operational decisions (based on different strategies). Thus, the proposed model is expected to work better when the customers – in the view of the supplier – are similar, which is a common situation.

- The distribution network is assumed to include a third-Party Logistics (3PL) provider, which serves as a rental vehicle company; multimodality is not considered, which might be an interesting option in many countries, particularly when seeking emissions reduction. Thus, the model is expected to work well when the distances are not too much significant, so that the commonest choice is road.
- Since the focus of this research is on the implications of different carbon control policies on a general IRP, considerations on waste are neglected, assuming an infinite expiration date. Where this assumption does not apply, the vehicle speed could become a lever to better cope with the perishability of the goods, which is in contrast with the assumption of a fixed vehicle speed (equal to 80 km/h) proposed in this research. Perishable goods have peculiarities and the model should be revised when targeting any supply chain (such as the food one) dealing with them. The same applies to particularly demanding (in terms of fast delivery) supply chains such as the pharmaceutical one.
- Demand that cannot be fulfilled in one period is assumed to potentially be backlogged in the next period, and no shortages costs are considered. Thus, the model is expected to work well when substitutability is not a relevant problem.

In any case, the solutions provided by the model has always to be accurately checked, so as not to introduce a systematic backlog, which, in the long run, might be detrimental for the market share of the supplier.

- Customers are assumed to have unlimited capacity warehouses, which is of course a strong simplification; thus, the model is expected to work well when the cost for the installed capacity at the customers' premises is sufficiently low as not to imply a constraint in terms of available routine capacity. This is likely to be true when the shipped goods need relatively small cubic area in a standard warehouse.
- The drivers of the vehicles are assumed to be paid hourly, which is the current mirror of what really happens. Nevertheless, any particular contractual situation would need some revision of the proposed model.

In terms of further development of the presented research, some avenues are proposed:

- Quantitatively evaluating how the introduction of emissions policies affect the vertical collaboration between suppliers and customers, analysing how the diverse costs (inventory holding, driver, fuel, emissions...) are distributed among the actors; potentially, taking into account contextual factors such as the size and dominance of the actors.
- When modelling in a more accurate way the customer service level as a decision variable and assuming a shortage cost, investigating how the introduction of policies can affect the customer satisfaction side of the problem.

- Analysing how emissions restrictive measures affect a three-echelon supply chain, properly modelling the up-stream stage that represents the availability of products at the supplier's site at each period.
- Given the simplistic choice of considering the uncertainty of the demand only by delivering an additional quantity of product (consistent with the existing literature), the proposed model would strongly benefit from further development so as to take into account that the "normal" level of uncertainty of the demand in the next decade might significantly change (reaching a "new normality").

Annex A: Data of the problem

Table 5

Data of expected customer demand per period.

Customer	Customer Demand [kg]					
	Weeks					
	1	2	3	4	5	6
C1	2000	3200	3000	1800	2600	1900
C2	1400	2600	3400	1600	2800	1400
C3	2600	4800	800	7000	400	300
C4	6000	1000	2200	2400	1400	2000
C5	1200	2200	1800	2400	4000	1800
Total	13200	13800	11200	15200	11200	7400

Table 6

Distances between the nodes of the network.

	Distance [km]						
	Depot	Supplier	C1	C2	C3	C4	C5
Depot	0	86.1	126	178.8	172	221.6	150.1
Supplier	85.8	0	42.6	187	245	297	173
C1	126	41.7	0	175	287	339	214
C2	179	187	173	0	285	385	310
C3	172	245	288	282	0	169	166
C4	222	297	339	383	170	0	112
C5	150	171	215	312	170	114	0

Table 7

Vehicle parameters of the heterogeneous fleet employed in this research.

	Notation	LDV	MDV	HDV	Unit of measure
Vehicle common parameters					
Fuel-to-air mass ratio	ξ	1	1	1	-
Gravitational constant	g	9.81	9.81	9.81	[m/s ²]
Air density	ρ	1.2041	1.2041	1.2041	[kg/m ³]
Coefficient of rolling resistance	C_r	0.01	0.01	0.01	-
Efficiency parameter for diesel engines	ω	0.45	0.45	0.45	-
Heating value of a typical diesel fuel	κ	44	44	44	[kJ/g]
Vehicle speed	f	22.2	22.2	22.2	[m/s]
Conversion factor	ψ	737	737	737	[g/l]
Road angle	ϕ	0	0	0	-
Vehicle specific parameters					
Kerb-weight	μ^k	3500	5500	13154	[kg]
Maximum payload (Capacity)	c^k	4000	12500	17236	[kg]
Engine friction factor	k_e^k	0.25	0.20	0.15	[kJ/rev/l]
Engine speed	N_e^k	38.3	36.7	30.2	[rev/s]
Engine displacement	V_e^k	4.50	6.90	6.66	[l]
Coefficient of aerodynamic drag	C_d^k	0.6	0.7	0.7	-
Frontal surface area	A^k	7.0	8.0	9.8	[m ²]
Vehicle drive train efficiency	ε^k	0.45	0.45	0.50	-

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