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

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Abstract in English

Carbon emissions produced by supply chain activities, and in particular by transportation, largely contribute to global warming. In order to tackle the problem, many governments and regulatory authorities have started to implement different carbon control policies, which may directly impact on the decisions of a company. In a traditional inventory routing problem, a supplier determines the optimal vehicles 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 taking simultaneously into account the uncertainty in customers demand, a comprehensive emissions model, and a heterogeneous fleet of vehicles. The proposed model is further deployed to address four different of these 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.

Abstract in Italian

Le emissioni di anidride carbonica prodotte dalle attività di supply chain, ed in particolare dal trasporto, contribuiscono largamente al surriscaldamento globale. Per affrontare il problema, diversi governi e autorità regolatrici hanno iniziato ad istituire politiche volte al controllo delle emissioni di CO_2, le quali possono influire direttamente sulle decisioni di un'azienda. In un tipico Inventory Routing Problem, il fornitore, basandosi sui livelli di scorte dei clienti, determina la schedulazione ottimale delle consegne e le relative tratte dei veicoli, al fine di minimizzare i costi dell'intero sistema. Il contributo della presente tesi consiste nella modellazione del problema considerando simultaneamente l'incertezza della domanda dei clienti, un modello completo di stima delle emissioni ed una flotta di veicoli eterogenea. Il modello proposto è successivamente modificato per prendere in considerazione quattro differenti politiche di controllo delle emissioni, in particolare il cap, la carbon tax, il cap-and-trade ed il cap-and-offset. Sulla base di un caso studio, le implicazioni economiche e ambientali di ogni politica sono analizzate e discusse, concentrandosi in particolare sulle decisioni operative del modello proposto.

Parole chiave: inventory routing problem, emissioni di carbonio; politiche di controllo delle emissioni; flotta eterogenea; modello completo di stima delle emissioni; incertezza della domanda.

Executive summary

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

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Abstract

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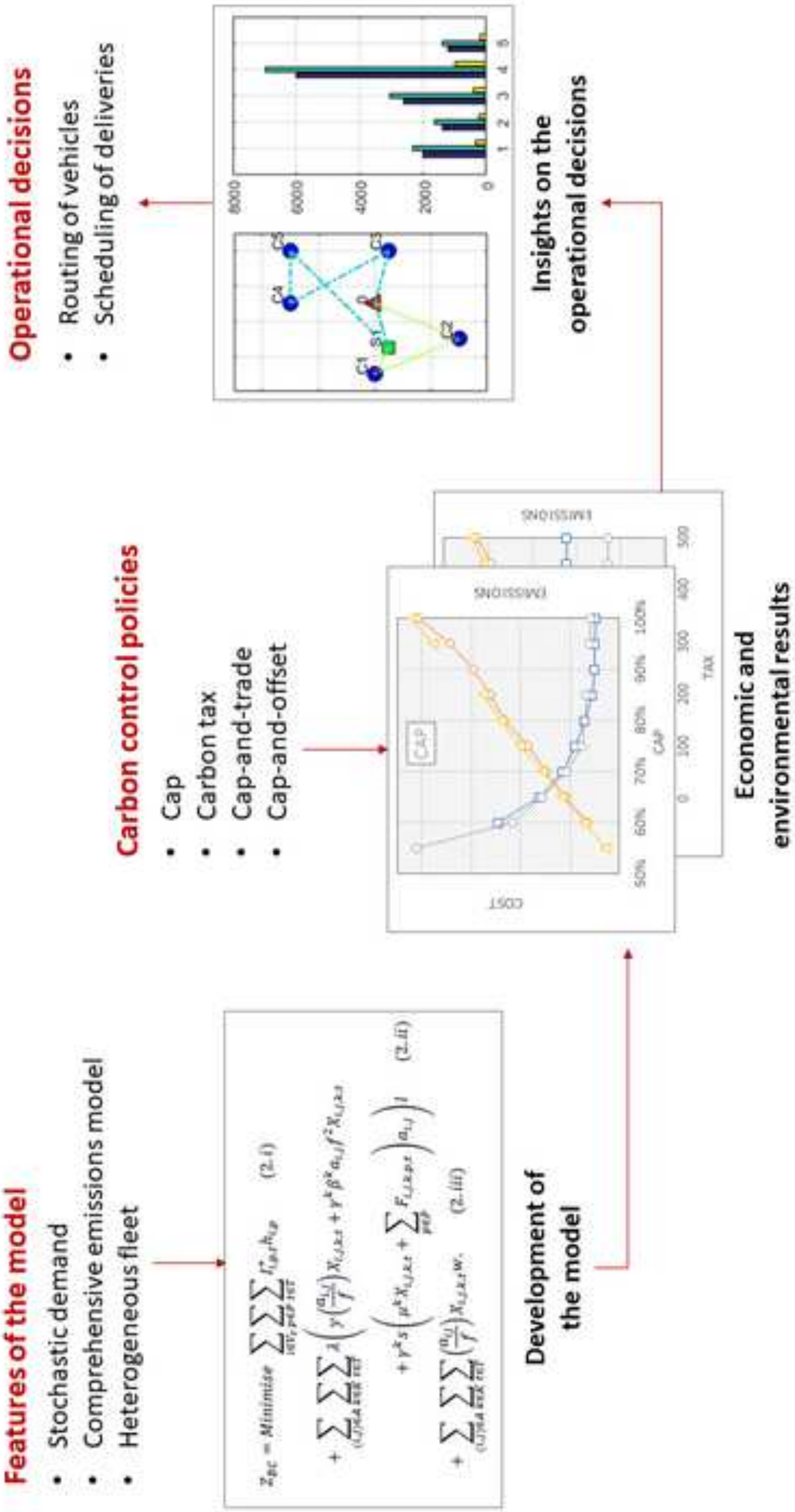
Paper type Research Paper


Features of the model
Stochastic demand
Comprehensive emissions model
Heterogeneous fleet
Development of the model
Carbon control policies
Cap
Carbon tax
Cap-and-trade
Cap-and-offset
Economic and environmental results
Operational decisions
Routing of vehicles
Scheduling of deliveries
Insights on the operational decisions

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

Highlights

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

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

Abstract

Carbon emissions produced by supply chain activities, and in particular by transportation, largely contribute to global warming. In order to tackle the problem, many governments and regulatory authorities have started to implement different carbon control policies, which may directly impact on the decisions of a company. In a traditional inventory routing problem, a supplier determines the optimal vehicles 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 taking simultaneously into account the uncertainty in customers demand, a comprehensive emissions model, and a heterogeneous fleet of vehicles. The proposed model is further deployed to address four different of these 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.

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1. Introduction

Climate change is one of the most serious threat 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 gases emissions (GHGs), driven by economic and population growth, have increased exponentially since the pre-industrial era, reaching levels untouched before (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 Statistic Explained, 2017). Emissions from light-duty (LDVs) and heavy-duty vehicles (HDVs) represent the 37.6% of the total road transportation sector, which in turn accounts for the 72.9% of the total emissions from transportation.

In this context, it emerges how supply chain activities, which include production, transportation, and inventory management, largely contribute to the GHGs emissions, representing one of the main sectors where researchers have focused their efforts to find ways to curb emissions. Besides the academic world, also companies have 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 consumer towards "green" products; (ii) governments and policymakers have started to regulate environmental impacts of companies; (iii) high emissions generated by the operations of a company are often 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 on the problem.

Concerning the third aspect pointed out by Treitl et al., Benjafaar et al. (2013) highlight how the tendency of focusing on the 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, analyses the environmental impact of the best practices of lean logistics (just-in-time, postponement, vendor-managed inventory (VMI)), showing how VMI, can reduce the transportation-related emissions. The logistics problem that describes the VMI is the inventory routing problem (IRP), which is a variant of the vehicle routing problem. 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 minimize 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 understand how carbon emissions considerations 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, it is conducted a literature review of those papers that already tackled this problem and based on the highlighted literature gaps, it is developed a partially new formulation of the environmentally-extended IRP. Then, different carbon control policies are applied to this formulation, and insights on the economic and environmental implications of the policies are provided.

2. Literature review

The Scopus online database is used to find those articles that already tackled the environmental extension of the IRP. The keyword “inventory routing problem” is combined with the keywords “emissions”, “green”, “environmental”, “sustainable” “pollution”, and the following selection criteria are considered: (i) time frame of publication up to 2017; (ii) articles written in English; (iii) exclusion of document type different from academic papers and conference proceedings. Then, the abstract and content analysis allows excluding those articles which do not explicitly consider IRPs and the related carbon emissions. The resulting set, composed of twelve papers is shown in **Table 1.** Although the IRP makes its first appearance in 1983 (Bell et al., 1983), the integration with environmental considerations appears only in 2014, in the pioneer 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, 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 network. In the one-to-one network, one supplier serves one customer. None of the analysed articles show this solution. In the one-to-many case, one supplier serves a set of customers. This is so far the most diffused approach to set the IRP, and it is employed by two-thirds of the papers analysed ([2][3][5][6][7][9][10][11]). 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. This approach is used by three papers ([1][4][12]). Finally, in the many-to-many distribution network, a set of suppliers serve a set of customers. Only ([8]) considers this case. Concerning the fleet of vehicles, all the articles consider a multi-vehicles problem; the majority ([1][2][3][6][7][9][12]) considers a heterogeneous fleet, while the rest consider a homogeneous fleet ([4][5][8][10][11]).

Concerning the modelling of the demand, that represents the consumption rate of the downstream stage of the distribution network, one paper considers a static demand pattern over periods [11], five papers consider a variable, deterministic pattern ([3][4][6][7][12]), while six papers use non-deterministic approaches, which implies a proper modelling of the stock out occurrences at the customer's sites. In particular, two papers 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 ([10][8]); two papers employ a fuzzy distribution and, using multi-objective models, maximise the customer service level or minimise the stock-out occurrences ([2][9]); two papers consider a multi-scenario framework with deterministic data of demand for each scenario and use proper shortage costs associated with the stock-out occurrences ([1][5]).

The majority of the analysed papers adopts an economic single-objective function, thus maximise profit or minimise costs ([3][4][5][8][10][11][12]). The remaining papers adopt multi-objective models, where the traditional economic objective function is integrated with different types of objective functions, such as minimizing GHGs emissions ([2][6]), maximise social concerns ([7]), or both minimize GHGs emissions and maximise customer service level ([2][9]).

Concerning emissions generated by transportation, six papers use constant linear functions depending on vehicle type and travelled distance ([1][2][6][7][9][12]), while the remaining use more complex formulations: four papers adopt a comprehensive emissions model ([3][8][10][11]), and two papers adopt a simplified emissions model based on travelled distance, vehicle type and vehicle payload ([4][5]).

Lastly, regarding environmental concerns, four papers, adopting multi-objective models use one objective function to minimise GHGs emissions ([1][2][6][9]); three papers indirectly minimise emissions by including the explicit fuel cost in the cost-minimising objective function ([5][8][10]); five papers apply a carbon control policy. In particular two papers impose a constraint, called "carbon cap", on the maximum allowed amount of emissions ([7][12]); one applies a carbon tax proportional to the volume of emissions produced ([3]); one considers the combination of the carbon cap and the carbon tax ([11]); one analyses the same model under four different carbon control policies, namely the cap, the cap-and-trade, the cap-and-offset and the carbon tax ([4]). **Table 1** summarises the descriptive analysis of the reviewed papers.

Table 1

Descriptive analysis of the reviewed paper in chronological order.

	Article - Authors	**Network topology**	**Fleet type**	**CO_2 emissions model**	**Demand**	**Environmental concerns**	**Model**
[1]	**Mirzapour A. et al., 2017**	many-to-one	heterogeneous	constant	stochastic	minimizing objective function	multi-objective
[2]	**Rahimi et al., 2017**	one-to-many	heterogeneous	constant	stochastic	minimizing objective function	multi-objective
[3]	**Cheng et al., 2017**	one-to-many	heterogeneous	comprehensive	deterministic	carbon control policy	single-objective
[4]	**Cheng et al., 2016**	many-to-one	homogeneous	simplified	deterministic	carbon control policy	single-objective
[5]	**Soysal, 2016**	one-to-many	homogeneous	simplified	stochastic	explicit fuel consumption	single-objective
[6]	**Franco et al., 2016**	one-to-many	heterogeneous	constant	deterministic	minimizing objective function	multi-objective
[7]	**Rahimi et al., 2016**	one-to-many	heterogeneous	constant	deterministic	carbon control policy	multi-objective
[8]	**Soysal et al., 2016**	many-to-many	homogeneous	comprehensive	stochastic	explicit fuel consumption	single-objective
[9]	**Niakan and Rahimi, 2016**	one-to-many	heterogeneous	constant	stochastic	minimizing objective function	multi-objective
[10]	**Soysal et al., 2015**	one-to-many	homogeneous	comprehensive	stochastic	explicit fuel consumption	single-objective
[11]	**Treitl et al., 2014**	one-to-many	homogeneous	comprehensive	deterministic	carbon control policy	single-objective
[12]	**Mirzapour A. and Rekik, 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 are not still investigated, to properly contribute to the development of the topic.

Treitl et al. (2014) show how shifting from the retailer-managed inventory policy to the vendor-managed inventory policy is possible to achieve a 12.29% reduction in the total cost of the system and a 15.97% reduction in the vehicle CO_2 emissions. 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 Rekik (2014) consider a IRP with transhipment. They illustrate the "greenness" of the transhipment 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, showing that the latter leads to a 0.8% decrease in the total carbon emissions and a 0.2% decrease in the total cost. 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 GHGs 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 as the horizontal collaboration case leads to a win-win situation characterized by a 29.3% reduction in GHGs emissions and a 17.1% reduction in total cost. Rahimi et al. (2016) address social issues in a reverse logistics IRP, developing a bi-objective mathematical model that consider 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), showing the benefits of integrating forward and reverse logistics: the integrated model leads to 41.6% reduction in total cost and a 50.8% reduction of emissions compared with the non-integrated model. Cheng et al. (2016) develop four different models that address respectively the cap policy, the cap-and-trade policy, the cap-and-offset policy and the carbon taxing policy, and propose a hybrid-genetic algorithm to solve them. Analysing the cap policy, they show how tightening the cap, the model reduces the emissions (-41.4%) while the total cost increases exponentially (+428.5%), 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 illustrate the benefits of adopting a heterogeneous fleet of instead of, and they show how a comprehensive objective function outperforms the traditional objective function, in terms of total cost (-6.71%) and total emissions (-23.09%). Rahimi et al. (2017) develop a multi-objective model that simultaneously consider economic, service level, and green criteria, and address perishability of products considering recycling costs and emissions generated by the recycling process. The authors highlight how multi-objective models allows the decision maker to identify those solutions that with a small profit decrement, achieves a major increase of customer service level. Lastly, Mirzapour Al-e-hashem et al. (2017) study the economic and environmental performance of a transhipment-enabled stochastic IRP (TIRP) in a many-to-one logistics network. They develop a bi-objective stochastic programming model showing that transhipment strategy can be effective in reducing the total travel distance and GHGs through merging the trips.

With respect to the descriptive analysis, it emerges how none of the analysed single-objective models simultaneously address a heterogeneous fleet, a comprehensive emissions model and uncertainty of demand. These three features, as shown by the reviewed literature, lead to better results in terms of economic and environmental performances (Cheng et al. 2017) and to a closer description of reality (Soysal et al. 2016). Moreover, despite the growing concerns towards 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. It is developed a chance-constrained programming model 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, it is presented an emissions-minimising model and a constant emissions model. The former provides insights on the modifications of the operational decisions in an environmentally-concerned context, while the latter quantifies the accuracy of results when using a comprehensive emissions model.

The proposed models are applied to a real logistics problem described by a supplier and a set of customers and, for each policy, it is performed a sensitivity analysis 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 that developed by Soysal et al. (2016), which address 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 the 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:

- Demand of customer i, of product type $p \in P$, at time $t \in T$, is indicated by $d_{i,p,t}$ and it is assumed to be normally distributed with mean $\mu_{i,p,t}$ and standard deviation $\sigma_{i,p,t}$. 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. Vehicles have different payload capacity c^k and different drive parameters.
- Vehicles routings start and end at 3PL and it is not allowed more than one route per period.
- Split deliveries are allowed, so customers can be visited by more than one vehicle per period.
- Inventory holding cost are denoted by $h_{i,p}$, and depends 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. No inventory holding cost is considered at the supplier's site.
- Both supplier and customers are characterized 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 routing of vehicles and scheduling of deliveries that minimise the expected total cost, given by the sum of routing and inventory holding cost. The decision variables are the following:

- $\boldsymbol{X_{i,j,k,t}}$: 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.
- $\boldsymbol{B_{i,k,p,t}}$: 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].
- $\boldsymbol{Q_{i,k,p,t}}$: 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].
- $\boldsymbol{I_{i,p,t}}$: 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 $I_{i,p,0} = 0, \forall i \in V_C, p \in P$.
- $\boldsymbol{I^{+}_{i,p,t}}$: 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].
- $\boldsymbol{F_{i,j,k,p,t}}$: 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].
- $\boldsymbol{U_{i,k,t}}$: 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 (2008). 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), that reviewed 25 different emissions models, the comprehensive emissions model is the best in terms of robustness, reliability, and applicability in optimization. Given a vehicle speed f (m/s), a travelled distance $a_{i,j}$ (m), a curb weight μ^k, and a payload $F_{i,j,k,p,t}$ (kg), the fuel consumption in litre, is given by:

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

where $\lambda = \xi/(\kappa\psi)$, and $s = \tau + g sin\phi + gC_r cos\phi$. The vehicle type-dependent parameters are $\gamma^k = 1/(1000\ \varpi\varepsilon^k)$, $\beta^k = 0.5C_d^k\rho A^k$, and $y^k = k_e^k N_e^k V_e^k$. Parameters' definitions are reported in **Table 8**. The related carbon emissions, expressed in $kgCO_2e$, are obtained 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, is and it is described by the following objective function that minimise the sum of the operational costs:

$$Z_{BC} = Minimise \sum_{i\in V_c}\sum_{p\in P}\sum_{t\in T} I^{+}_{i,p,t} h_{i,p} \qquad (2.i)$$

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

$$+ \sum_{(i,j)\in A}\sum_{k\in K}\sum_{t\in T} \left(\frac{a_{ij}}{f}\right) X_{i,j,k,t} w. \qquad (2.iii)$$

The term $(2.i)$ calculates expected the inventory holding cost, the term $(2.ii)$ calculates fuel cost adopting the comprehensive emissions model and the term $(12.iii)$ calculates drivers cost. The model is subjected to the following constraints:

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

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

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

Constraints $(3) - (5)$ concern inventory decisions. Constraint (3) calculates the expected inventory levels at each customer for each period of the planning horizon. 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. 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 following linear constraint:

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

where C_p is the coefficient of variation and Z_α is the standard normal random variate with cumulative probability α. In addition, the model is subjected to the following routing-related constraints:

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

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

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

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

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

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

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

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

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

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

Constraint (6) concerns the conservation of 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. Constraint (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:

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

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

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

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

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

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

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.

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

subject to constraints $(3)-(4)$, (5^*), $(6)-(15)$, $(16)-(21)$.

3.4. Constant emissions model

The constant emissions model, indicated as Z_{const}, is developed to quantify the incremental accuracy in fuel consumption calculation when the comprehensive emissions model is used. Thus, routing cost and emissions are computed based solely on the travelled distance, neglecting the decision variable on vehicle payload $F_{i,j,p,k,t}$.

$$min\ Z_{const} = \sum_{i\in V_C} \sum_{p\in P} \sum_{t\in T} I^{+}_{i,p,t} h_{i,p} + \sum_{i\in V} \sum_{j\in V} \sum_{k\in K} \sum_{t\in T} uc_k \cdot \frac{a_{i,j}}{1000} \cdot X_{i,j,k,t} \qquad (23)$$

subject to constraints $(3)-(4)$, (5^*), $(6)-(15)$, $(16)-(21)$. The parameter uc_k denotes the unitary routing cost expressed in €/km, calculated as the ratio between the routing cost and the driven kilometres of a single-vehicle base case instance, for each vehicle type k. The related emissions are estimated as:

$$E^{const}_{CO_2} = \sum_{i\in V} \sum_{j\in V} \sum_{k\in K} \sum_{t\in T} \frac{1}{ac_k} \cdot \frac{a_{i,j}}{1000} \cdot X_{i,j,k,t} \cdot u \qquad (24)$$

where ac_k denotes the average fuel consumption expressed in km/litre, calculated as the ratio between the driven kilometres and the fuel consumed of a single-vehicle base case instances, for each vehicle type k.

3.5. Cap policy model

Under cap policy, the overall emissions cannot exceed a fixed threshold. Having defined the solution of the base case model as Z_{BC}, the cap policy model is described by the following objective function:

$$minimise\ Z_{cap} = Z_{BC} \qquad (25)$$

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 $kgCO_2e$:

$$\sum_{(i,j)\in A} \sum_{k\in K} \sum_{t\in T} \lambda \left(y\left(\frac{a_{i,j}}{f}\right) X_{i,j,k,t} + \gamma^k \beta^k a_{i,j} f^2 X_{i,j,k,t} + \gamma^k s \left(\mu^k X_{i,j,k,t} + \sum_{p\in P} F_{i,j,k,p,t} \right) a_{i,j} \right) u \leq Cap \qquad (26)$$

3.6. Carbon tax policy

Under the carbon tax policy, carbon emissions are priced proportionally to the volume of emissions. A carbon pricing approach can be spontaneously adopted by companies that want to incorporate the externality of their activities in their decisions 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 €/$kgCO_2e$.

$$Z_{carbon\ tax} = Minimise \sum_{i\in V_c} \sum_{p\in P} \sum_{t\in T} I^{+}_{i,p,t} h_{i,p} \qquad (27.i)$$

$$+ \sum_{(i,j)\in A} \sum_{k\in K} \sum_{t\in T} \lambda \left(y\left(\frac{a_{i,j}}{f}\right) X_{i,j,k,t} + \gamma^k \beta^k a_{i,j} f^2 X_{i,j,k,t} + \gamma^k s \left(\mu^k X_{i,j,k,t} + \sum_{p\in P} F_{i,j,k,p,t} \right) a_{i,j} \right) (l + u \cdot tax) \qquad (27.ii)$$

$$+ \sum_{(i,j)\in A} \sum_{k\in K} \sum_{t\in T} \left(\frac{a_{ij}}{f}\right) X_{i,j,k,t} w, \qquad (27.iii)$$

subject to constraints $(3) - (4)$, (5^*), $(6) - (15)$, $(16) - (21)$.

3.7. 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 most diffused method. Companies that emit more than the allocated allowances, can purchase extra allowances from those companies that emit less than the allocated emissions. 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.

$$Z_{cap\ and\ trade} = minimise\ Z_{BC} + \chi^{trade} \cdot (e^{+} - e^{-}) \qquad (28)$$

subject to constraints $(3)-(4)$, (5^{*}), $(6)-(15)$, $(16)-(21)$, plus the constraint on the total allowed emissions:

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

3.8. Cap-and-offset policy

Under the cap-and-offset policy, the overall emissions can exceed the imposed maximum limit, only buying extra credits by investing in emissions-reduction projects (Carbon Tax Center, 2017). 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.

$$Z_{cap\ and\ trade} = minimise\ Z_{BC} + \chi^{offset} \cdot e^{+} \qquad (30)$$

subject to constraints $(3)-(4)$, (5^{*}), $(6)-(15)$, $(16)-(21)$, plus the constraint on the total allowed emissions:

$$\sum_{(i,j)\in A}\sum_{k\in K}\sum_{t\in T}\lambda\left(y\left(\frac{a_{i,j}}{f}\right)X_{i,j,k,t}+\gamma^k\beta^k a_{i,j}f^2X_{i,j,k,t}\right.$$
$$\left.+\gamma^k s\left(\mu^k X_{i,j,k,t}+\sum_{p\in P}F_{i,j,k,p,t}\right)a_{i,j}\right)u\ \leq Cap+\ e^{+}. \qquad (31)$$

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 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 fleet saturation, (vii) total number of vehicles, $(viii)$ fleet mix composition. When considering the application of a policy, the related implications on the operational cost and the emissions are reported. In order to gather insights on 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 numerical data of the vehicle parameters are shown in **Table 8**, based on the data of Koç et al. (2014) and Cheng et al. (2017). It is assumed a fixed vehicle speed equal to 80 km/h. The expected demand of the customers per each period is reported in **Table 6**, while the distance between the nodes of the network is reported in **Table 7**. The planning horizon of the problem is set equal to 6 periods, and each period corresponds to one week. Customers incur in 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 in kilograms of emitted CO_2, is set equal to 2.63kg/litre (DEFRA, 2007).

4.2. Description of the analysed cases

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

- Cap policy is analysed 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.
- Carbon tax policy is analysed modifying progressively the imposed carbon tax from a null value (equal to the base case) to 500€/tonCO_2e.
- Cap-and-trade is analysed 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€/ tonCO_2e, corresponding to the actual price in the EU ETS (EUA, 2017). In addition, it is analysed varying the emissions allowance price from a null value (equal to the base case), to 500€/tonCO_2e, keeping the cap fixed and equal to 50%.
- Cap-and-offset is analysed 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€/tonCO_2e, 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 optimization package. The solutions are obtained on a personal computer with the following characteristics:

- Processor: Intel® Core™ i5-3210M, CPU 2.50 GHz.
- RAM: 4.0 Gigabyte.

5. Results and discussion

5.1. Base case model

Results of the base case model are shown in **Table 2**. 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 2

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%
Emission [kgCO_2e]	7635.91	7753.90	-1.52%
Total cost [€]	8948.71	9159.39	-2.30%
Average saturation [%]	86.21%	62.06%	24.15%
Number of vehicles	10	10	0.00%
LDV	4	-	-
MDV	6	-	-
HDV	0	-	-

Figure 1 and **Figure 2** illustrate the routing and deliveries configuration of the base case models. Concerning routing decisions, the lower number of deliveries with the homogeneous fleet (customer C2 is not visited in the last period) leads to lower drivers cost. Given the same number of used vehicles, the heterogeneous fleet can choose smaller vehicles, providing less fuel consumption and, globally, lower routing cost and carbon emissions. In this sense, the flexibility of the heterogeneous fleet provides better results from an economic and environmental perspective. Concerning inventory decisions, the homogeneous fleet case is characterised by higher cost because it delivers the same quantity with less trips, and this globally leads to a higher total cost.

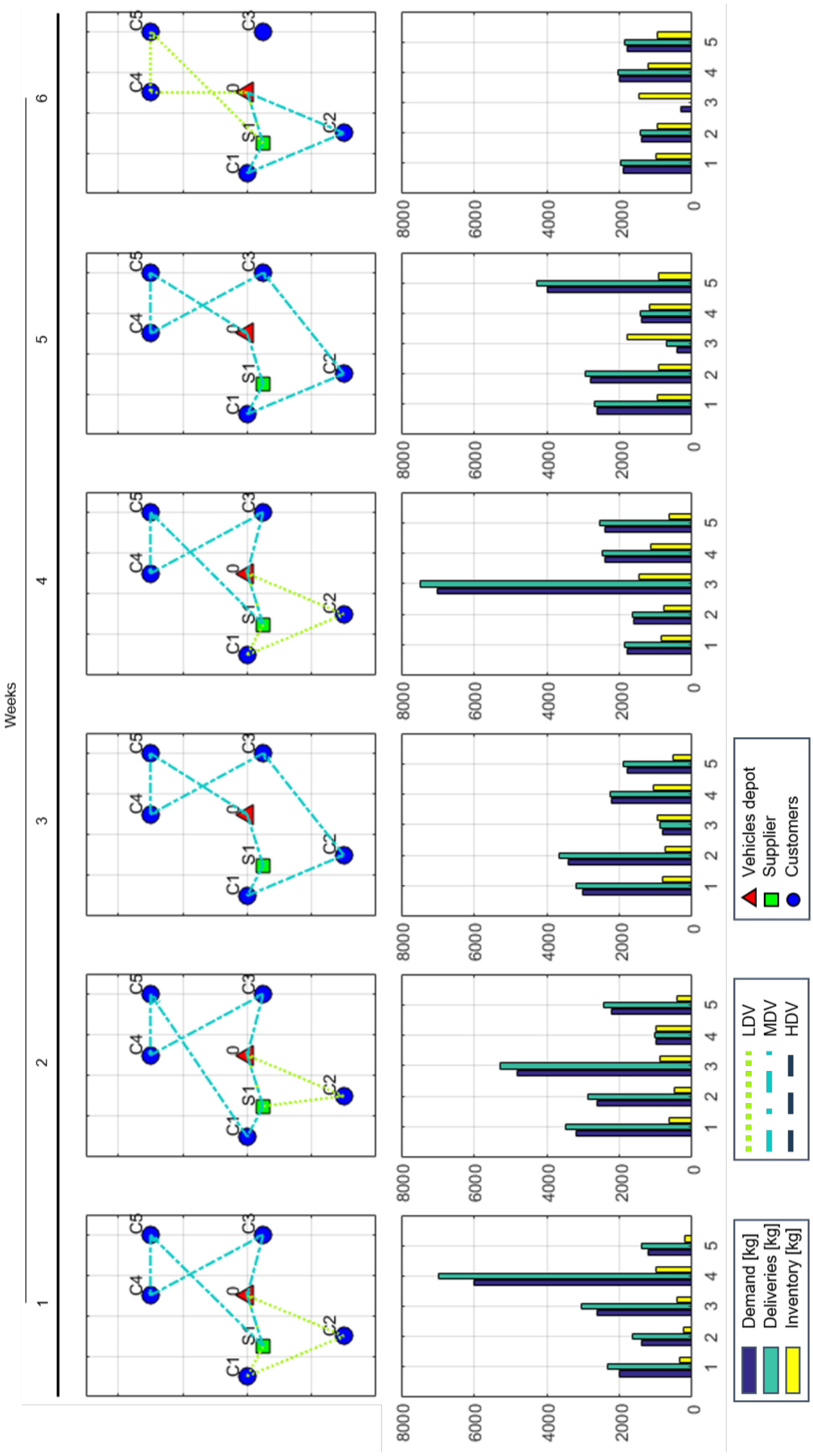

Figure 1 - Base case with heterogeneous fleet: routing and deliveries configuration.

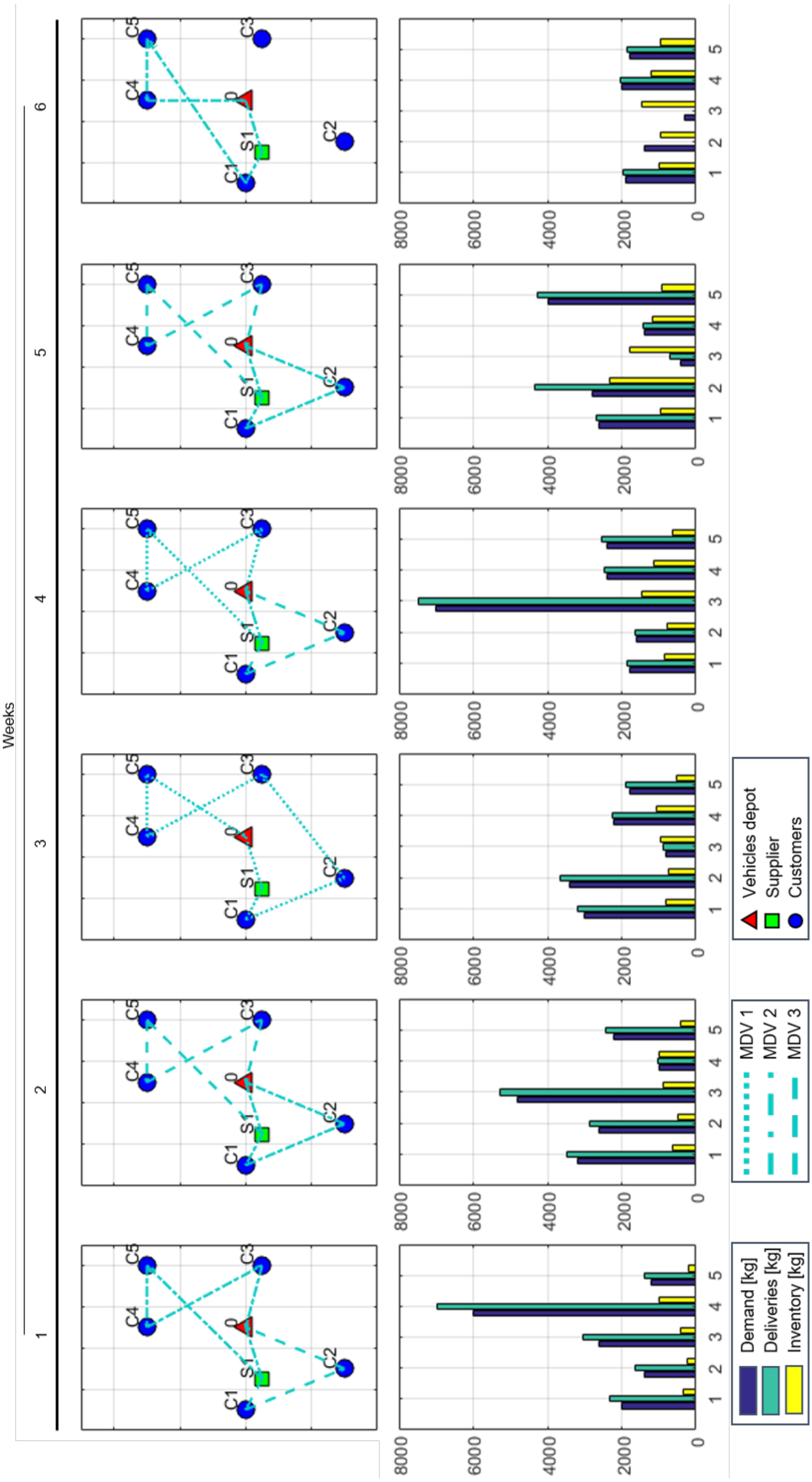

Figure 2 - Base case with heterogeneous fleet: routing and deliveries configuration.

5.2. Emissions-minimising model

Results of the emissions-minimising model are reported in **Table 3**. The model aims at minimising the number of trips, therefore using fewer vehicles and increasing saturation. 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. Concerning the heterogeneous fleet case, the fleet mix pass from 6 MDVs and 4 LDVs to 3 HDVs, 2 MDVs and one LDV.

Table 3
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%
Emission [kgCO₂e]	-47.53%	-45.15%
Total cost [€]	+115.59%	+121.25%
Average saturation %	+10.68%	+26.60%
Number of vehicles	-40.00%	-30.00%

Figure 3 and Figure *4* illustrate the routing and deliveries configuration of the emissions-minimising model, which reflects the solely environmental concerns. 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 exponentially increasing the inventory holding cost. Routing cost decreases following the emissions reduction because of the lower fuel consumption and driven kilometres. The heterogeneous fleet achieve better economic and environmental results because of the employment of HDVs able to deliver the same quantity with less vehicles. These considerations on 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.

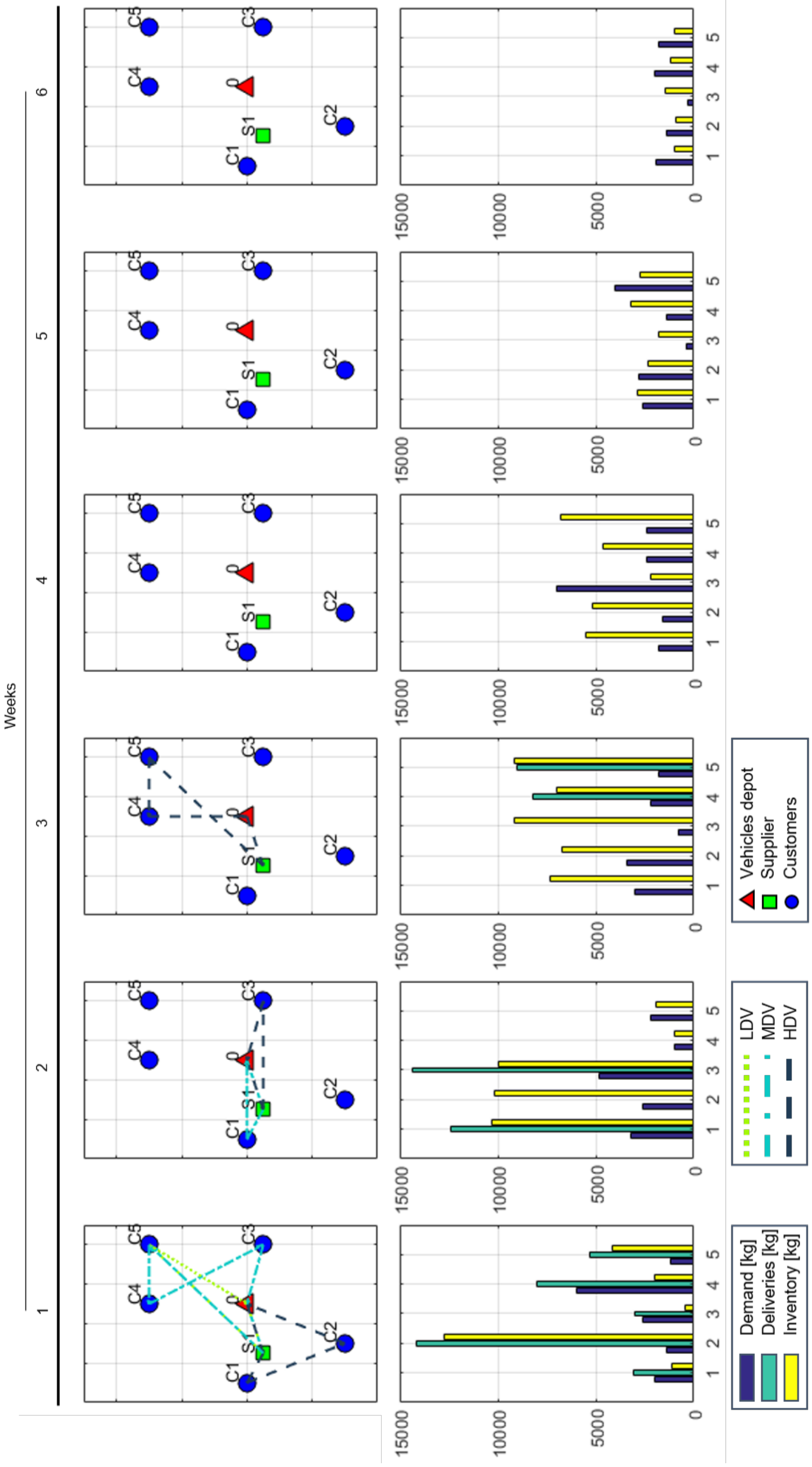

Figure 3 - Emissions-minimising model with heterogeneous fleet: routing and deliveries configuration.

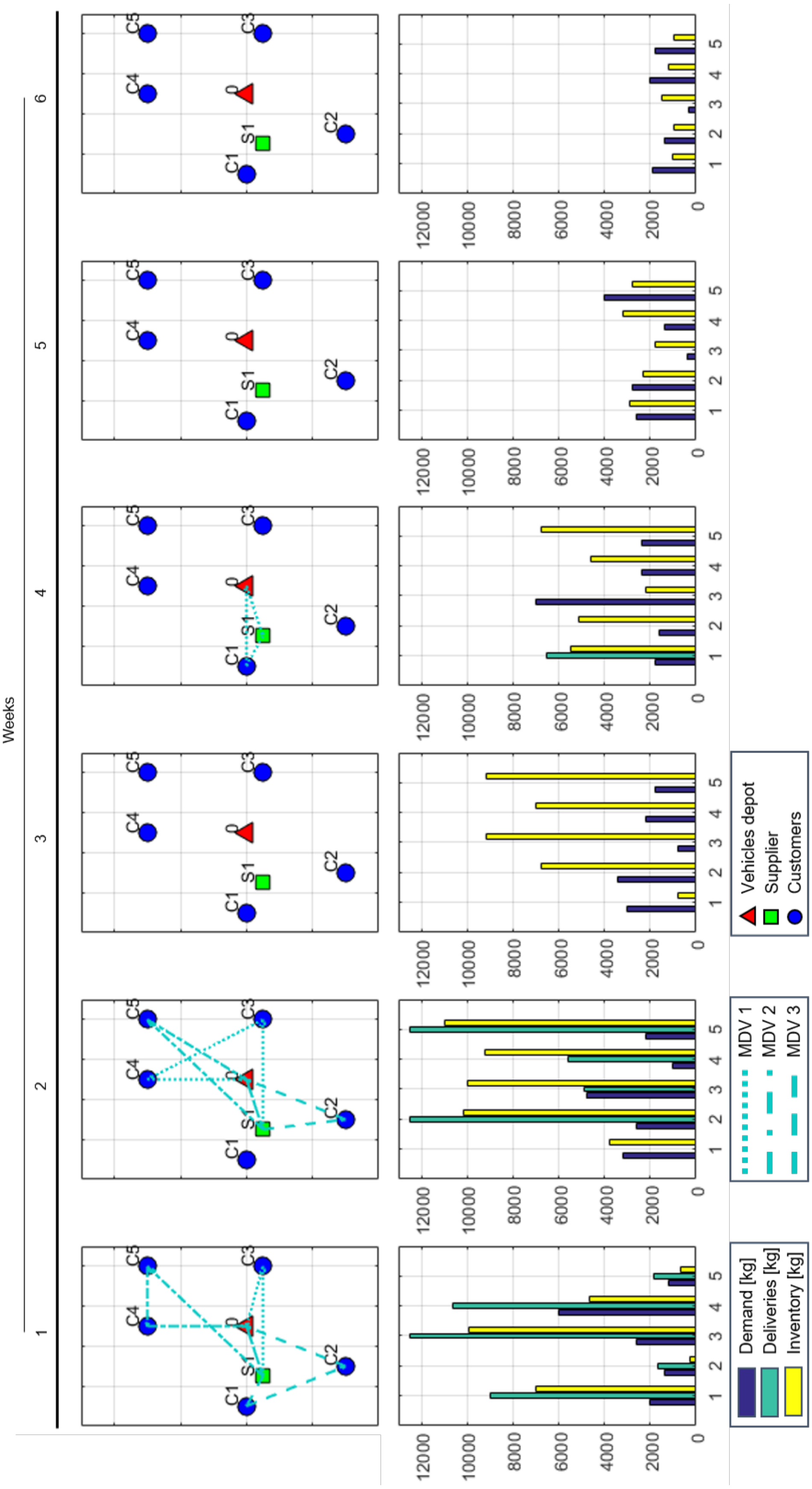

Figure 4 - Emissions-minimising model with homogeneous fleet: routing and deliveries configuration.

5.3. Constant emissions model

The unitary routing cost uc_k and average consumption ac_k are reported in **Table 4.** They have been obtained running the base case model with a single vehicle and setting the demand equal to one-quarter of the base case demand for the light-duty instance, and equal to half of the base case demand for the medium-duty and heavy-duty vehicle instances.

Table 4
Constant emissions model - Unitary routing cost and average consumption per vehicle type.

	Driven distance [km]	Fuel consumption [litre]	Routing cost [€]	Unitary routing cost [€/km]	Average consumption [km/litre]
LDV	4472.37	1455.79	3078.61	**0.69**	**3.07**
MDV	4053.55	1852.26	3696.06	**0.91**	**2.19**
HDV	4053.55	2204.77	4295.35	**1.06**	**1.84**

Results of the constant emissions model are reported in **Table 5.** They are computed for three cases, based on different data set of demand: *Case 1* corresponds to the initial data set of demand used for the computation of unitary routing cost and average consumption of MDVs and HDVs; *Case 2* corresponds to two times the initial demand data set; *Case 3* corresponds to three times the initial demand data set.

Table 5
Constant emissions model: comparison of results with respect to the comprehensive emissions model.

Demand instance [%]	Routing cost [€]	Carbon emissions [kgCO2e]	Approximate routing cost [€]	Approximate emissions [kgCO2e]	Error on routing cost [%]	Error on emissions [%]
Heterogeneous fleet						
Case 1	3548.3	4598.5	3516	4551.4	**-0.91%**	**-1.02%**
Case 2	5864.92	7659.37	5717.4	7432.55	**-2.52%**	**-2.96%**
Case 3	7205.89	9709.44	6690.36	8924.82	**-7.15%**	**-8.08%**
Homogeneous fleet						
Case 1	3696.06	4871.43	3685.05	4863.1	**-0.30%**	**-0.17%**
Case 2	5917.27	7799	5626.9	7425.7	**-4.91%**	**-4.79%**
Case 3	6718.72	8879.04	6192.73	8162.05	**-7.83%**	**-8.08%**

Results show that a constant emissions approach can be suitable for static contexts where demand is not subjected to high variations. Differently, when demand is highly variable and there is the need to precisely estimate emissions, as in contexts characterised by carbon control policies, a constant emissions model is not sufficiently precise, and a comprehensive emissions model is required.

5.4. Cap policy

The results, in term of total cost and emissions, of the sensitivity analysis on the cap value are shown in **Figure 5**. Complete results are reported in **Table 9** and **Table 10**. Missing points on the chart correspond to the instances for which the solver failed to find a solution. Results show that the increase in 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 performances, 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 Benjafaar et al. (2013): it is possible to achieve great 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% of operational costs increment, while for the homogeneous fleet case, a 16.54% reduction in emissions corresponds to a 1.92% cost increment. This because, in the early tightening of the cap, the total cost increment caused by the inventory cost is offset by the reduction of routing cost (driver cost plus fuel cost), caused by the reduced number of driven kilometres. 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 increments. 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 leas to a 121.25% total cost increment, while the cap model with a 55% cap only leads to a 77.10% increment.

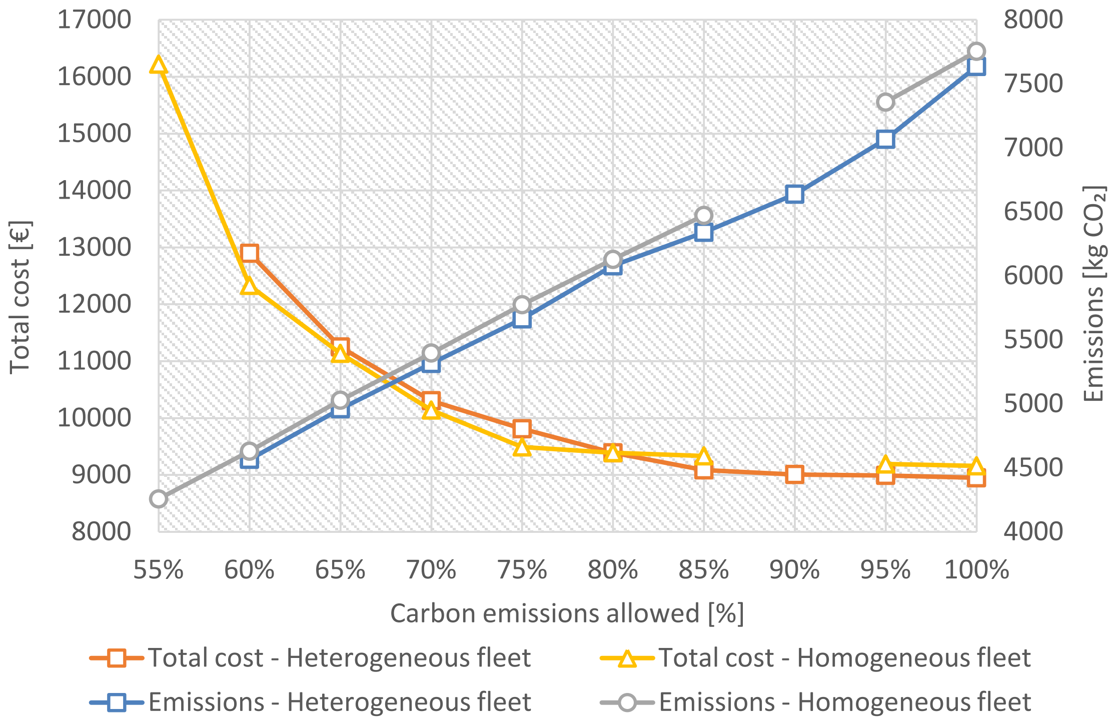

Figure 5 - Cap policy: comparison of the heterogeneous fleet and homogeneous fleet instances

5.5. 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 shown in **Figure 6**. Complete results are reported in **Table 11** and **Table 12**. 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 increment 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 increment 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 could be not 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 contexts, this policy could be an effective incentive to move towards lower-emissions configurations. A tax comprises 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€/tonCO_2 and 168€/tonCO_2.

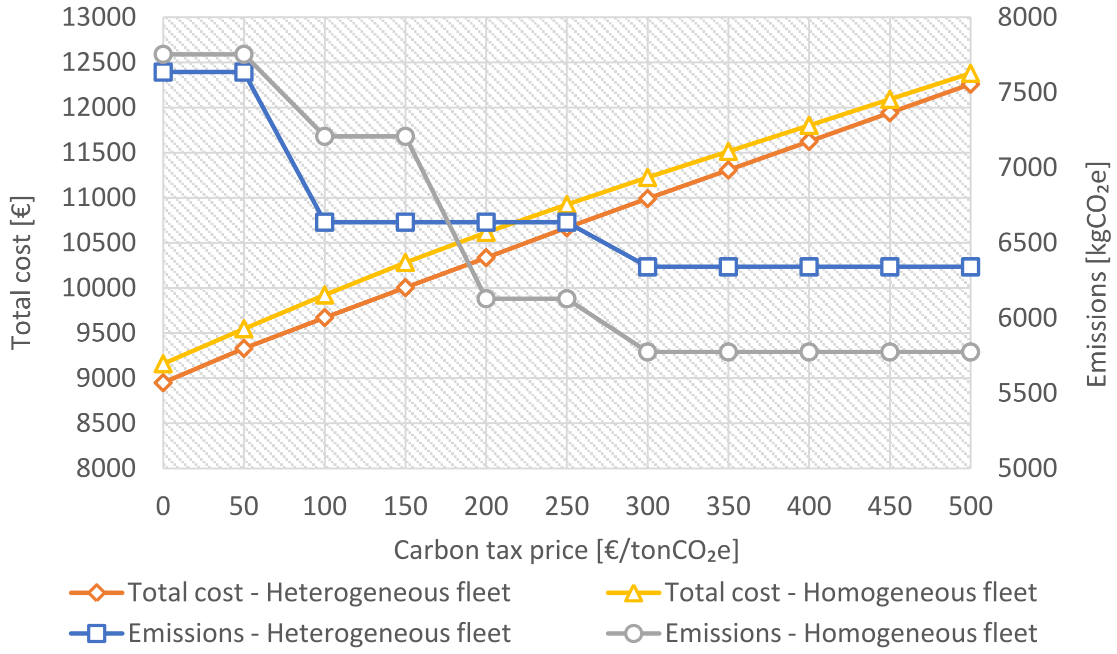

Figure 6 - Carbon tax policy: comparison of the heterogeneous fleet and homogeneous fleet instances

5.6. Cap-and-trade policy

The results, in term of total cost and emissions, of the sensitivity analysis on the cap value of the cap-and-trade policy model are shown in **Figure 7**. Complete results are reported in **Table 13** and **Table 14**. The emissions allowance price is fixed and set equal to 7€/tonCO_2e. The figure shows 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 total cost lower than the base case model by selling the surplus allocated emissions allowances; (ii) it is possible to imposed 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 provide other tools to meet the cap, as the possibility of purchasing extra allowances.

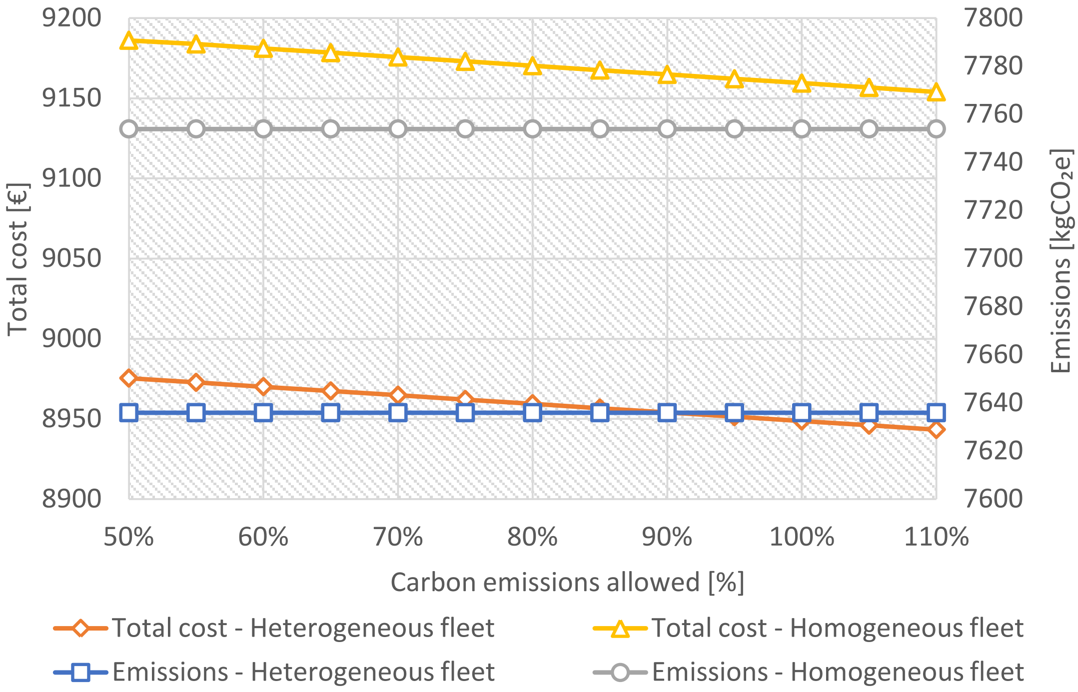

Figure 7 - Cap-and-trade policy with fixed allowance price (7€/tonCO_2e): comparison of the heterogeneous fleet and homogeneous fleet instances.

The results of the sensitivity analysis on the allowance price, given a fixed cap value equal to 50%, are shown in **Figure 8.** Complete results are reported in **Table 15** and **Table 16.** 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 first consideration, in reality, being the cap-and-trade 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 increment of the emissions allowance price.

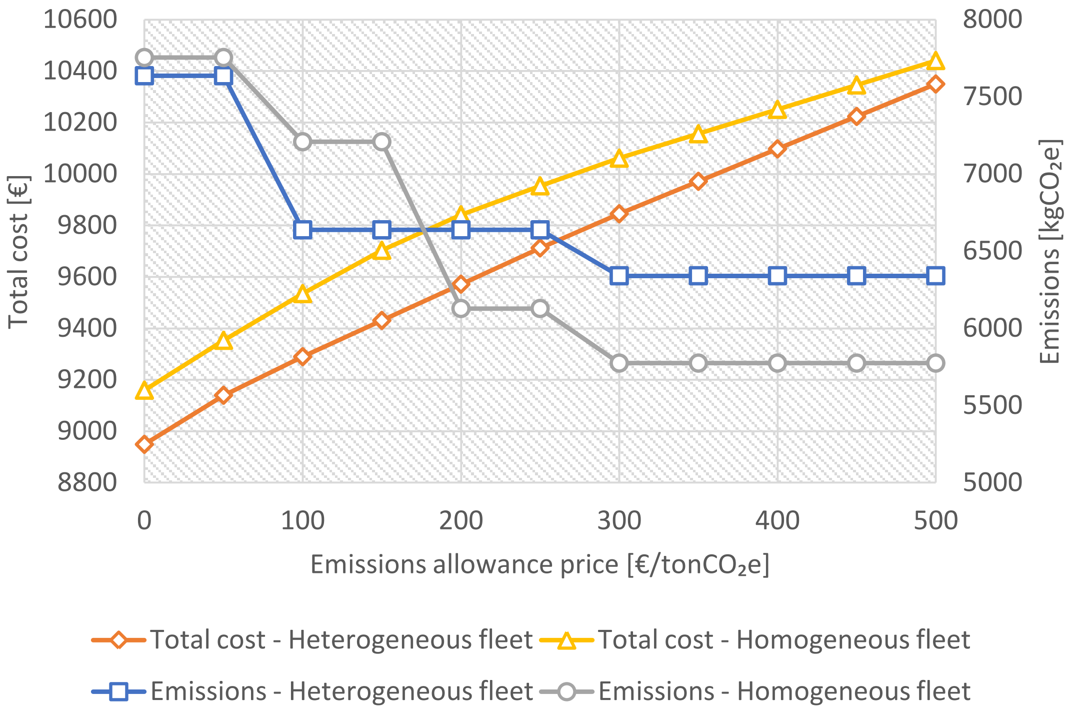

Figure 8 - Cap-and-trade policy with fixed cap value (50%): comparison of the heterogeneous fleet and homogeneous fleet instances

5.7. Cap-and-offset policy

The results, in term of total cost and emissions, of the sensitivity analysis on the cap value are shown in **Figure 9.** Complete results are reported in **Table 17** and **Table 18**. The emissions credit price is fixed and set equal to 7.27€/tonCO_2e. The results are similar to those obtained under the cap-and-trade, but in this case, given an overallocation 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.

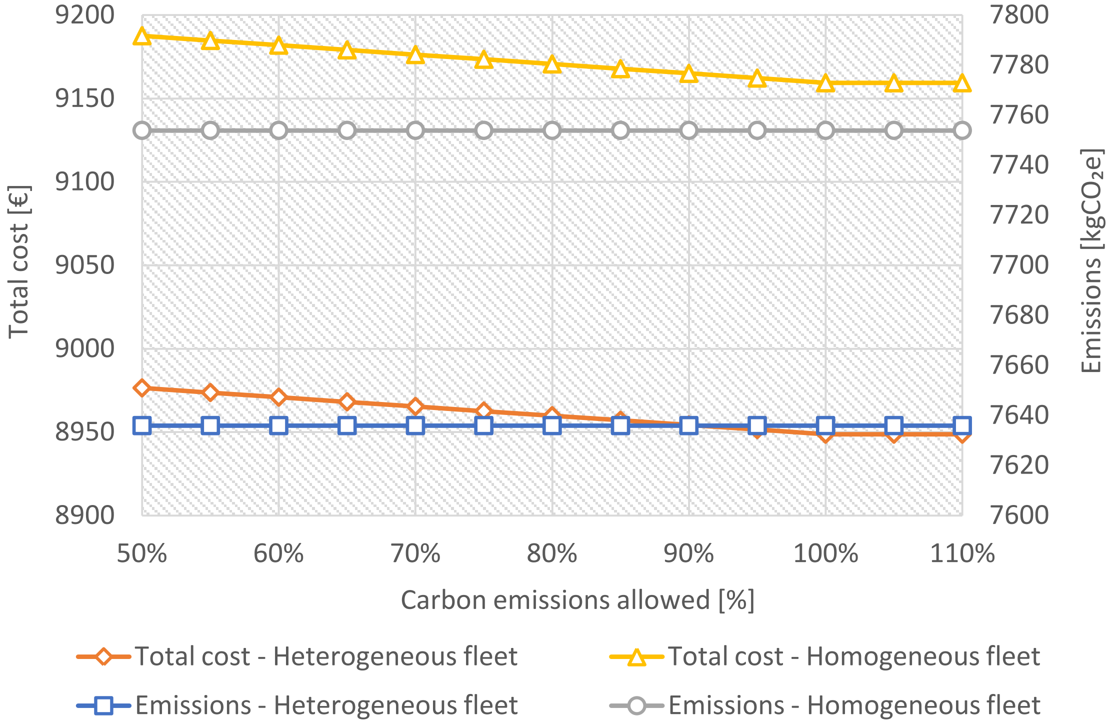

Figure 9 - Cap-and-offset policy with fixed credit price (7.27€/tonCO_2e): comparison of the heterogeneous fleet and homogeneous fleet instances.

6. 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. Results provide companies with insights on the optimal operational configurations under the different policies, highlighting the economic and environmental implications of each policy. Given the novelty of the topic, the paths for future studies are numerous. First, it is interesting to quantitatively evaluate 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. Secondly, properly modelling the customer service level as a decision variable and assuming a shortage cost, it is relevant to investigate how the introduction of policies can affect the customer satisfaction's side of the problem. Lastly, it is interesting to analyse how emissions restrictive measures affect a three-echelons supply chain, properly modelling the up-stream stage that represents the availability of products at the supplier's site at each period.

Annex A: Data of the problem

Table 6

Data of expected customers demand per each period.

	Customers Demand [kg]					
	Weeks					
Customer	**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 7

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 8
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	$\boldsymbol{\xi}$	1	1	1	-
Gravitational constant	$\boldsymbol{g}$	9.81	9.81	9.81	[m/s²]
Air density	$\boldsymbol{\rho}$	1.2041	1.2041	1.2041	[kg/m³]
Coefficient of rolling resistance	$\boldsymbol{C_r}$	0.01	0.01	0.01	-
Efficiency parameter for diesel engines	$\boldsymbol{\varpi}$	0.45	0.45	0.45	-
Heating value of a typical diesel fuel	$\boldsymbol{\kappa}$	44	44	44	[kJ/g]
Vehicle speed	$\boldsymbol{f}$	22.2	22.2	22.2	[m/s]
Conversion factor	$\boldsymbol{\psi}$	737	737	737	[g/l]
Road angle	$\boldsymbol{\phi}$	0	0	0	-
Vehicle specific parameters					
Curb-weight	$\boldsymbol{\mu^k}$	3500	5500	13154	[kg]
Maximum payload (Capacity)	$\boldsymbol{c^k}$	4000	12500	17236	[kg]
Engine friction factor	$\boldsymbol{k_e^k}$	0.25	0.20	0.15	[kJ/rev/l]
Engine speed	$\boldsymbol{N_e^k}$	38.3	36.7	30.2	[rev/s]
Engine displacement	$\boldsymbol{V_e^k}$	4.50	6.90	6.66	[l]
Coefficient of aerodynamic drag	$\boldsymbol{C_d^k}$	0.6	0.7	0.7	-
Frontal surface area	$\boldsymbol{A^k}$	7.0	8.0	9.8	[m²]
Vehicle drive train efficiency	$\boldsymbol{\varepsilon^k}$	0.45	0.45	0.50	-

Annex B: Results of the sensitivity analysis on policies parameters

Table 9

Cap policy with heterogeneous fleet: sensitivity analysis on cap.

Cap value [%]	95%	85%	75%	65%	55%
Driving time [h]	80.20	71	58.76	46.85	-
Inventory cost [€]	3558.32	4220.19	5515.64	7535.97	-
Driver cost [€]	866.16	770.00	634.62	505.96	-
Fuel cost [€]	4567.90	4098.16	3660.81	3206.88	-
Routing cost [€]	5434.07	4868.16	4295.42	3712.84	-
Emissions [kgCO_2e]	7066.82	6340.10	5663.48	4961.24	-
Total cost [€]	8992.39	9088.35	9811.07	11248.81	-
Operational cost [€]	8992.39	9088.35	9811.07	11248.81	-
Operational cost incr. [%]	0.49%	1.56%	9.64%	25.70%	-
Emissions reduction [%]	7.45%	16.97%	25.83%	35.03%	-
Average saturation [%]	93.45%	90.17%	94.27%	83.29%	-
Number of vehicles	10	10	8	7	-
LDV	5	5	3	1	-
MDV	5	4	3	4	-
HDV	0	1	2	2	-

Table 10

Cap policy with homogeneous fleet: sensitivity analysis on cap.

Cap value [%]	95%	85%	75%	65%	55%
Driving time [h]	76.21	66.29	59.09	50.56	42.78
Inventory cost [€]	3613.04	4435.77	5121.33	7340.27	13007.64
Driver cost [€]	823.04	715.92	638.22	546.04	462.01
Fuel cost [€]	4755.38	4183.27	3732.45	3250.12	2751.45
Routing cost [€]	5578.42	4899.19	4370.67	3796.16	3213.46
Emissions [kgCO_2e]	7356.86	6471.76	5774.31	5028.12	4256.65
Total cost [€]	9191.46	9334.96	9491.99	11136.43	16221.10
Operational cost [€]	9191.46	9334.96	9492.00	11136.43	16221.10
Operational cost incr. [%]	0.35%	1.92%	3.63%	21.58%	77.10%
Emissions reduction [%]	5.12%	16.54%	25.53%	35.15%	45.10%
Average saturation [%]	68.96%	77.58%	77.58%	88.66%	88.66%
Number of vehicles	9	8	8	7	7

Table 11

Carbon tax policy with heterogeneous fleet: sensitivity analysis on carbon tax price.

Carbon tax price [€/tonCO_2e]	0	100	200	300	400	500
Driving time [h]	84.63	70.74	70.74	71.30	71.30	71.30
Inventory cost [€]	3098.95	3952.93	3952.93	4220.19	4220.19	4220.19
Driver cost [€]	914.00	763.99	763.99	770.00	770.00	770.00
Fuel cost [€]	4935.76	4290.58	4290.58	4098.16	4098.16	4098.16
Routing cost [€]	5849.76	5054.56	5054.56	4868.16	4868.16	4868.16
Emissions [kgCO_2e]	7635.91	6637.78	6637.78	6340.10	6340.10	6340.10
Total cost [€]	8948.71	9671.27	10335.05	10990.38	11624.39	12258.40
Emissions cost [€]	0.00	663.78	1327.56	1902.03	2536.04	3170.05
Operational cost [€]	8948.71	9007.49	9007.49	9088.35	9088.35	9088.35
Emissions reduction [%]	0.00%	13.07%	13.07%	16.97%	16.97%	16.97%
Operational cost incr. [%]	0.00%	0.66%	0.66%	1.56%	1.56%	1.56%
Average saturation [%]	86.21%	85.34%	85.34%	90.17%	90.17%	90.17%
Number of vehicles	10	9	9	10	10	10
LDV	4	3	3	5	5	5
MDV	6	5	5	4	4	4
HDV	0	1	1	1	1	1

Table 12

Carbon tax policy with homogeneous fleet: sensitivity analysis on carbon tax price.

Carbon tax price [€/tonCO_2e]	0	100	200	300	400	500
Driving time [h]	81.20	74.78	62.56	59.09	59.09	59.09
Inventory cost [€]	3270.39	3734.67	4753.91	5121.33	5121.33	5121.33
Driver cost [€]	876.97	807.64	675.65	638.22	638.22	638.22
Fuel cost [€]	5012.03	4659.39	3961.21	3732.45	3732.45	3732.45
Routing cost [€]	5889.00	5467.02	4636.85	4370.67	4370.67	4370.67
Emissions [kgCO_2e]	7753.90	7208.35	6128.22	5774.32	5774.32	5774.32
Total cost [€]	9159.39	9922.53	10616.41	11224.29	11801.72	12379.16
Emissions cost [€]	0.00	720.83	1225.64	1732.30	2309.73	2887.16
Operational cost [€]	9159.39	9201.69	9390.77	9492.00	9492.00	9492.00
Emissions reduction [%]	0.00%	7.04%	20.97%	25.53%	25.53%	25.53%
Operational cost incr. [%]	0.00%	0.46%	2.53%	3.63%	3.63%	3.63%
Average saturation [%]	62.06%	68.96%	77.58%	77.58%	77.58%	77.58%
Number of vehicles	10	9	8	8	8	8

Table 13

Cap-and-trade policy with heterogeneous fleet and fixed allowance price (7€/tonCO_2e): sensitivity analysis on cap.

Cap value [%]	110%	100%	90%	80%	70%	60%	50%
Driving time [h]	84.63	84.63	84.63	84.63	84.63	84.63	84.63
Inventory cost [€]	3098.95	3098.95	3098.95	3098.95	3098.95	3098.95	3098.95
Driver cost [€]	914.00	914.00	914.00	914.00	914.00	914.00	914.00
Fuel cost [€]	4935.76	4935.76	4935.76	4935.76	4935.76	4935.76	4935.76
Routing cost [€]	5849.76	5849.76	5849.76	5849.76	5849.76	5849.76	5849.76
Emissions [kgCO_2e]	7635.91	7635.91	7635.91	7635.91	7635.91	7635.91	7635.91
Total cost [€]	8943.36	8948.71	8954.05	8959.40	8964.74	8970.09	8975.43
Emissions cost [€]	0.00	0.00	5.35	10.69	16.04	21.38	26.73
Emissions revenue [€]	5.35	0.00	0.00	0.00	0.00	0.00	0.00
Operational cost [€]	8948.71	8948.71	8948.71	8948.71	8948.71	8948.71	8948.71
Emissions reduction [%]	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
Operational cost incr. [%]	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
Average saturation [%]	86.21%	86.21%	86.21%	86.21%	86.21%	86.21%	86.21%
Number of vehicles	10	10	10	10	10	10	10
LDV	4	4	4	4	4	4	4
MDV	6	6	6	6	6	6	6
HDV	0	0	0	0	0	0	0

Table 14

Cap-and-trade policy with homogeneous fleet and fixed allowance price (7€/tonCO_2e): sensitivity analysis on cap.

Cap value [%]	110%	100%	90%	80%	70%	60%	50%
Driving time [h]	81.20	81.20	81.20	81.20	81.20	81.20	81.20
Inventory cost [€]	3270.39	3270.39	3270.39	3270.39	3270.39	3270.39	3270.39
Driver cost [€]	876.97	876.97	876.97	876.97	876.97	876.97	876.97
Fuel cost [€]	5012.03	5012.03	5012.03	5012.03	5012.03	5012.03	5012.03
Routing cost [€]	5889.00	5889.00	5889.00	5889.00	5889.00	5889.00	5889.00
Emissions [kgCO_2e]	7753.90	7753.90	7753.90	7753.90	7753.90	7753.90	7753.90
Total cost [€]	9153.96	9159.39	9164.82	9170.24	9175.67	9181.10	9186.11
Emissions cost [€]	0.00	0.00	5.43	10.86	16.28	21.71	26.73
Emissions revenue [€]	5.43	0.00	0.00	0.00	0.00	0.00	0.00
Operational cost [€]	9159.39	9159.39	9159.39	9159.39	9159.39	9159.39	9159.39
Emissions reduction [%]	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
Operational cost incr. [%]	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
Average saturation [%]	62.06%	62.06%	62.06%	62.06%	62.06%	62.06%	62.06%
Number of vehicles	10	10	10	10	10	10	10

Table 15

Cap-and-trade policy with heterogeneous fleet and fixed cap (50%): sensitivity analysis on allowance price.

Allowance price [€/tonCO_2e]	0	100	200	300	400	500
Driving time [h]	84,63	70,74	70,74	71,30	71,30	71,30
Inventory cost [€]	3098,95	3952,93	3952,93	4220,19	4220,19	4220,19
Driver cost [€]	914,00	763,99	763,99	770,00	770,00	770,00
Fuel cost [€]	4935,76	4290,58	4290,58	4098,16	4098,16	4098,16
Routing cost [€]	5849,76	5054,56	5054,56	4868,16	4868,16	4868,16
Emissions [kgCO_2e]	7635,91	6637,78	6637,78	6340,10	6340,10	6340,10
Total cost [€]	8948,71	9289,48	9571,46	9845,00	10097,21	10349,42
Emissions cost [€]	0,00	281,98	563,96	756,64	1008,86	1261,07
Emissions revenue [€]	0,00	0,00	0,00	0,00	0,00	0,00
Operational cost [€]	8948,71	9007,49	9007,49	9088,35	9088,35	9088,35
Emissions reduction [%]	0,00%	13,07%	13,07%	16,97%	16,97%	16,97%
Operational cost incr. [%]	0,00%	0,66%	0,66%	1,56%	1,56%	1,56%
Average saturation [%]	86,21%	85,34%	85,34%	90,17%	90,17%	90,17%
Number of vehicles	10	9	9	10	10	10
LDV	4	3	3	5	5	5
MDV	6	5	5	4	4	4
HDV	0	1	1	1	1	1

Table 16

Cap-and-trade policy with homogeneous fleet and fixed cap (50%): sensitivity analysis on allowance price.

Allowance price [€/tonCO_2e]	0	100	200	300	400	500
Driving time [h]	81.20	74.78	62.56	59.09	59.09	59.09
Inventory cost [€]	3270.39	3734.67	4753.91	5121.33	5121.33	5121.33
Driver cost [€]	876.97	807.64	675.65	638.22	638.22	638.22
Fuel cost [€]	5012.03	4659.39	3961.21	3732.45	3732.45	3732.45
Routing cost [€]	5889.00	5467.02	4636.85	4370.67	4370.67	4370.67
Emissions [kgCO_2e]	7753.90	7208.35	6128.22	5774.32	5774.32	5774.32
Total cost [€]	9159.39	9534.83	9841.02	10061.21	10250.94	10440.68
Emissions cost [€]	0.00	333.14	450.25	569.21	758.95	948.68
Emissions revenue [€]	0.00	0.00	0.00	0.00	0.00	0.00
Operational cost [€]	9159.39	9201.69	9390.77	9492.00	9492.00	9492.00
Emissions reduction [%]	0.00%	7.04%	20.97%	25.53%	25.53%	25.53%
Operational cost incr. [%]	0.00%	0.46%	2.53%	3.63%	3.63%	3.63%
Average saturation [%]	62.06%	68.96%	77.58%	77.58%	77.58%	77.58%
Number of vehicles	10	9	8	8	8	8

Table 17

Cap-and-offset policy with heterogeneous fleet and fixed credit price (7.27€/tonCO_2e): sensitivity analysis on cap.

Cap value	110%	100%	90%	80%	70%	60%	50%
Driving time [h]	84.63	84.63	84.63	84.63	84.63	84.63	84.63
Inventory cost [€]	3098.95	3098.95	3098.95	3098.95	3098.95	3098.95	3098.95
Driver cost [€]	914.00	914.00	914.00	914.00	914.00	914.00	914.00
Fuel cost [€]	4935.76	4935.76	4935.76	4935.76	4935.76	4935.76	4935.76
Routing cost [€]	5849.76	5849.76	5849.76	5849.76	5849.76	5849.76	5849.76
Emissions [kgCO_2e]	7635.91	7635.91	7635.91	7635.91	7635.91	7635.91	7635.91
Total cost [€]	8948.71	8948.71	8954.26	8959.81	8965.36	8970.91	8976.46
Emissions cost [€]	0.00	0.00	5.55	11.10	16.65	22.21	27.76
Operational cost [€]	8948.71	8948.71	8948.71	8948.71	8948.71	8948.71	8948.71
Emissions reduction [%]	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
Operational cost incr. [%]	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
Average saturation [%]	86.21%	86.21%	86.21%	86.21%	86.21%	86.21%	86.21%
Number of vehicles	10	10	10	10	10	10	10
LDV	4	4	4	4	4	4	4
MDV	6	6	6	6	6	6	6
HDV	0	0	0	0	0	0	0

Table 18

Cap-and-offset policy with homogeneous fleet and fixed credit price (7.27€/tonCO_2e): sensitivity analysis on cap.

Cap value	110%	100%	90%	80%	70%	60%	50%
Driving time [h]	81,20	81,20	81,20	81,20	81,20	81,20	81,20
Inventory cost [€]	3270,39	3270,39	3270,39	3270,39	3270,39	3270,39	3270,39
Driver cost [€]	876,97	876,97	876,97	876,97	876,97	876,97	876,97
Fuel cost [€]	5012,03	5012,03	5012,03	5012,03	5012,03	5012,03	5012,03
Routing cost [€]	5889,00	5889,00	5889,00	5889,00	5889,00	5889,00	5889,00
Emissions [kgCO_2e]	7753,90	7753,90	7753,90	7753,90	7753,90	7753,90	7753,90
Total cost [€]	9159,39	9159,39	9165,03	9170,66	9176,30	9181,94	9187,57
Emissions cost [€]	0,00	0,00	5,64	11,27	16,91	22,55	28,19
Operational cost [€]	9159,39	9159,39	9159,39	9159,39	9159,39	9159,39	9159,39
Emissions reduction [%]	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%
Operational cost incr. [%]	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%
Average saturation [%]	62,06%	62,06%	62,06%	62,06%	62,06%	62,06%	62,06%
Number of vehicles	10	10	10	10	10	10	10

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1. Introduction

Climate change is one of most serious threat that mankind has to face in this century. The warming of the atmosphere and the oceans, the exponential increase of extreme natural events, the reduction in the amount of snow and ice and the raising of the sea level, observed since the 1950s, undoubtedly prove that a climate change is taking place (IPCC, 2014).

The scientific community has reached a wide and strong consensus in establishing that the causes of the global warming are anthropogenic. In 2013, Cook et al. reviewed 11944 climate abstracts matching the topics "global climate change" and "global warming", showing that, 97.1% of those papers that explicitly express a position on anthropogenic climate change, endorse the consensus position that global warming is caused by human's activities (Cook et al., 2013).

Anthropogenic greenhouse gas emissions, driven largely by economic and population growth, have increased exponentially since the pre-industrial era, reaching levels untouched before. The time evolution pattern of greenhouse gas emissions follows the observed increase in the oceans and land temperatures, accurately measured since 1880s, linking together the two phenomena (IPCC, 2014). The increase in temperature leads to the progressive dissolution of the larger glaciers, which in turn implies the rise of the sea level (**Figure 1** and **Figure 2**).

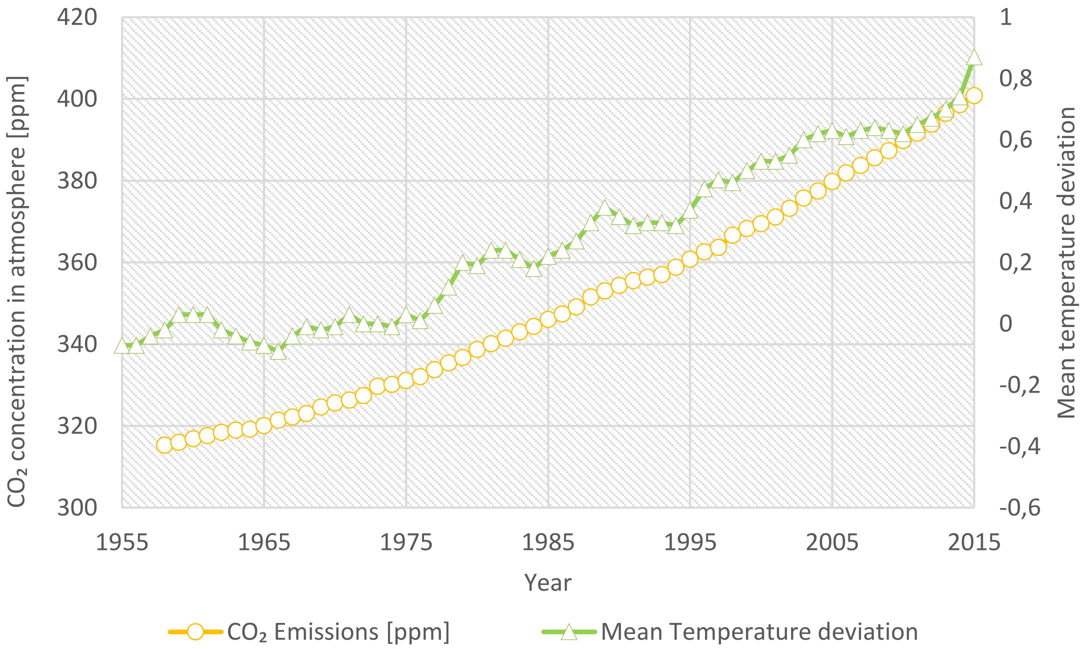


Figure 1 - Increasing of mean temperature and CO_2 concentration in the atmosphere in the last 60 years. Source: IPCC, 2014.

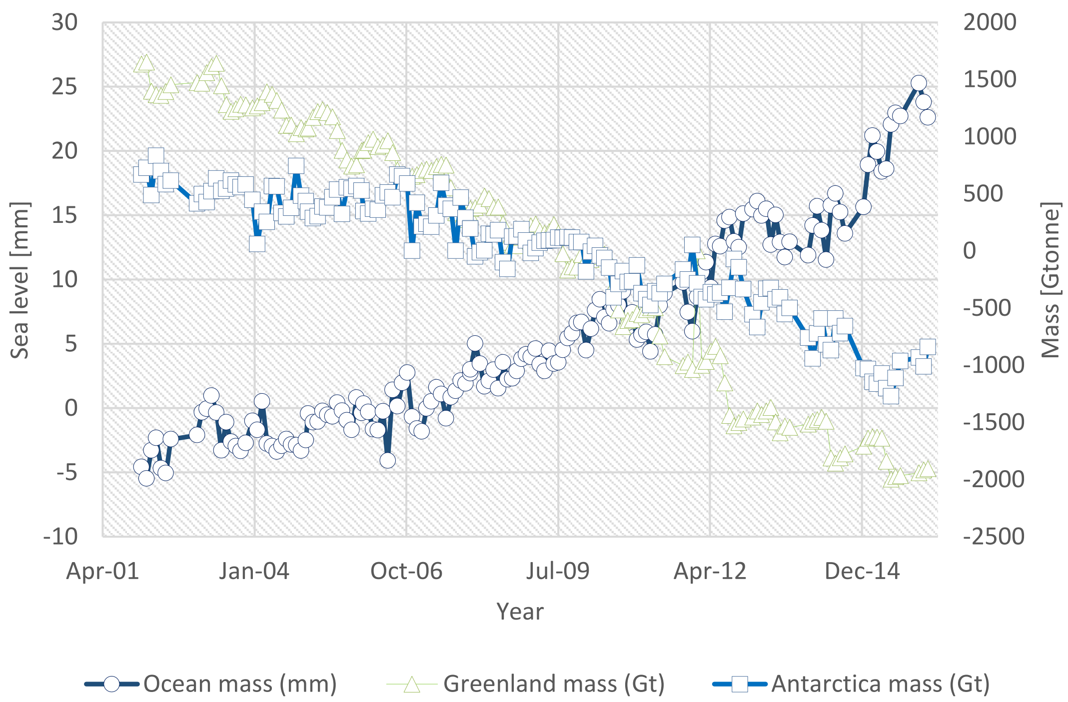


Figure 2 - Increasing of sea level and reduction of Greenland and Antarctica masses. Source: IPCC, 2014.

Among the different greenhouse gases present in the atmosphere (water vapour, carbon dioxide, methane, ozone...), scientists and researchers focus mainly on the CO_2 emissions, for two fundamental reasons: (i) CO_2 is the greenhouse gas with the highest Radioactive Force (RF) defined as "the capacity of a gas or other forcing agents to affect that energy balance of the atmosphere, thereby contributing to climate change" (Carbon Offset Research & Education, www.co2offsetresearch.org, last accessed on: 3.11.2017); (ii) differently from the other greenhouse gases, the lifecycle of CO_2 is very long and a consistent percentage of CO_2 gases emitted now, remains in the atmosphere for approximately 800 years, against the 10-years lifetime of methane, or the 100-years lifetime of nitrous oxide (United States Environmental Protection Agency, www.epa.gov, last accessed on: 3.11.2017). Conventionally, the emissions of the other gases are converted in carbon dioxide equivalents using the concept of "global warming potential", and the overall amount of emitted greenhouse gases are expressed in terms of CO_2e, where the "e" stands for "equivalents". Besides the effects on the climate, CO_2 is also responsible for the progressive acidification of the ocean, which leads irreversible modifications in the marine ecosystem.

The economic sectors differently contribute to the overall greenhouse gases emission. As reported by the European Environment Agency in 2014 that analyses the European greenhouse gases emissions, the energy supply sector is the most important emitter of greenhouse gases, followed by the transport sector, which accounts for approximately the 23% of the total emissions. The transport sector was characterized by constant growth, largely driven by the global demographic growth and by the global markets expansion. Differently from the other emitter sectors, this growth has led to a consistent increment of the CO_2 emissions in the last twenty years, as shown in **Figure 3**.

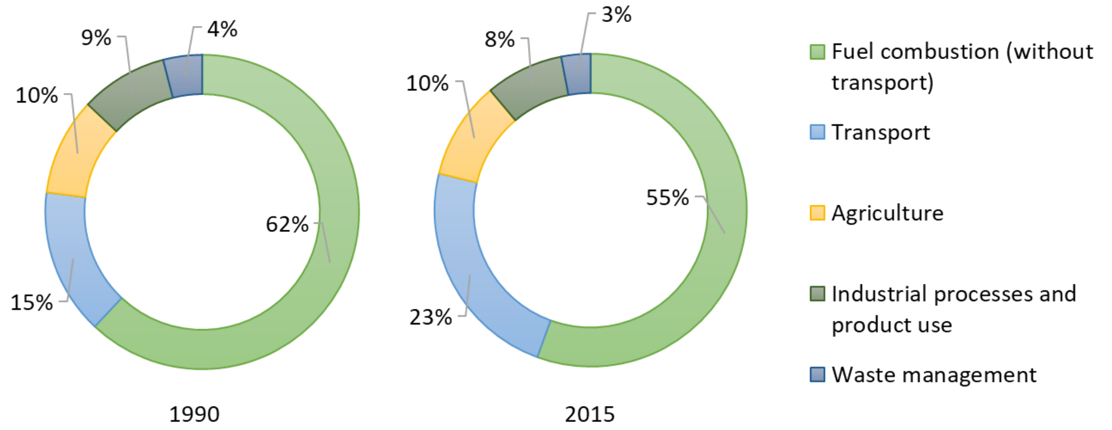


Figure 3 - Difference in the share of carbon emissions by economic sectors in the EU 28 between 1990 and 2015. Source: European Environment Agency, 2017.

The carbon emissions from transportation are unevenly distributed among the transportation modes. As shown in **Figure 4**, concerning the European context, the overall total share of carbon emissions is almost entirely dominated by the road transport emissions. The road transport comprises the passenger transportation and the freight transportation. The latter in particular, represented by the emissions of light-duty and heavy-duty vehicles, accounts for the 37.6% of the total emission of the transport sector.

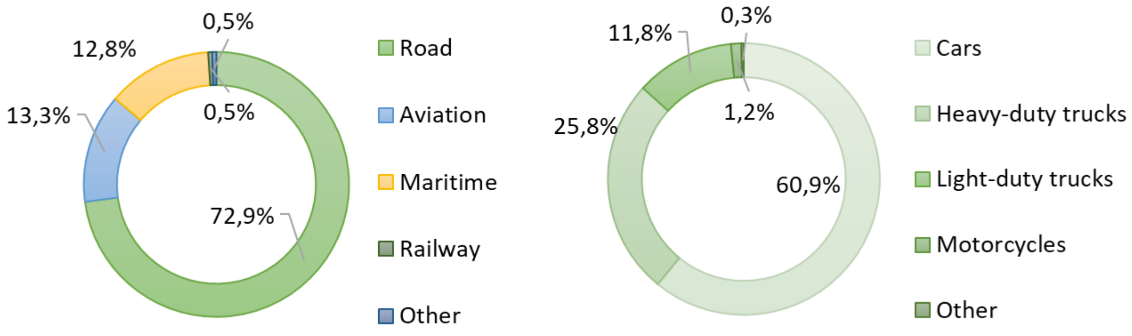


Figure 4 - Share of carbon emissions by transport modes and by road transportation modes in the EU 28. Source: European Environment Agency, 2017.

In this context, it emerges clearly how supply chain activities, which include production, transportation and inventory, largely contribute to the overall greenhouse gases emissions, representing one of the main sectors where researchers have focused their efforts, in order to find ways to curb emissions.

Besides the academic world, also companies have started to concentrate their attention on finding possible solutions to cut emissions deriving from supply chain activities. The well-known trade-off between minimising the overall supply chain costs while guaranteeing a high customer service level has begun to be integrated with environmental considerations on the ecological footprint of the economic activities of the company (Dekker et al, 2012). As indicated by Treitl et al. (2014), there are three main reasons that push companies to take into account environmental considerations in their decision-making processes:

- Today's consumers are more sensitive to environmental issues, and this sensitivity is reflected in the choice of the products they buy. The result is an increasing demand for "green" products which lead to the development of new marketing strategies, such as "eco-labelling" initiatives, or company's decisions to employ electric vehicles for distributing their products.
- Governments, policymakers and organizations have started to regulate the environmental impacts of the economic activities, and companies that need to comply with those regulations necessarily have to take into account their impacts.
- High emissions generated by the operations of a company are often a symptom of inefficiencies, and from this perspective the managerial decision to curb those emissions can result in a win-win situation, being cost-effective and environmentally friendly.

The last two aspects highlighted by Treitl et al., are particularly crucial. With respect to the growing concern about the environmental implications of economic activities, **Figure 5** shows the response of governments and policymakers in limiting carbon emissions.

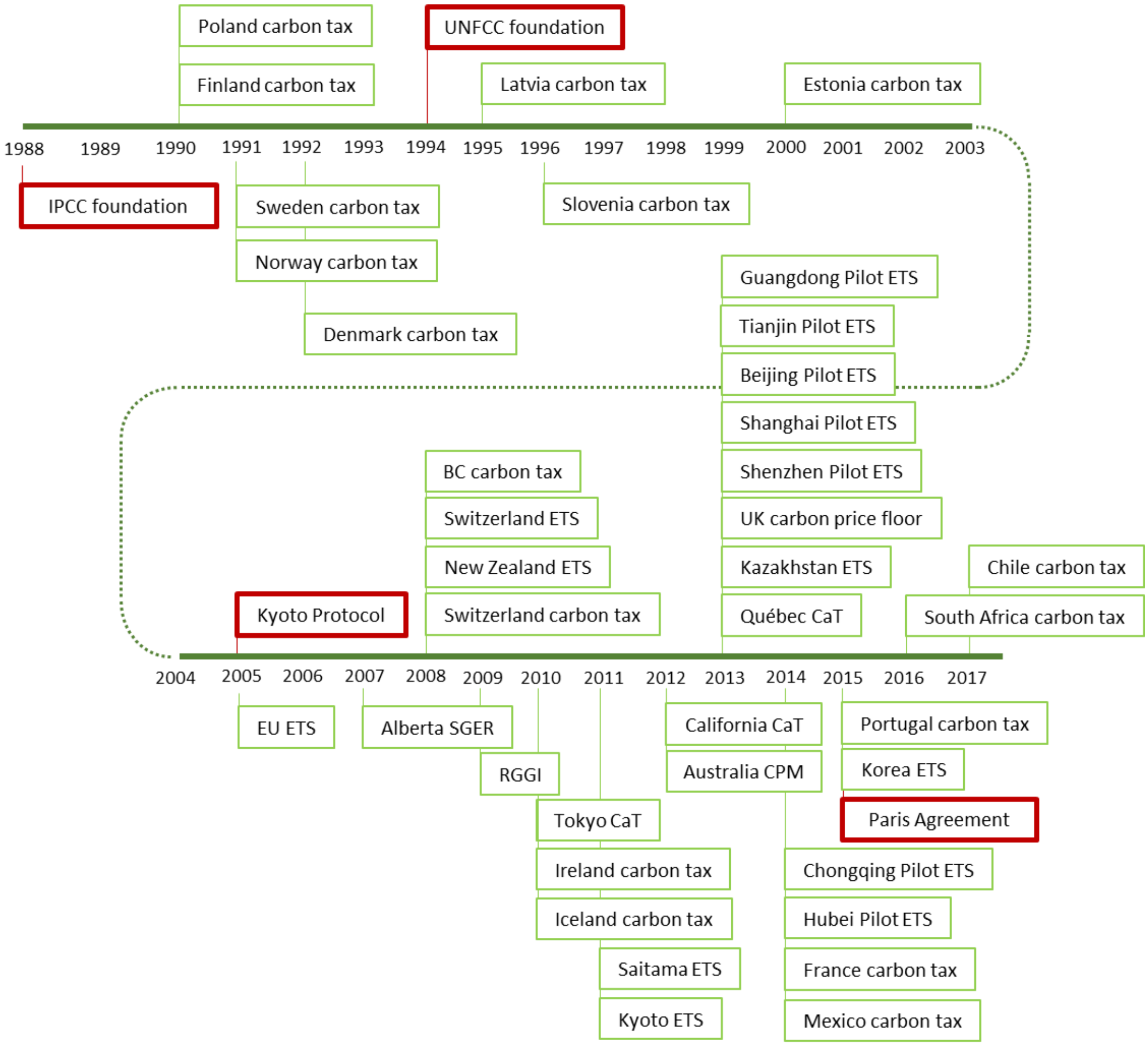


Figure 5 - Regional, national, and subnational carbon control policies already implemented or scheduled for implementation, in chronological order, and date of constitution of the main international organization on climate change. Source: Kossoy et al., 2015.

The incremental diffusion of carbon reduction policies goes in parallel with the constitution of international organizations that specifically address the climate change problem. Given the global nature of the problem, a global and coordinated response is needed. The most important result of in this sense is the Kyoto Protocol, adopted in 1997 and entered into force in 2005, which commits State Parties to reduce their greenhouse gas emissions in order to meet the target of stabilising global warming at 2°C above the average temperature of the pre-industrialised era. However, even if only a fraction of the actually implemented policies addresses the carbon emissions from transportation (for example the California and British Columbia emissions trading system or the Sweden carbon tax), the inclusion of this sector in the carbon control policies is widely debated (Achtnicht et al., 2015).

This scenario is particularly fragmented because of the non-prescriptive nature of the Kyoto Protocol, which provides flexibility to the State Parties in choosing the most suitable set of tools to meet the agreed target. Concerning the European situation for example, since the European Emissions Trading System, which is the pillar of the European environmental policy, does not address the transport sector, each EU member implements voluntary initiatives to curb those emissions. In this sense, it is therefore important to analyse the effects of different emissions reduction measures on the same economic activity, in order to provide both companies and policymakers with insights on the problem.

With respect to the third aspect pointed out by Treitl et al., companies addressing environmental concerns have traditionally focused on the emissions of physical processes, for example replacing energy inefficient equipment and facilities, redesigning products and packaging, finding less polluting sources of energy, or instituting energy savings programs. Benjafaar et al. (2013) highlight how the tendency of focusing on the process-based source of emissions, may lead to the overlooking of potentially significant fields of emissions reduction, which is represented by the operational practices of a company. The authors in particular states that, from an environmental perspective, the modification in the current operational practices can be as effective as a costly low-carbon investment. In this sense, Ugarte et al. (2016), focusing on supply chain activities, analyses the environmental impact of the current best practices of the lean logistics. The authors compare the emissions generated by the traditional EOQ approach with the product postponement, the just-in-time and vendor-managed inventory (VMI) approaches. They show how the product postponement and the vendor-managed inventory practices lead to lower carbon emissions because they increase the flexibility of the system to manage the uncertainty in the demand and supply, resulting in a reduction of the transportation-related emissions. On the contrary, the just-in-time inventory management is characterised by higher emissions due to the increase in the frequency of deliveries.

The vendor-managed inventory, in particular, is linked with another important aspect pointed out by Benjafaar et al. in their work, which is the collaboration and coordination between different companies constituting the supply chain. The single-company's traditional focus on process-based emissions cannot properly reveal the hidden potential of emission reductions represented by the interaction among many companies.

Differently from the traditional inventory management practices, where the supplier receives from the customers the time and size of the orders, in a vendor-managed inventory environment, the size and time of deliveries are determined by the supplier, based on the observed customer’s inventory levels. The supplier, in this case, has to assure that the customers do not run out of stock. The VMI is considered as a win-win strategy: (i) the supplier, based on the observed levels of inventory, can better forecast the product demand and thus can better arrange the deliveries, exploiting the possibility of joint deliveries; (ii) the customers do not have to allocate resources to inventory management (Soysal et al., 2015). The logistics problem that describes the vendor-managed inventory is the inventory routing problem (IRP). The inventory routing problem is a variant of the well-known vehicle routing problem consisting in the cost-minimising arrangement of the routing of a set of vehicles, given the time and the size of the requested orders. In an inventory routing problem, the decision maker has to determine at the same time: (i) when to deliver the products to each customer; (ii) how much to deliver to each served customer; (iii) the routing of each vehicle. These decisions should minimise the overall total cost for the planned period (Soysal et al., 2015). **Figure 6**, based on the classification of the activities of supply chain management (Moin and Salhi, 2007), illustrates how the inventory routing problem simultaneously addresses two problems that are typically optimised separately.

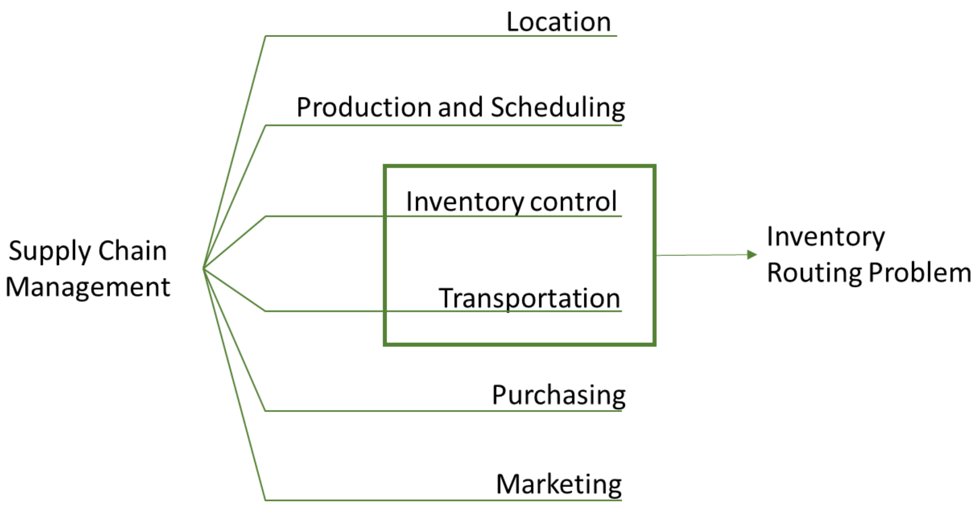


Figure 6 - Main activities in Supply Chain Management

Again Benjafaar et al. in their work stress the need of extending the traditional cost-minimising objective to include environmental concerns, developing quantitative-based models useful to understand how carbon emissions considerations could affect the operational decisions. Moreover, with regard to the operation research literature, they highlight the lack of studies that focus on the effect of carbon control policies on the operational decisions. In this sense, an environmentally-concerned quantitative-based model is fundamental to get all the operational implications of a specific carbon control policy.

Given these assumptions, this thesis will address the effects of different carbon control policies on an environmentally-extended inventory routing problem. First, it is conducted a literature review of the papers that already tackled the environmental extension of the inventory routing problem. Based on the gaps highlighted by this review it is developed a partially new formulation of the environmentally-extended inventory routing problem. Then, different carbon control policies are applied to this formulation, and insights on the economic and environmental implications of the policies are provided.

2. Literature review

2.1. Research protocol

The scope of the literature review is to find all those articles that have tackled the inventory routing problem, explicitly considering the GHGs emissions embedded in the process and focusing in particular on the emissions originated in the transportation phase. Since road transportation is the predominant transport mode in logistics, this review will focus on those papers addressing specifically this transport mode. Although the inventory routing problem tackles the transportation and inventory management activities, from an environmental point of view this review will mainly focus on the carbon emissions generated in the transportation processes. As shown by Ugarte et al. (2016), when tackling the operational dimension of the problem, where the environmental impacts are linked with the decision variables on the delivered quantities and vehicle routing, the emissions associated with transportation are significantly greater than those associated with facilities.
The first step of the review is the selection of the databases to search for the articles to be included in the review. The choice falls on the online database Scopus, since it is less selective than other online scientific databases, such as Web of Science. This allows retrieving a wider cluster of articles, which could result to be more sensitive to the novelty of this topic.
Once selected the database, the first batch of articles is obtained searching for those articles containing in their title, keywords or abstract the keyword "inventory routing problem", combined once a time with the preselected words used to address the environmental related part of the problem, respectively the keywords "emissions", "green", "environmental". The keywords "emissions" and "green" have been chosen since they generalize the keywords "carbon emissions", "greenhouse gas", "CO_2 emissions".
The following inclusion criteria are chosen to determine univocally the batch of articles to analyse: (i) date of publication, (ii) language, (iii) document type and (iv) subject area. The time frame of publication of the articles is chosen to include all the articles published up to 2017. Considering the relative novelty of the addressed topic there is no need to include also a lower boundary for the time frame. The language of the articles must be English. Concerning the document type, it has been decided to review papers published in both academic papers and conference proceedings. The decision to include also the conference proceedings is justified by the fact that, enlarging the inclusion criteria to the address also the so-called "grey literature", it is possible, to comprise papers not already subjected to the peer review process, but that show novel and relevant findings on the topic (Ghezzi et al., 2017). Articles contained in

books are excluded from the review. Finally, concerning the subject area of the articles, no inclusion criteria have been applied, in order to embrace articles coming from different research fields that tackle the same topic from slightly different perspectives.

The title, abstract and keywords of the articles found with these inclusion criteria and preliminary keywords are then analysed in order to find the presence of other expressions, and so other keywords, used to address the environmental aspect of the problem. This analysis leads to the inclusion of the keywords "sustainable" and "pollution". The articles found with these new keywords are then added to the preliminary batch of the articles. articles. This first step of the research protocol is depicted in **Figure 7.**

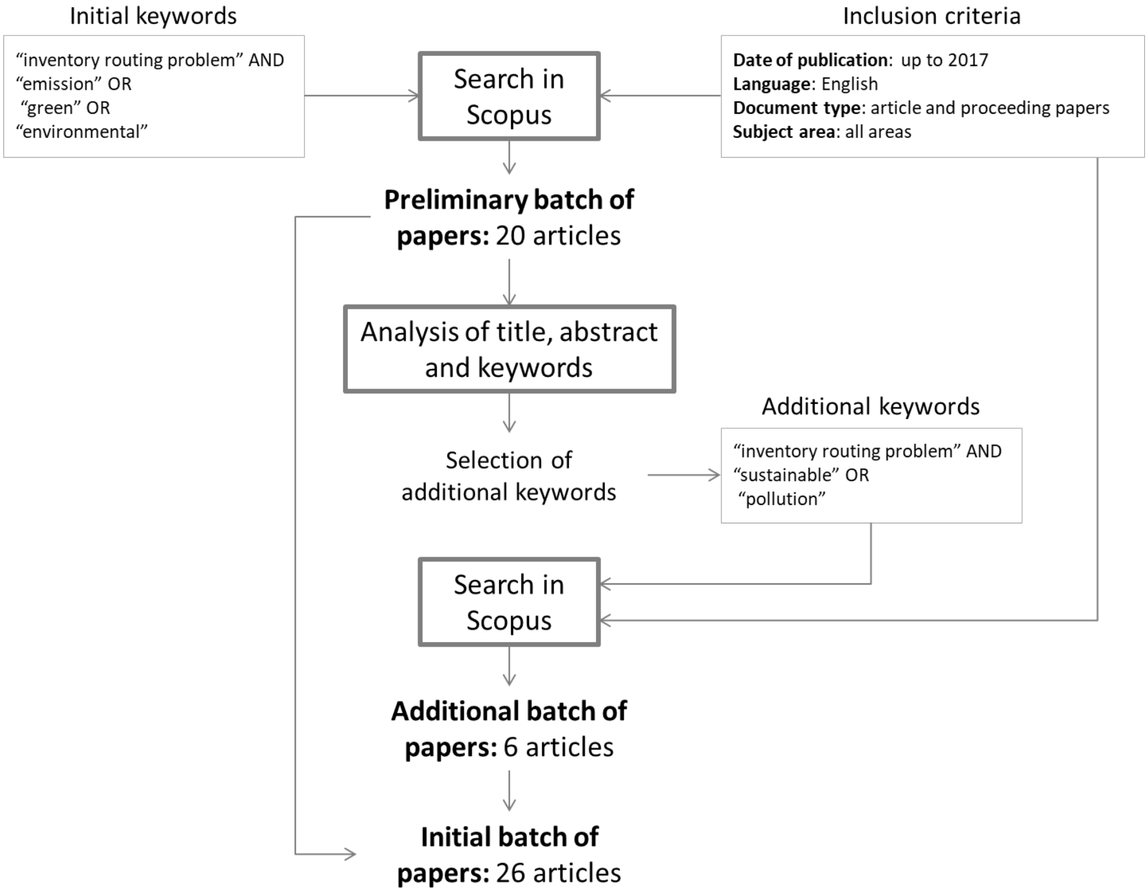


Figure 7 - Research protocol (1).

The following step of literature review is to determine the pertinence of the articles with the addressed topic, going through a systematic analysis of the abstract, in order to find those articles defined "out of scope", so not tackling directly and explicitly one of the two main components of the problem, respectively the inventory routing problem and the GHGs emission generated in the road transportation process. Those papers that successfully pass the abstract analysis are finally analysed in detail, in order to decide whether including them in the final batch of papers or not.

2.2. Application of the research protocol

The first step of the research, which employs the preliminary keywords ("inventory routing problem" AND "emissions" OR "green" OR "environmental") combined with the four inclusion criteria, carried on the Scopus online database, leads to a batch of 20 papers. The second search is carried using the keywords "sustainable" and "pollution", and it leads to 6 more articles not included in the previous search results. This batch of 26 papers is then submitted to the abstract analysis in order to identify those articles not related to the analysed topic.

The analysis of the abstracts leads to the exclusion of 8 papers. The reasons that have determined the exclusion from the batch are explained in detail. Two papers deal with maritime inventory routing and fleet operations, so they are consequently defined out of scope since the focus of the thesis is on the emissions generated by road transportation operations (De et al., 2017; van Tol et al., 2016). Three papers deal with waste management problems and the environmental impact of certain kind of waste products without considering GHGs emissions embedded in the processes (Nolz et al., 2014a; Nolz et al., 2014b; Mes et al., 2014). Two papers consider a generic "sustainable development" linked with the inventory routing problem, again without considering the GHGs emissions (Wong and Moin, 2014; Moin et al., 2014). Lastly, one paper addresses the problem of the deteriorating inventory of liquefied natural gas, focusing on the environmental impact but without considering GHGs emissions (Ghiami et al., 2015).

The resulting batch contains 18 articles is submitted to a content analysis in order to detect those articles considered out of scope that has passed the abstract analysis. The content analysis of the articles leads to the exclusion of 6 papers. The reasons are shown below.

Azadeh et al. (2017) propose a genetic algorithm to solve an inventory routing problem with the transhipment. Here the environmental concerns are related to the perishability of stored products without mentioning GHGs emissions. Iassinovskaia et al. (2017) study the inventory routing problem in a closed-loop supply chain focusing on the employment of returnable transport items (RTIs), considered a driver for reducing the environmental impacts of the supply chain operations, but without going into the details of the environmental aspects and not tackling GHGs emissions involved in the process. Xiao and Rao (2016) develop a fuzzy genetic algorithm to solve the inventory routing problem with time constraints, indicated as one the main topics addressed when dealing with green supply chain operations. However, the environmental impacts and the GHGs emissions are not tackled. Deng et al. (2014) propose a model for the location-inventory-routing problem in a reverse logistics network design, but it deals with the environmental benefits linked with the re-manufacturing of the collected disposed products, without tackling the environmental impacts of the distribution operational processes. Kuo et al. (2014) analyse a vehicle routing problem, modified in order to explore the selection of appropriate suppliers for carbon inventory compilation. This article considers the GHGs emitted at the supplier's site from the exploitation and manufacturing of raw materials, as well as assembly, use, discard, or recovery of products, but it is not an inventory routing problem since it does not feature a distribution process of products, so it can be considered out of scope for this review. Finally, the paper from He et al. (2016a), although the abstract analysis shows a strong affinity with the analysed topic, it appears not to be available, neither supplied under request to the author. This second step of the research protocol is depicted in **Figure 8.**

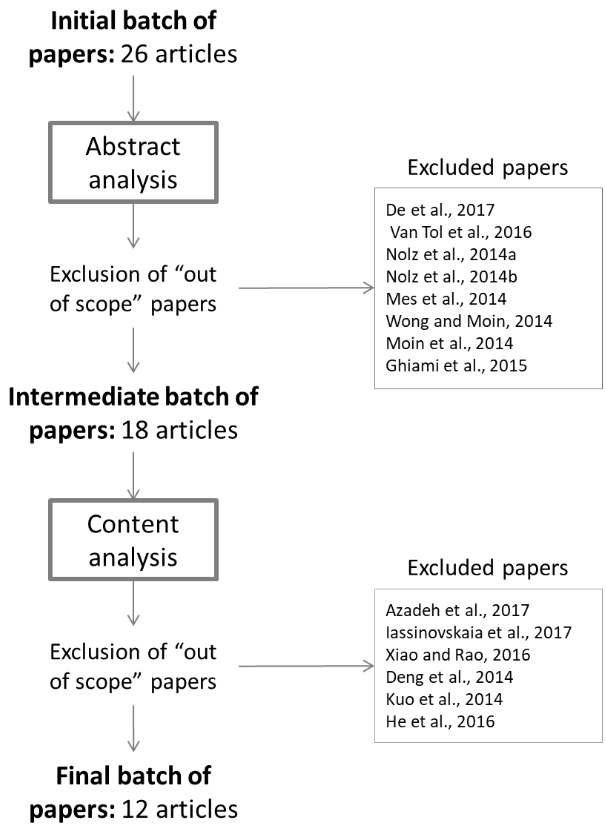


Figure 8 - Research protocol (2).

The final batch obtained from the analysis is composed of 12 papers, shown in the following table (**Table 1**). All these papers tackle different variants of the inventory routing problem, explicitly considering the GHGs emissions generated in the transportation phase of the process.

	Authors	Title
[1]	**Mirzapour Al-e-hashem et al., 2017**	A hybrid L-shaped method to solve a bi-objective stochastic transhipment-enabled inventory routing problem
[2]	**Rahimi et al., 2017**	Multi-objective inventory routing problem: A stochastic model to consider profit, service level and green criteria
[3]	**Cheng et al., 2017**	Modelling a green inventory routing problem with a heterogeneous fleet
[4]	**Cheng et al., 2016**	Multi-period inventory routing problem under carbon emission regulations
[5]	**Soysal, 2016**	Closed-loop Inventory Routing Problem for returnable transport items
[6]	**Franco et al., 2016**	A column generation approach for solving a green bi-objective inventory routing problem
[7]	**Rahimi et al., 2016**	Sustainable Inventory Routing Problem for Perishable Products by Considering Reverse Logistic
[8]	**Soysal et al., 2016**	Modelling a green inventory routing problem for perishable products with horizontal collaboration
[9]	**Niakan and Rahimi, 2016**	A multi-objective healthcare inventory routing problem; a fuzzy possibilistic approach
[10]	**Soysal et al., 2015**	Modelling an Inventory Routing Problem for perishable products with environmental considerations and demand uncertainty
[11]	**Treitl et al., 2014**	Incorporating environmental aspects in an inventory routing problem. A case study from the petrochemical industry
[12]	**Mirzapour Al-e-hashem and Rekik, 2014**	Multi-product multi-period Inventory Routing Problem with a transhipment option: A green approach

Table 1 - Reviewed papers in chronological order.

2.3. Descriptive analysis

The aim of the following analysis is to describe the general structure and characteristics of the body of literature considered. Then, the gathered information is used to detect the common patterns and trends shared by different articles, in order to draw conclusions on the batch from a general perspective.
The first consideration concerns the date of publication of the analysed papers, that reveals the novelty of the topic addressed. Although the inventory routing problem makes its first appearance in the 1983 (Bell et al., 1983), the integration with the environmental considerations appears only in 2014, in the pioneer works developed by Treitl et al. (2014) and Mirzapour Al-e-hashem and Rekik (2014), which are the first to consider the concepts of green logistics in inventory routing problems. The scarcity of

papers addressing the integration of environmental aspects in IRPs is highlighted also by other authors (Rahimi et al., 2017; Cheng et al., 2016). Although the time frame of publication of the analysed articles is relatively tight, it is still possible to draw conclusions on the growing interest in this topic, demonstrated by the increasing number of publications over the past years. The citations overview represented in **Figure 9**, representing the number of citations of the analysed articles per year, confirms this trend. In particular, the depicted data describes the literature on the considered topic up to the mid-2017. The number of citations for the entire 2017 is expected to confirm the trend of 2016.

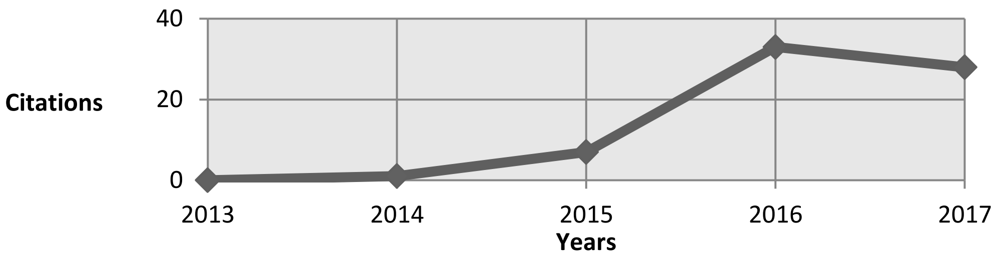


Figure 9 - Number of citations of the reviewed papers.

Due to the mixed nature of the problem, which involves different academic disciplines, the subject areas touched by this topic are heterogeneous. The analysis conducted on the online Scopus database shows that the majority of the papers belong to “Decision Sciences” ([1][2][3][4][8][9][10][11][12]), “Business, Management and Accounting” ([1][2][3][4][9][10][12]), and “Engineering” ([1][4][7][10][11[12]) subject areas. The other fields involved in the topic are “Social Sciences” ([2][3][5][9]), “Economics, Econometrics and Finance” ([1][4][12]), “Computer Sciences” ([6][8]), “Mathematics” ([6][8]), and “Environmental Sciences” ([5]).

Concerning the sources of publication of the analysed articles, there is less heterogeneity, since almost two-thirds of the papers appear in only two journals, respectively the “International Journal of Production Economics” ([1][4][10][12]), and the “Transportation Research Part E: Logistics and Transportation Review” ([2][3][9]). The rest of the articles appear in the “Transportation Research Part D: Transport and Environment” ([5]), in the “Flexible Services and Manufacturing Journal” ([11]), in the “Computers and Operations Research” ([8]), in the “Lecture Notes in Computer Science” ([6]), and in “IFAC-Papers Online” ([7]).

According to Mirzapour Al-e-hashem and Rekik (2014), the traditional criteria used to classify the different variants of the inventory routing problem are the following: finite or infinite planning horizon, single or multiple periods, single or multiple customers, single or multiple products, homogeneous or heterogeneous vehicles, deterministic or stochastic demand. In order to highlight the neglected aspects of this classification, the traditional criteria are integrated with the following: single or multi-objective, topology of the network, typology of emissions model, whether shortage is ignored or taken into account, how environmental concerns are taken into account and in particular, whether a carbon control policy is applied or not. The criteria for the classification of the environmentally-extended inventory routing problems are schematised in **Figure 10**.

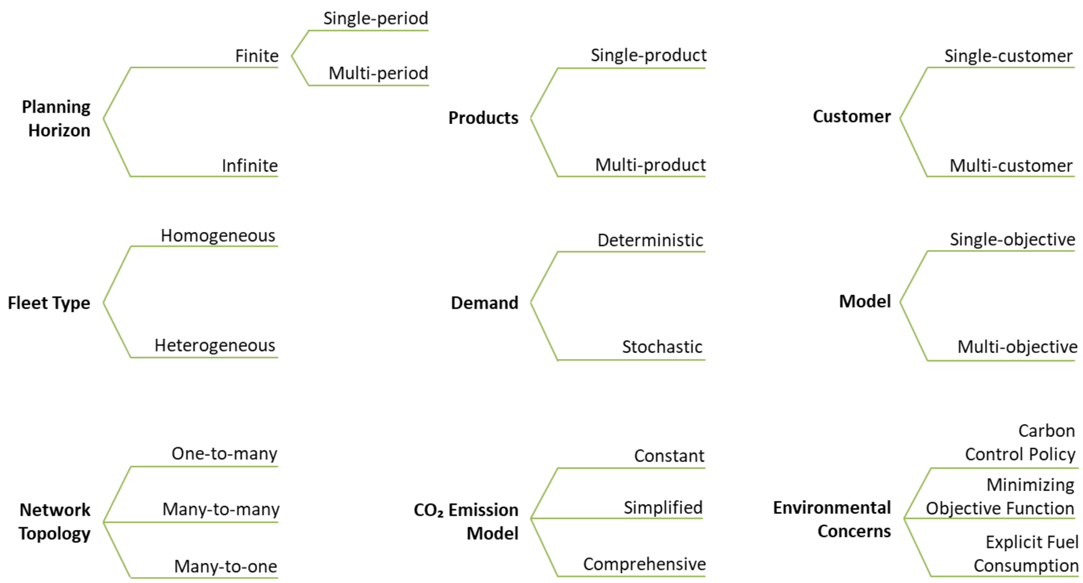


Figure 10 - Classification criteria of environmentally-extended IRPs.

All the articles contained in the final batch address the IRP from a finite planning horizon perspective. The objective is to determine the customers visited and the corresponding quantity delivered for each period. This provides more flexibility and allows the decision maker to modify the initial decisions due to variations in the input data of the problem. On the contrary, the infinite planning horizon approach, determining the optimal replenishment frequency for each customer, provides a static decision which needs to be updated every time a change in the input data occurs.

For similar reasons all the analysed articles employ multi-period models, going from a minimum of two periods for small instances, to a maximum of 21 periods for very large instances. 5 papers ([2][4][6][7][9]) perform a sensitivity analysis on this parameter, testing the same model on a different number of periods. As indicated by Moin and Salhi (2007), in general, the risk related to the short-term approaches, is the tendency to defer as many deliveries as possible to the next planning period.

The parameter on the number of customers is strictly linked with the topology of logistics network examined, which in turn partially affects the decisions of considering a single or multi-product case. According to Soysal et al. (2016), in the IRP literature, the type of logistics network is classified based on the number of suppliers and customers involved. In particular, they individuate three main cases: (i) one-to-one network, (ii) one-to-many network and (iii) many-to-many network. In the one-to-one case, one supplier is in charge of serving one customer. None of the articles analysed show this solution. In the one-to-many case, one supplier serves a set of customers. This is so far the most diffused approach to set the inventory routing problem, and it is employed by two-thirds of the papers analysed ([2][3][5][6][7][9][10][11]). The outbound logistics problem of a one-to-many distribution network is equivalent to the inbound logistics problem of a many-to-one network (Cheng et al. 2016). In this context, a set of vehicles is in charge of the collection of predetermined quantities of products from several geographically dispersed suppliers. This approach is used by three articles ([1][4][12]). Finally, in the many-to-many distribution network, a set of suppliers serve a set of customers. Only ([8]) considers this case.

The many-to-one and many-to-many distribution networks imply the consideration of a multi-product problem since in a multi-supplier context it is likely that each supplier provides a different product. It is noteworthy to underline how the multi-product definition is applied to the overall system since the four papers adopting a multi-supplier scenario, consider only one product per supplier ([1][4][8][12]). In the one-to-one and one-to-many case there is no such a kind of constraint and the analysed papers adopt both the single product solution ([3][6][10][11]) and the multi-product solution ([2][5][7][9]), where one supplier provides different type of products.

Concerning the quantity and the type of vehicles used, all the articles consider a multi vehicles problem, but the majority ([1][2][3][6][7][9][12]) considers a heterogeneous fleet of vehicles, while the rest consider a homogeneous fleet ([4][5][8][10][11]).

The data of demand represent the consumption rate of the products held at the downstream stage of the distribution network. This definition is valid for all the different kind of distribution networks. Half of the analysed papers, ([3][4][6][7][11][12]), consider the demand as known and deterministic, further distinguishing the static data of demand over periods from the variable demand over different periods. Only one paper in the batch considers a static demand pattern over periods [11]. However, as indicated by Soysal et al. (2015), in real applications the customer consumption rate for each period is not known at the beginning of the planning horizon, so a non-deterministic approach to address the uncertainty of demand is required. Six papers adopt a non-deterministic approach, and in particular two of them model the demand with a normal distribution ([10][8]), other two use fuzzy distribution ([2][9]), while the remaining two consider a multi-scenario framework with deterministic data of demand for each scenario ([1][5]).

Addressing the uncertainty in the demand implies taking into account the possibility of stock out occurrences at the customer’s sites. These shortages can be modelled as lost sales or backorders based on the possibility to meet the customer initial request in the following periods or not. Two articles, adopting this characterization of shortages and assigning a proper shortage cost, correctly project the consequences of the uncertainty of demand into the objective function ([1][5]). Another possibility when dealing with the implications of non-deterministic demand is to determine a priori a certain customer service level to assure at the downstream stage, and model it as a constraint of the problem ([8][10]). Finally, in multi-objective models, a single-objective function could be entirely dedicated to the maximisation of the customer service level or to the minimisation of stock out occurrences ([2][9]).

The majority of the analysed papers solve the inventory routing problem adopting a single-objective function, expressed in monetary terms, so maximising the profit or minimising the overall costs. This approach provides a single optimal solution ([3][4][5][8][10][11][12]). The other possibility to address the inventory routing problem is to employ a multi-objective model, where the traditional economic objective function is integrated with different types of objective functions, such as minimising GHGs emissions ([2][6]), maximise social concerns ([7]), or both minimise GHGs emissions and maximise customer service level ([2][9]). The multi-objective approach, differently from the single-objective, provides a set of optimal solutions, called the Pareto frontier, and therefore it involves the active participation of the decision maker in choosing the single optimal solution to be implemented, based on his/her priorities.

The carbon emissions generated by the transportation operations can be modelled in two different ways. Half of the addressed papers consider a linear function where emissions are directly proportional to the travelled distance between two nodes ([1][2][6][7][9][12]). Since all of these papers consider a heterogeneous fleet, each type of vehicle has its characteristic linear emissions function. The other approach used to address carbon emissions is based on the estimation of the fuel consumption of the vehicle, as a function of many different parameters ([3][4][5][8][10][11]). According to Demir et al. (2011) and Demir et al. (2014a), the fuel consumption is influenced by several factors, namely vehicle-related factors (vehicle curb weight, vehicle shape, engine size/type, engine temperature, transmission, fuel type/composition, oil viscosity), environmental related factors (roadway gradient, pavement type, ambient temperature, altitude, wind conditions), traffic-related factors (speed, acceleration/deceleration, congestion), driver-related factors (driver aggressiveness, gear selection, idle time) and operations related factors (fleet size and mix, payload, empty kilometres, number of stops). This classification is schematised in **Figure 11.**

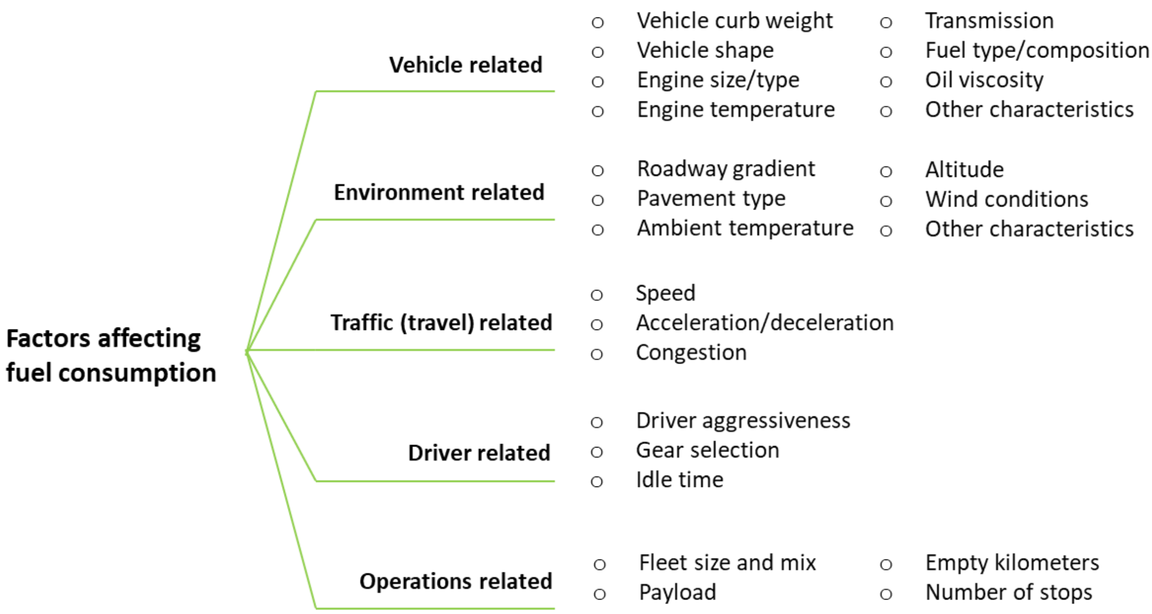


Figure 11 - Main factors affecting fuel consumption - Source: Demir et al. (2014a).

Reasonably, none of the analysed articles consider all these factors at the same time, but only a restricted set of them. The only factor in common among all the six models that estimate the fuel consumption is the load of the vehicle, expressed as the sum of the vehicle curb weight and its payload. The payload is the fundamental factor to link the routing decisions with the inventory management decisions, since a heavier vehicle tends to consume more fuel, and consequently leading to higher emissions. The fuel consumption approach implies the use of a proper conversion factor to finally obtain the emissions generated. Among the six papers that employ the fuel consumption approach, four of them ([3][8][10][11]) use a comprehensive emissions model, while the other two ([4][5]) use a simplified emissions model.

Concluding, the environmental concerns in the analysed articles are addressed in three different ways. Four articles, adopting a multi-objective model, simply use an objective function exclusively dedicated to the minimisation of the GHGs emissions produced, without applying any carbon control policy ([1][2][6][9]). Three articles deduce the environmental benefits of their model quantifying the reduction of fuel consumption of the vehicles, which is directly proportional to the quantity of GHGs emitted in the atmosphere ([5][8][10]). Lastly, five papers consider the application of carbon control policies and respectively two of them apply a carbon cap on the overall emissions of the system ([7][12]), one applies a carbon tax proportional to the volume of emissions produced ([3]), one considers the combination of the carbon cap and carbon taxing policies ([11]) and one analyses the same model under four different carbon control policies, respectively cap policy, cap-and-trade policy, cap-and-offset policy and carbon taxing policy ([4]). The following table (**Table 2**) summarises the descriptive analysis of the reviewed papers.

	Article	Topology	Fleet type	CO_2 emissions model	Demand	Environmental concerns	Model
[1]	**Mirzapour A. et al., 2017**	many-to-one	heterogeneous	constant	stochastic	minimising objective function	multi-objective
[2]	**Rahimi et al., 2017**	one-to-many	heterogeneous	constant	stochastic	minimising objective function	multi-objective
[3]	**Cheng et al., 2017**	one-to-many	heterogeneous	comprehensive	deterministic	carbon control policy	single-objective
[4]	**Cheng et al., 2016**	many-to-one	homogeneous	simplified	deterministic	carbon control policy	single-objective
[5]	**Soysal, 2016**	one-to-many	homogeneous	simplified	stochastic	explicit fuel consumption	single-objective
[6]	**Franco et al., 2016**	one-to-many	heterogeneous	constant	deterministic	minimising objective function	multi-objective
[7]	**Rahimi et al., 2016**	one-to-many	heterogeneous	constant	deterministic	carbon control policy	multi-objective
[8]	**Soysal et al., 2016**	many-to-many	homogeneous	comprehensive	stochastic	explicit fuel consumption	single-objective
[9]	**Niakan and Rahimi, 2016**	one-to-many	heterogeneous	constant	stochastic	minimising objective function	multi-objective
[10]	**Soysal et al., 2015**	one-to-many	homogeneous	comprehensive	stochastic	explicit fuel consumption	single-objective
[11]	**Treitl et al., 2014**	one-to-many	homogeneous	comprehensive	deterministic	carbon control policy	single-objective
[12]	**Mirzapour A. and Rekik, 2014**	many-to-one	heterogeneous	constant	deterministic	carbon control policy	single-objective

Table 2 - Descriptive analysis of the reviewed papers in chronological order.

2.4. Content analysis

The main purpose of the following analysis is to highlight the specific contribution of every single article to the body of literature of the environmentally-extended inventory routing problems. The second important purpose is to identify those aspects that are not still investigated by the existing literature, in order to properly contribute to the development of the considered topic.

The primal analysis of the topic was simultaneously developed in two distinctive works, respectively by Treitl et al. (2014) and by Mirzapour Al-e-hashem and Rekik (2014).

The first compares the retailer managed inventory policy (RMI) with the vendor managed inventory policy (VMI) in a petrochemical industry real case, where a homogeneous fleet of trucks, starting from an infinite capacity depot, have to replenish the inventories of the limited capacity company's own filling stations. They show how shifting from the RMI policy to the VMI policy is possible to achieve a 12.29% reduction in the total cost of the system and a 15.97% reduction in the vehicle CO_2 emissions. This win-win situation is achieved due to the coordination of deliveries and the shift of the decision-making process from the filling stations (retailers) to the depot (supplier). In an RMI context, each filling station tends to order full truckload quantities and vehicles are forced to perform a pendulum route, coming back to depot empty. Using the price value of one ton of CO_2 charged in the EU ETS, they further illustrate that the application of a carbon price regime on the emissions does not affect the decision if the price is too low. They also show that an exclusively minimising emissions function would lead to a further 1.35% reduction in the vehicle carbon emission, causing only a 0.55% increase in the total costs, with respect to the optimal VMI solution.

Mirzapour Al-e-hashem and Rekik (2014) consider an inbound logistics problem of an assembly plant, where a fleet of heterogeneous vehicles has to collect the requested components from geographically dispersed suppliers. However, they extend the traditional IRP taking into consideration the transhipment option. Under this policy, a product of a supplier could be temporarily stored at another supplier's site and a vehicle could pick it up on a successive trip. Under this assumption, they apply a limit on the total carbon emissions produced showing that the green model with the carbon cap leads to 4.67% reduction of GHGs emissions and a 9.77% increase in the total costs compared with the relaxed model where there is no constraint on the overall emissions. This increment in the supply chain cost is due to the employment of more fuel-efficient (and so more expensive) vehicles, and due to the transhipment option, that reduces the number of trips while increasing the inventory holding costs at the intermediate suppliers. In this sense they show the "greenness" of the transhipment option, demonstrating that this is not an expensive strategy for moderating GHGs emissions levels.

Soysal et al. (2015) investigate the environmentally-extended inventory routing problem taking into consideration the uncertainty of the customer demand, the perishability of the distributed products and the explicit fuel consumption concern. They develop a chance-constrained programming model to take into account the customer service level, and they applied it to a real distribution network where a fleet of homogeneous vehicles leaving a distribution centre is responsible for providing fresh tomatoes to a set of supermarkets. They solve this problem developing a simulation algorithm and with a commercial mixed integer linear programming solver, showing that with both solution methods, the relaxation of the perishability constraints leads to an increase in the overall costs, driven by the increase of the waste cost, but it results in a decrease of the total carbon emissions due to the reduction of the number of vehicles trips. They also show how taking into account the explicit fuel consumption function leads to a 0.8% decrease in the total carbon emissions and a 0.2% decrease in the total cost. As in the paper by Treitl (2014), they modify the objective function in order to take into account only the waste and fuel costs. This environmental friendly objective function leads to a further 2% total emissions reduction against a 25.2% increase in the total costs, caused by a considerable increment in the inventory holding cost.

Niakan and Rahimi (2015) address the healthcare inventory routing problem (HIRP) where a supplier is in charge of the distribution of medicinal drugs to a set of healthcare facilities. They develop a multi-objective mathematical model in order to minimise the operational costs of transportation, inventory holding and shortages, maximise the customer service level reducing the demand forecasting errors and the number of expired drugs, and minimise the vehicles GHGs emissions. They adopt a smoothing approach to forecast demand in order to reduce the errors and increase the customer service level. Their experimental results confirm the importance of considering GHGs emissions in the model. In fact, increasing the relative importance of the coefficient associated with the environmental objective function, the model tends to use few large size vehicles reducing the number of transportation and the relative GHGs emissions, while increasing the operational costs. They apply the model to a real case study of a pharmaceutical supplier in charge of the distribution of two medicinal drugs to twelve customers over a planning horizon of one year, demonstrating that the variation of the coefficients of importance of the objective functions leads to the modification of the vehicle fleet, and the increase in the shortage cost of the products causes the increment of the inventory level and the reduction of the forecast error.

Soysal et al. (2016) extend their previous work developing a chance-constrained model taking into account perishability of products, uncertainty of demand and explicit fuel consumption in a many-to-many distribution network, where many suppliers have to distribute different products to a set of customers. In particular, they investigate the benefits of horizontal collaboration between the suppliers, which jointly cooperate using a fleet of homogeneous vehicles provided by a 3PL logistics company. They apply their model to a real case study where two suppliers have to provide two different perishable products (cherries and figs) to five wholesale market halls. They illustrate as the horizontal collaboration case leads to a win-win situation characterized by a 29.3% reduction in the total GHGs emissions and a 17.1% reduction in the total costs of the system. Performing sensitivity analysis on the size of the suppliers and on the number of common customers they further illustrate that as the supplier's size decreases, the total cost benefits from cooperation with other larger supplier increases, and the benefits obtained from jointly working decreases as the number of common customers decreases.

Rahimi et al. (2016) address social issues in a reverse logistics IRP, developing a bi-objective mathematical model that consider social and economic criteria, while green criteria are considered as constraints. The social issues addressed are the rate of accidents during distribution of products and gathering of expired products, the number of expired products and the control of vehicle noise emissions. The first is minimised with an objective function while the other two are modelled as constraints setting the maximum allowed limits. The environmental concerns are addressed setting a cap policy consisting of a maximum allowed value of GHGs emissions for each period of the planning horizon. They test the model on two instances showing that when the relative importance of social issues is increased, the accident rate and the number of expired products decrease. This 23% improvement in the social issues is counterbalanced by a 17.3% decrease in profit because the model attempts to use routes characterized by lower speed (so lower accident rate) and adopts more vehicles to reduce the number of expired products.

Franco et al. (2016) concentrate on the resolution side of the environmentally-extended inventory routing problem, developing a bi-objective mathematical model that takes into account operational costs given by transportation and inventory holding, and GHGs emissions generated by the routing of the vehicles and by the inventory holding. They integrate the Non-Inferior Set Estimation (NISE) algorithm used to solve multi-objective problems with a column generation method in order to create attractive routes and improve the objective function. This solution allows reducing the computational time of resolution. Finally, testing the model on different size instances, they show that the size of the instances does not affect the number of points in the Pareto set, while increasing the number of customers leads to higher computational times.

Soysal (2016) addresses the Closed-loop inventory routing problem (CIRP), where a vendor is responsible for the distribution of products to a set of customers, that consists in the forward routing of the vehicles. The products are delivered using Returnable Transport Items (RTIs) that have to be collected by the same fleet of vehicles during the backward routing. The probabilistic mixed linear programming (MILP) model developed by the author takes into account forward and reverse logistics operations, explicit fuel consumption, demand uncertainty and multiple products. The model is applied to a real case study consisting of a soft drink company in charge of the distribution of soda to eight geographically dispersed retailers. They evaluate the economic and environmental performance of the model using an optimization solver based on the probability of occurrence of different demand scenarios and a simulation model that takes in inputs the delivery and routing schedules generated by the MILP solver. The authors show the benefits of integrating forward and reverse logistics: the integrated model leads to 41.6% reduction of the total costs and a 50.8% reduction in the total emissions compared with the non-integrated model. As in their previous works, the authors consider a pure environmentally-driven objective function, showing that it leads to further 7% reduction in the total emissions and a 59.7% increment in the total cost compared to the base model.

Cheng et al. (2016) investigate the effects of different carbon emissions regulations on a multi-period inventory routing problem (MIRP) and examine the relationships involved. In particular, they develop four different models that take into account respectively the cap policy, the cap-and-trade policy, the cap-and-offset policy and the carbon taxing policy. They set the problem in a many-to-one topology network where a homogeneous fleet of vehicles has to collect different components from a set of suppliers and deliver them to an assembly plant. Due to the computational complexity of solving large instances problems with commercial optimization solvers, they propose a hybrid genetic algorithm (HGA) to solve the cap model, showing that HGA outperforms the optimization solver in all the instances tested. Comparing the cap model with the model without any regulation and varying the value of the cap limit, the authors highlight the sensitivity of the inventory holding cost to the environmental constraints. In fact, as the cap becomes tighter the cap-and-offset model tends to decrease the emissions (-41.4%) while the total cost increases exponentially (+428.5%), driven almost exclusively by the inventory holding levels. Finally, performing sensitivity analysis on the unit fuel price and the unit carbon price, they provide further observation on the interrelationships between the operational decisions and the carbon control policy adopted.

The work of Cheng et al. (2017) is the first to consider a comprehensive emissions model in a green inventory routing problem characterized by a heterogeneous fleet (GIRP-H). Their purpose is to investigate an IRP where both the fuel consumption and the GHGs emissions are explicitly taken into account. They address the speed of the vehicles as a decision variable, showing how all the types of considered vehicles reach their minimum fuel consumption (and consequently GHGs emissions) when they travel at a constant speed comprised between the 30 and 40 km/h. They further show how a comprehensive objective function that considers inventory costs, variable and fixed transportation costs, emissions cost and fuel cost, outperforms the traditional objective function consisting of the inventory costs and the distance travelled cost, both in terms of total cost of the system (-6.71%) and total emissions (-23.09%). They also illustrate the benefits of adopting a heterogeneous fleet of vehicles, instead of a single type of vehicles. As in the previous work, the sensitivity analysis on the unit inventory holding cost shows that the total costs increase linearly with the inventory holding cost while the GHGs emissions present a staircase increasing trend. The sensitivity analysis on the unit emission price shows similar results, with a linear increment of total costs and a decreasing staircase pattern of the emissions level.

Rahimi et al. (2017) consider an environmentally-extended inventory routing problem with time windows constraints for the distribution of different perishable products to a set of customers. They develop a multi-objective model that simultaneously takes into account economic, service level and green criteria. They address the perishability of the products considering the recycling of expired products costs and the GHGs emissions generated by the recycling process. Besides the emissions from the recycling process, the model takes into account the GHGs emissions produced by the vehicles and the emissions generated by the loading/unloading phases. The service level

objective is developed in detail considering the rate of delivery delay, the rate of backorder and the rate of the backorder frequency. Due to the fuzzy nature of demand, variable transportation cost and vehicle speed, a meta-heuristics solution method is proposed to solve the multi-objective model. The obtained solution provides the decision maker with an optimal Pareto frontier involving him/her in the choice of the solution based on his/her own managerial judgment on the preference and priority of the different objective functions. The authors highlight how exogenously choosing a certain target of customer service level could can considerably impact on the logistics cost, so splitting the economic objective and the service level objective function allows the decision maker to identify those solutions that with a small decrease in the profit, achieves a major increase in the customer service level.
Mirzapour Al-e-hashem et al. (2017) study how the transhipment impact on the economic and environmental performance of a transhipment-enabled stochastic inventory routing problem (TIRP) in a many-to-one logistics network. They develop a bi-objective stochastic programming model addressing the total costs of the supply chain given by the inventory holding, shortage, transportation costs and costs of the disposal process, and the GHGs emissions produced by the vehicle during transportation and those produced by the products during the disposal process. The model, solved with a variant of the L-shaped method, is applied to an IRP of a hospital supplied by eight different drugstores that provide five different highly perishable medicines. The environmental concerns are considered varying the value of the coefficients of the relative importance of the objective functions, showing that transhipment strategy can be effective in reducing the total travel distance and GHGs through merging the trips. However, the authors highlight how the vehicle capacity plays a key role directly impacting on the fixed and variable transportation costs. The sensitivity analysis on the relative importance coefficient of the environmental objective function shows that the reduction of GHGs emissions fits an exponential trend while the increase in the total costs is almost linear. Due to the multi-scenario nature of the problem, the authors illustrate how the transhipment option can act as an absorber of uncertainty, illustrating how the number of transhipment increases if the number of scenarios increases.

2.5. General considerations

The content analysis of the reviewed literature has highlighted how the different authors, starting from the pioneering work of Treitl et al. (2014) that introduces the concept of environmentally-extended inventory routing problem, have added different contributions to the topic, exploring and tracing new paths by considering diverse interrelated aspects. **Figure 12** summarises all the main research extensions of the environmentally-extended inventory routing problems analysed in the content analysis.

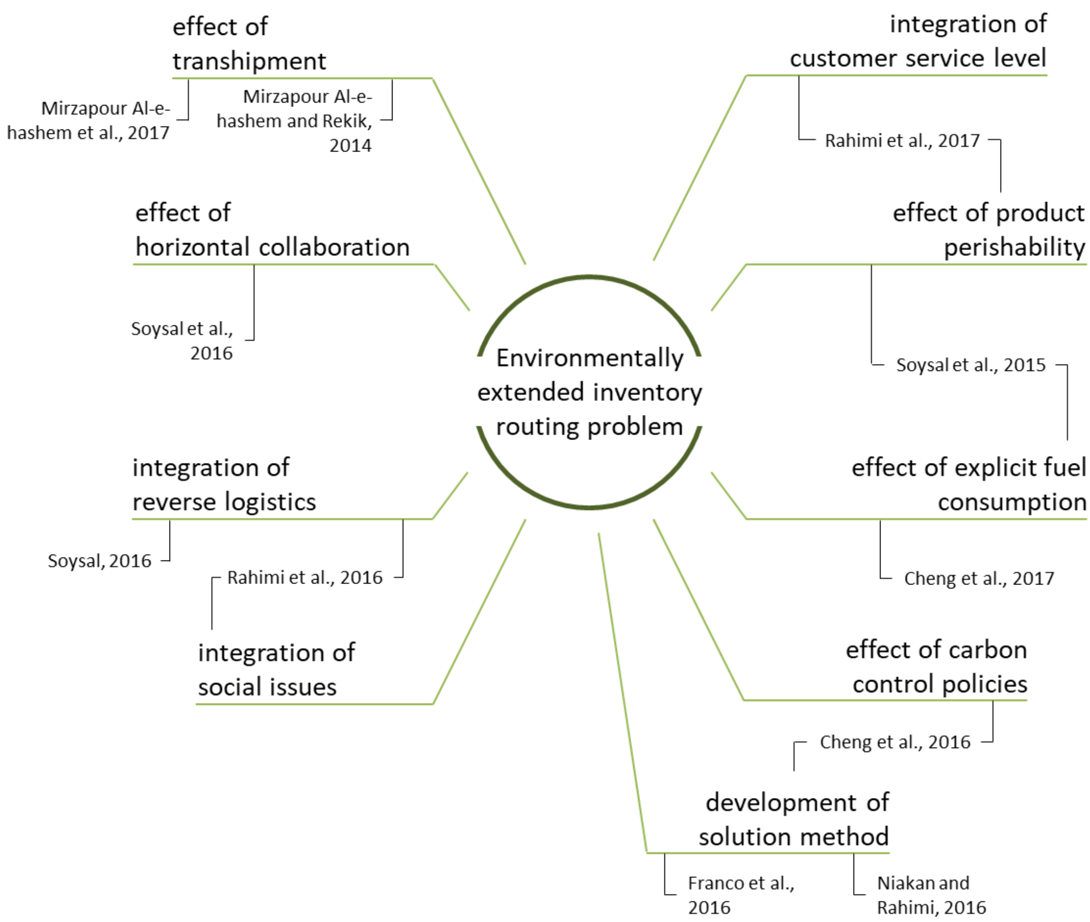


Figure 12 - Main research extensions of the environmentally-extended IRPs.

As shown, there is not a strongly preferred path, apart from the area of development of solution method. This aspect, in particular, is strictly linked with the mathematical nature of the inventory routing problem, which is a later extension of the more traditional vehicle routing problem. The inventory routing problem in fact, like the vehicle routing problem, is a member of the class of the NP-Hard problems. The existing algorithms for solving this class of problem are not able to find the optimal solution for large instances in an acceptable time frame, since the solution time is not proportional to the size of the instance. For this reason, many researchers have focused their effort on finding heuristics algorithm able to solve large instances of this type of problems. The analysed works of Cheng et al. (2016), Franco et al. (2016), Niakan and Rahimi (2016) focusing on this aspect also consider the environmental implications of the inventory routing problem. The perishability of products is another aspect frequently addressed by the analysed authors. Although only two works specifically focus on the effects of product perishability (Soysal et al. (2015), Rahimi et al. (2017)), other works consider the distribution of perishable products. The inventory routing problem, in fact, describes properly many distribution networks characterised by product perishability. For example, the works of Niakan and Rahimi (2016) and Mirzapour Al-e-hashem et al. (2017) consider the problem of distribution of medicinal drugs characterised by a known expiration date. Moreover, the perishability of products is linked with one of the pillars of the inventory routing problem, which is the inventory management, since the addressed product can stay in the warehouses only for a finite time.

Another interesting area of extension of the environmentally-extend routing problem is that traced by the work of Cheng et al. (2016), which focus on the effect of carbon control policies on the considered inventory routing problem. The introduction of a carbon control policy is tackled by diverse analysed works (Mirzapour Al-e-hashem and Rekik, (2014), Treitl et al. (2014), Rahimi et al. (2016), Cheng et al. (2017)), but they focus only on one specific policy. Differently, the work of Cheng et al. (2016) focuses at the same time on the four most diffused type of policies. As shown in the introduction of this thesis, the spreading of regulations and measures to mitigate the carbon emissions is becoming a fundamental aspect that companies have to take into account. Even the freight transportation sector, that is not one of the main regulated sectors at the moment, sooner or later have to face the environmental implications of its activities. For this reason, the choice of focusing on the environmental and economic implications of different types of policies assumes a significant importance.

However, the paper of Cheng et al. analyses the case of a many-to-one logistics network where many suppliers have to provide different products to a single customer. The proposed model features a homogeneous fleet of vehicles and assumes deterministic demand. It was previously shown that taking into account a heterogeneous fleet provides some degree of flexibility in determining the optimal solution, and better describes the reality of logistics problems. For the similar reasons, the choice of considering deterministic demand could be restrictive and not able to properly represent the variability of real cases.

Given these assumptions, the purpose of the thesis is to analyse how different carbon control policies affect the solutions of an environmentally-extended inventory routing problem with a heterogeneous fleet, stochastic demand and a comprehensive emissions model. Based on the works analysed in literature, it is developed a chance-constrained programming model that addresses at the same time 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. Besides the mathematical formulation of each policy-modified model, it is provided a general overview and a description based on the actual implementations worldwide. In addition, it is presented a formulation of the problem based solely on environmental concern, thus characterised by an emissions-minimising objective function, and it is presented a constant emissions model to quantify the increment of the accuracy of the results when it is used the comprehensive emissions model. Then, the proposed models are applied to a real distribution case described by a supplier and a set of customers and, for each policy, it is performed a sensitivity analysis on the characterising parameters, highlighting all the economic and environmental implications with respect to the base case model where no carbon control policy is applied.

3. Models formulation

3.1. Choice of the reference model

The first decision concerning the model is about the nature of the objective function. The reviewed literature employs both single-objective and multi-objective models, designing a specific carbon emissions-minimising objective function to address the environmentally-related part of the multi-objective models. However, as previously shown, the multi-objective approach requires the active involvement of the decision maker, who has to conscientiously select the proper values to assign to the weights of the objective functions.

The carbon control policies investigated in the literature and addressed by this thesis are intrinsically characterized by economic implications, since they are designed to curb the emissions of the designated parties, by directly acting on their economic results. For this reason, the environmentally-related part of problems addressing carbon control policies is incorporated in the minimising-cost objective function, resulting in single-objective models. From this point of view, single-objective models prove to be straightforward and simpler to manage since the results of the different policies could be easily synthetized by one single indicator which is the overall total cost.

Given these assumption, the model proposed in this thesis is described by a single-objective function minimising the overall total cost.

The following step is to identify, among the single-objective models analysed in the literature review, one to set as a reference. In particular this model should address in its formulation: (i) the uncertainty in the customers demand, (ii) a comprehensive emissions model, (iii) the employment of a heterogeneous fleet of vehicles. Each of these features, as demonstrated by the reviewed literature, has proved to lead to better results in terms of economic and environmental performances (Cheng et al. 2017) and to a closer description of the reality (Soysal et al. 2016).

As shown by the following table (**Table 3**), none of the analysed papers addresses at the same time all these three features. Specifically, Cheng et al., (2017) address the heterogeneity of a fleet of vehicle with a comprehensive emissions model, but using deterministic data of demand, while Soysal et al. (2015), Soysal (2016) and Soysal et al. (2016) focus on the uncertainty in the demand along with the comprehensive emissions model, but using a homogeneous fleet of vehicles.

Article	Heterogeneous fleet	Comprehensive CO_2 emissions model	Stochastic demand
Cheng et al., 2017	✓	✓	
Cheng et al., 2016		✓	
Soysal, 2016		✓	✓
Soysal et al., 2016		✓	✓
Soysal et al., 2015		✓	✓
Treitl et al., 2014		✓	
Mirzapour Al-e-hashem and Rekik, 2014	✓		
This thesis	✓	✓	✓

Table 3 - Single-objective papers reviewed in literature: focus on heterogeneous fleet, comprehensive CO_2 emissions model and stochastic demand.

Since it is relatively simple to implement a heterogeneous fleet on a model which already takes into consideration a fleet of homogeneous vehicle, it has been decided to take as a reference one of the three model developed by Soysal et al., and in particular the model proposed by Soysal et al. (2016).
The original model of Soysal et al. (2016) is set in a many-to-many environment where different suppliers serve a set of different customers. Each supplier provides one single type of product characterized by an expiration date, which leads to the inclusion of considerations on waste quantities and waste cost in the objective function and in some of the constraints.
Since the objective of this thesis is to analyse how different carbon control policies affect the decisions of a general environmentally-extend inventory routing problem, without focusing on a specific class of product, such as the perishable products, the additional analysis on the waste of perished products is considered out of scope. As a result, the first hypothesis of the model introduced in this thesis is that the products are characterized by an infinite expiration date. This is obtained deleting from the reference model the two constraints related to the waste quantities and the related decision variable. The same result could be obtained also setting the expiration date of the products higher than the planning time horizon of the model. However, the simplification of the reference model obtained deleting constraints and waste variable results in a lean writing of the model and in less computational effort of the calculator.
The second difference from the reference model is in the variety of products managed by the model. The model of Soysal et al. takes into consideration a multi-product scenario since the focus of their work was to demonstrate the benefits of a horizontal collaboration between different suppliers with different products. As shown in the

literature review, a multi-supplier scenario implies in most of the cases a multi-product analysis, even if it is in theory possible to analyse a scenario characterized by many suppliers providing all the same kind of products.

The model proposed in this thesis features a one-to-many distribution network where a supplier provides only one kind of products to its customers. The choice to take into consideration a single-supplier single-product framework is motivated by two reasons: (i) a many-to-many distribution network structure represents an isolated case in the reviewed literature, since it was specifically developed to investigated the benefits of horizontal collaboration, while the general case is represented by the one-to-many distribution network; (ii) taking into consideration different class of products adds complexity to the problem, both in terms of mathematical writing and computational effort. Since the focus of the thesis is to provide insights on the implications of different carbon control polices imposed on a general distribution framework, the considerations on a multi-class of products is considered out of focus. However, the model's syntax of a many-to-many distribution network with different products is still valid for the one-to-many single-product framework analysed in this thesis, as shown by the authors in their single-product analysis, necessary to show the benefits of the horizontal collaboration. For this reason, 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.

The other element in common between the reference model and the proposed model is the involvement of a third-party logistics (3PL), which is charge of the distribution of the products from the supplier to the customers. The depot location of the 3PL is different from the supplier location, which means that the vehicles provided by the 3PL have to start their routing from the depot, pick up the freight from the supplier, deliver it to the different customers and conclude the routing at the 3PL's location. The following figure describes a generic representation of a one-to-many distribution network with the 3PL (**Figure 13**).

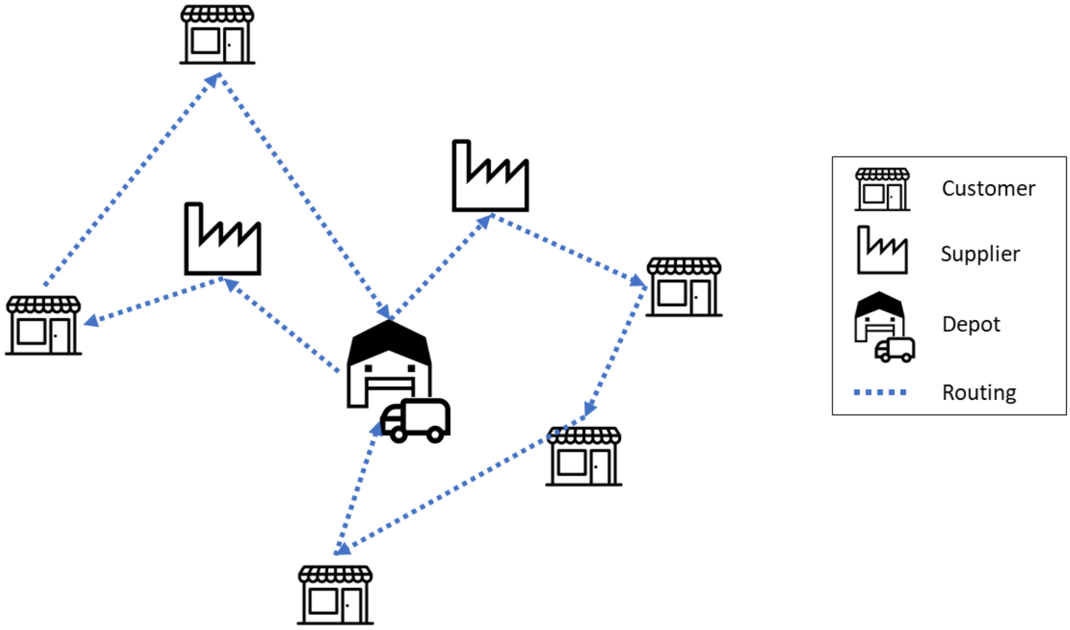


Figure 13 - Generic representation of an inventory routing problem with one supplier and multiple customers.

3.2. Parameters of the inventory routing problem

It is now proposed the formulation of the model keeping as a reference the notation used in the model of Soysal et al. (2016). It is firstly proposed the base case formulation of the problem where no carbon control policy is applied and consequently no environmental concerns are taken into consideration. Then the model is modified to take into account each carbon control policy under analysis. All the assumptions proposed for the base case model are still valid for the carbon control policy models.

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 (third party logistics) located at the node 0, and $A = \{(i, j): i, j \in V, i \neq j\}$ is the set of arcs. The distance between each pair of nodes is represented on a matrix where every element is denoted as $a_{i,j}$. This matrix is not symmetric since $a_{i,j} \neq a_{j,i}$, which means that the distance travelled to go to location i to location j could be different from the distance travelled on the way back. The set of vehicles is given as $K = \{1, 2 \dots, |K|\}$, the 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 proposed model features the following assumptions:

- The demand of product type $p \in P$ for each period $t \in T$ at each customer's site is indicated by $d_{i,p,t}$ and it is assumed to be normally distributed with mean $\mu_{i,p,t}$ and standard deviation $\sigma_{i,p,t}$. The demand of all the customers in each period must be satisfied with a probability of at least α.
- Shortages in each period are taken into account as backlogs. The demand that cannot be fulfilled in one period is backlogged in the next period. This assumption is strictly correlated with the modelling of the constraints explained in the following section, since the inventories at the customer's location could assume negative values.
- No shortages costs are considered. These costs, as explained in detail in the section on the linearization of the chance-constrained programming model, are implicitly taken into account setting a proper value of desired service level α.
- The fleet of vehicles is heterogeneous, limited and capacitated. Each vehicle type is characterized by different payload capacity and drive parameters. Vehicle capacity is denoted as c^k.
- Each vehicle starts and ends its routing at the 3PL's depot, and it can perform at most one route per time period.
- The maximum level replenishment policy is applied at each customer's location. This policy allows the delivery of any quantity of products, as long as the maximum customer's warehouse capacity is not exceeded.
- The total freight assigned to each customer in each period can be split between two or more vehicles. Hence each customer can be visited by more than one vehicle per each time period.
- Each customer incurs a constant unit inventory holding cost for each period a product $p \in P$ stays in the warehouse, indicated as $h_{i,p}$. The unit inventory holding cost could differ based on the product type and on the customer's site.
- The inventory level at each customer is equal to zero at the beginning of the planning horizon time.
- A limited quantity of product, indicated as $q_{i,p,t}$, is available for each period at the supplier's site. No inventory holding cost are considered at the supplier's site.
- Both supplier and customers are characterized by unlimited capacity warehouses.

These last two assumptions need to be explained in detail. The majority of the one-to-many papers reviewed in the literature do not consider the inventory at the supplier's site, neither in terms of inventory holding cost or maximum warehouse capacity. These considerations require a sort of further modelling of the upstream stage of the supply chain, in order to determine at each period, the optimal quantity of product available at the supplier's location. The result is a three-echelons supply-chain which is out of the scope of the examined environmentally-extended inventory routing problems. The only paper featuring a one-to-many distribution network that partially tries to model the inventory at the supplier's site is the work of Cheng et al. (2017), which assumes that at each period a quantity of product is available at the supplier, further assuming a unit inventory holding cost for the supplier equal to the unit inventory holding cost of the product at the customers. In this framework, the decision on the exact value of the available quantity at the supplier is particularly delicate, since it represents an input data of the problem, externally determined, which affects directly the overall inventory holding cost and the economic result of the problem. For this reason, it has been decided to follow the majority of the literature and to not consider any unit inventory holding cost at the supplier. This assumption could be strengthen reporting the considerations of Glock, that in his review on the joint economic lot size problems (JELS), states that in general, inventory holding costs at the buyer (customers) are much higher than inventory holding costs at vendor (supplier), (Glock, 2012).

Concerning the assumption on the unlimited capacity of the warehouse at the customer's sites it has been observed that all the papers that tackle the application of a carbon control policy to the IRP show an increase in inventory level, as the regulation becomes tighter. Since the focus of this thesis is to analyse how these regulations affect the decision variables of the models, it has been decided that, for each period, the upper bound on the delivery quantities is given by the overall capacity of the fleet of vehicles, without putting any limit on the warehouses capacity. This assumption allows to highlight more clearly the trade-off between the effort to reduce the carbon emissions by reducing the number of trips (so increasing the quantity delivered in each trip), and the effort to keep the inventory level as low as possible, in order to lower the inventory holding cost. Introducing a maximum allowed level of inventory would add a constraint that forces the model to find a different solution when it need to deliver a higher quantity of products. Moreover, real cases hardly face the complete exploitation of all the available space in warehouses.

Concerning the routing cost, w denotes the wage for the vehicle's driver expressed in €/s, while l denotes the fuel price expressed in €/litre. The driver is paid hourly, based on the total driven hours calculated at the end of each period of the planning horizon. The following table (**Table 4**) summarises the parameters of the proposed model.

Symbol	Meaning
$\boldsymbol{V_C}$	Set of customers, $V_C = \{1, 2 \dots, \lvert V_C \rvert\}$
$\boldsymbol{V_S}$	Set of suppliers, $V_S = \{1, 2 \dots, \lvert V_S \rvert\}$
$\boldsymbol{V}$	Set of all nodes including the depot, $V = V_C \cup V_S \cup \{0\}$
$\boldsymbol{A}$	Set of all arcs, $A = \{(i, j): i, j \in V, i \neq j\}$
$\boldsymbol{T}$	Set of all periods, $T = \{1, 2, \dots, \lvert T \rvert\}$
$\boldsymbol{P}$	Set of all products, $P = \{1, 2, \dots, \lvert P \rvert\}$
$\boldsymbol{K}$	Set of all vehicles, $K = \{1, 2, \dots, \lvert K \rvert\}$
$\boldsymbol{d_{i,p,t}}$	Demand of customer $i \in V_C$, for product type $p \in P$, in time period $t \in T$
$\boldsymbol{\mu_{i,p,t}}$	Mean of the normal random variable $d_{i,p,t}$
$\boldsymbol{\sigma_{i,p,t}}$	Standard deviation of the normal random variable $d_{i,p,t}$
$\boldsymbol{\alpha}$	Pre-defined satisfaction level of probabilistic inventory constraint
$\boldsymbol{c^k}$	Capacity of vehicle $k \in K$, in kg
$\boldsymbol{a_{i,j}}$	Distance between node i and j,$(i, j) \in A$, in m
$\boldsymbol{l}$	Fuel price per litre, in €/litre
$\boldsymbol{w}$	Wage rate for the drivers of the vehicles, in €/s
$\boldsymbol{h_{i,p}}$	Holding cost of product $p \in P$ per period at node $i \in V_C$, in €/kg
$\boldsymbol{q_{i,p,t}}$	Amount of product $p \in P$ available at supplier $i \in V_S$ in period $t \in T$, in kg

Table 4 - Parameters of the model: mathematical notation and meaning.

The objective of this problem is to determine for each period the route of each single vehicle, the quantity of product to be picked at the supplier's site and the quantity of product to deliver to each customer that minimise the expected overall cost, which are the sum of the routing cost and inventory holding cost. These three decisions are expressed by the following decision variables:

- $X_{i,j,k,t}$ is a 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.
- $B_{i,k,p,t}$ denotes the quantity of product $p \in P$ picked up from supplier $i \in V_S$ by vehicle $k \in K$ in the beginning of period $t \in T$, expressed in [kg].
- $Q_{i,k,p,t}$ denotes the 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 $[kg]$.

The other decision variables of the problem are linked to the previous ones by the constraints of the problem. They are necessary in order to calculate each single cost component of the objective-function, apart from the last one, which allows to eliminate vehicle subtours and it is explained in the constraints description.

- $I_{i,p,t}$ denotes the amount of inventory 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 $I_{i,p,0} = 0$, $\forall i \in V_C, p \in P$.

- $I^{+}_{i,p,t}$ is derived from the previous decision variable in order to calculate the 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].
- $F_{i,j,k,p,t}$ denotes the load of product $p \in P$ on vehicle $k \in K$ which goes from node $i \in V$ to node $j \in V$ in period $t \in T$, expressed in [kg].
- $U_{i,k,t}$ denotes the position of node $i \in V \setminus \{0\}$ in route $k \in K$ in period $t \in T$.

The time-relationships of the decision variables are better explained in the following figure (**Figure 14**), which shows a simple vehicle route and delivery example. At the beginning of the time period t, the quantity of product $q_{i,p,t}$ becomes available at the warehouse of the supplier i. Successively, the vehicle k visits the supplier i and picks up a quantity of product $B_{i,k,p,t}$, then it leaves the supplier and goes to the customer j, that receives the quantity of product $Q_{j,k,p,t}$. In this simple example, the pick-up quantity $B_{i,k,p,t}$ and the deliver quantity $Q_{j,k,p,t}$ are equal, but in reality, given the higher number of customers to be served, $B_{i,k,p,t}$ is assumed always greater than or equal to $Q_{j,k,p,t}$. In other words, the pick-up quantity at each period should at least satisfy the scheduled delivery of a network composed by only one customer. In the same period the customer j, faces a demand equal to $d_{j,p,t}$, thus the resulting inventory level at the customer warehouse at the end of the period t will be equal to $I_{j,p,t-1} + Q_{j,k,p,t} - d_{j,p,t}$, where $I_{j,p,t-1}$ denotes the inventory level of previous period. The highlighted area in figure (**Figure 14**) represents respectively the positive inventory level at the supplier i, the load on the vehicle k, and the positive inventory level at customer j. However, as reported in the assumptions of the proposed model, the inventory at the suppliers will be not taken into account.

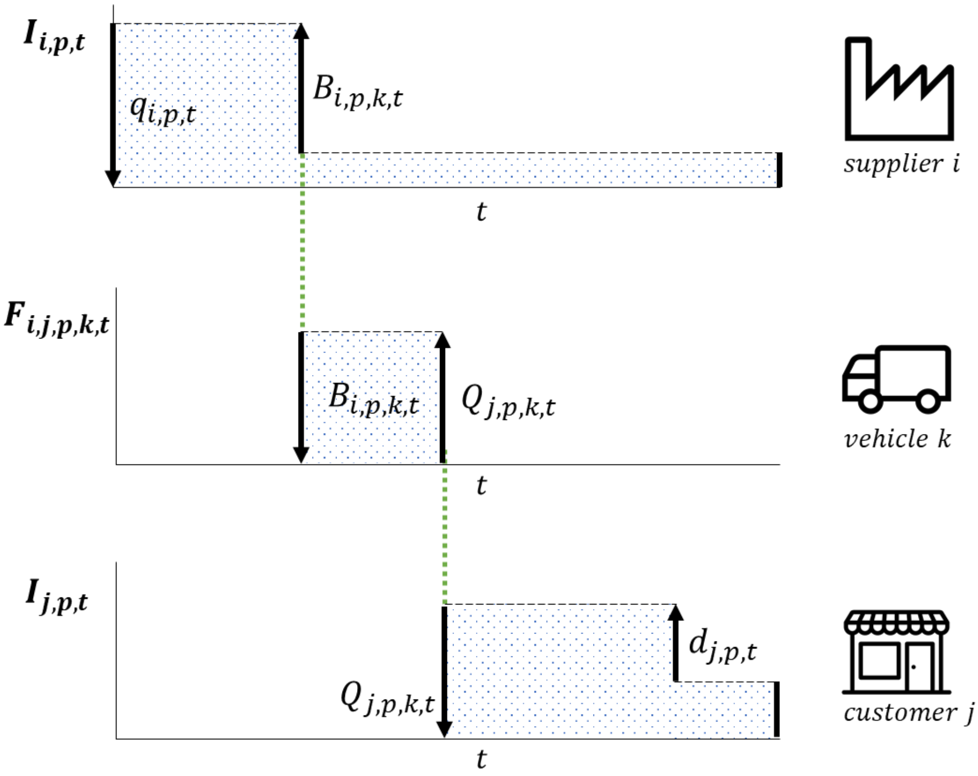


Figure 14 - Variation of inventory and payload levels of a supplier, a customer and a vehicle considering a simplified distribution network and a single time period.

3.3. Comprehensive emissions model

Before presenting the mathematical formulation of the problem, it is necessary to introduce the comprehensive emissions model adopted for the fuel consumption calculation and the related carbon emissions estimation for a given time instant. This model was developed in three works (Barth et al. (2005), Scora and Barth (2006), and Barth and Boriboonsomsin (2008)), and it was successfully applied to many vehicle routing problems concerning carbon emissions, known as the pollution-routing problems (Bektas and Laporte (2011), Demir et al. (2012), Demir et al. (2014b)). According to the classification of the emissions models developed by Demir et al. (2014a), the comprehensive emissions model belongs to microscopic models' category, since it estimates the instantaneous vehicle fuel consumption and emission rates (the other categories are the macroscopic models and the factor models). The authors compared 25 different fuel consumption models, according to the parameters previously cited and reported in **Figure 11**, showing how the comprehensive emissions model is the one that takes into account the greatest number of parameters, neglecting only the driver related parameters (driver aggressiveness, gear selection, idle time), the traffic congestion parameter and the empty kilometres and number of stops parameters. Moreover, the comprehensive emissions model is the best in terms of robustness, reliability and applicability in optimization.

In the context of environmentally-extended inventory routing problems, the comprehensive emissions model was adopted by Treitl et al. (2014), Soysal et al. (2015), Soysal et al. (2016) and Cheng et al. (2017). The latter, based on the work of Koc et al. (2014) which studies the impact of a heterogenous fleet in a pollution-routing problem, adapts the comprehensive emissions model to account for a heterogeneous fleet case in a green inventory routing problem. Following the approach of these two works, it is now presented the calculation of fuel consumption of a vehicle type k. The related carbon emissions are successively obtained multiplying the litres of fuel consumed by a specific unit conversion factor. In fact, carbon dioxide emissions, differently from the other greenhouse gases involved in the internal engine combustion, are directly proportional to the fuel consumption. The mathematical notation of the emission model is adapted to be coherent with the notation adopted by the reference model of Soysal et al. (2016).

$$FR^k = \xi\left(k_e^k N_e^k V_e^k + \frac{P^k}{\varpi}\right)\frac{1}{\kappa\psi} \qquad (1)$$

FR^k represent the fuel rate consumption of a vehicle type k expressed in litre/s, where ξ is the fuel-to-air mass ratio, k_e^k, N_e^k and V_e^k are three parameters related to the engine of the vehicle, respectively the engine friction factor (kJ/rev/litre), the engine speed (rev/s) and the engine displacement (litre), P^k is the engine instant power output (kW), ϖ is the efficiency parameter for diesel engines, κ is the heating value of a typical diesel fuel (kJ/g) and ψ is a conversion factor (g/litre).

The engine power output P^k could be calculated as:

$$P^k = \frac{P_{tract}^k}{\varepsilon^k} + P_{acc} \qquad (2)$$

where P_{tract}^k is the total tractive power requirement (kW) and P_{acc} represents the engine power demand associated with the engine running losses, and the additional power requirements of accessories such as lights and air conditioning. As assumption, P_{acc} is set equal zero. Finally, ε^k is the vehicle drive train efficiency of a vehicle of type k. P_{tract}^k could be further calculated as:

$$P_{tract}^k = \left(M^k\tau + M^k g sin\phi + \frac{1}{2}C_d^k\rho A^k f^2 + M^k g C_r cos\phi\right)\frac{f}{1000} \qquad (3),$$

where M^k is the total weight of the vehicle of type k expressed in kg. M^k is calculated as the sum of the curb weight of the vehicle k denotes as μ^k, and the payload on the vehicle k travelling from node i to node j during period t, denoted by the decision variable $F_{i,j,k,p,t}$. It is possible to deduce how this formulation introduce the link between the fuel consumption, the decision variable concerning the quantity to deliver to each customer at each time period and the related decision on the travelled route.
The parameter τ represents the acceleration of the vehicle (m/s²), g is the gravitational constant (m/s²), ϕ is the inclination of the road expressed in degrees, C_d^k is the coefficient of aerodynamical drag of a vehicle type k, ρ is the density of the air (kg/m³), A^k is the frontal surface area of a vehicle type k (m²), f is the vehicle speed (m/s) and C_r is the coefficient of rolling resistance.
Rearranging the equations (1), (2) and (3) is now possible to calculate the fuel rate consumption in litre/s as:

$$FR^k = \frac{\xi}{\kappa\psi}\left(k_e^k N_e^k V_e^k + \frac{f(M^k\tau + M^k g sin\phi + \frac{1}{2}C_d^k \rho A^k f^2 + M^k g C_r cos\phi)}{1000\varpi\varepsilon^k}\right) \qquad (4)$$

Introducing the vehicle-independent parameters:

$$\lambda = \xi/(\kappa\psi), \qquad (5)$$

$$s = \tau + g sin\phi + g C_r cos\phi, \qquad (6)$$

and the vehicle-dependent parameters:

$$\gamma^k = 1/(1000\,\varpi\varepsilon^k), \qquad (7)$$

$$\beta^k = \frac{1}{2}C_d^k \rho A^k, \qquad (8)$$

$$y^k = k_e^k N_e^k V_e^k, \qquad (9)$$

and introducing the travelled distance $a_{i,j}$ between node i and node j, it is finally possible to rewrite the expression of FR^k in order to calculate FC^k which is the amount of fuel in litres consumed by a vehicle of type k, travelling on the arc (i,j).

$$FC^k = \lambda\left(y\left(\frac{a_{i,j}}{f}\right) + \gamma^k\beta^k a_{i,j} f^2 + \gamma^k s\left(\mu^k + F_{i,j,k,p,t}\right)a_{i,j}\right) \qquad (10)$$

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 by the vehicle speed. The following figure (**Figure 15**) shows the behaviour of the fuel consumption of an empty vehicle (the total weight is given only by the curb weight) travelling a distance equal to 100 km, with respect to the speed of the vehicle. The numerical data of the analysed vehicle are shown in **Table 9**, and are referred to the medium-duty vehicle of Koc et al. (2014).

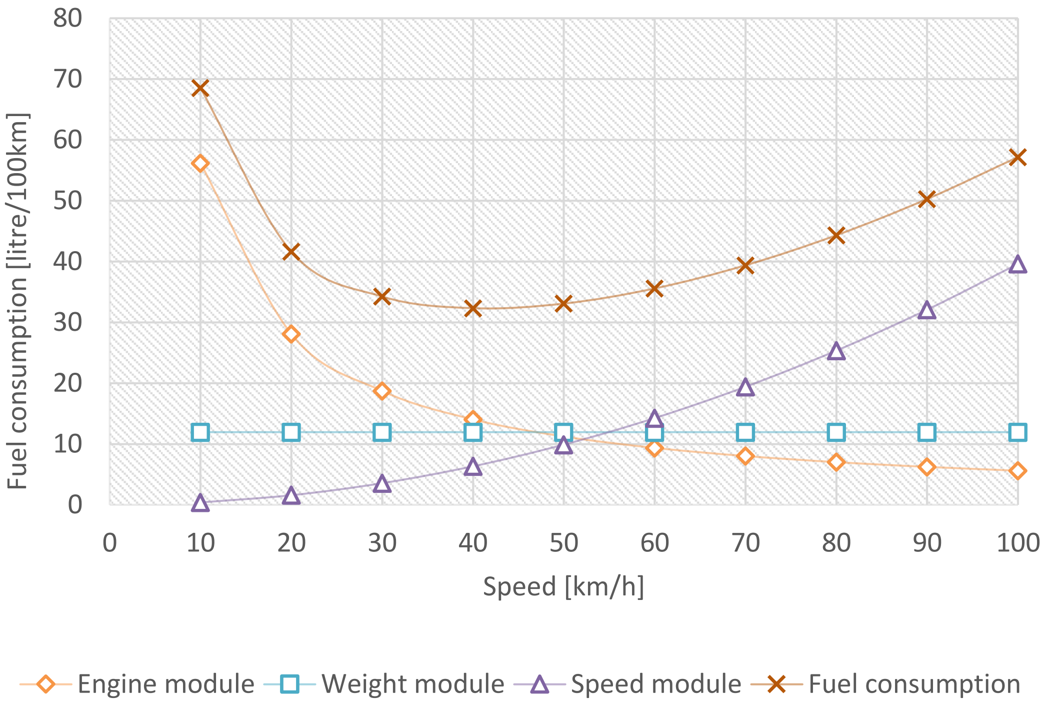


Figure 15 - Fuel consumption of a medium duty vehicle for 100 km.

Two main considerations can be drawn from the analysis of the fuel consumption curve. These considerations allow to make two additional assumptions. First, at very low speed (under 30 km/h) the engine module component of the fuel consumption function prevails over the other two components, leading to an exponential increase of the fuel consumption. These values of speed are typical of urban contexts where the maximum speed limit is usually 50 km/h. Urban contexts are also characterised by frequent starts and stops, that cause continual accelerations and decelerations. As reported by Demir et al. (2014a) driving in congested rush hours cause up to a 40% increase in the observed fuel consumption. These kinds of problems require other types of fuel consumption estimation functions, which better catch the dynamicity in the variation of speed. Since the problem proposed in this thesis is set in an

environment characterized by medium-long distance between nodes (40 ÷ 400 km), it is reasonable to assume that vehicles travel at constant speed, and the acceleration/deceleration component of the fuel consumption function could be considered negligible. For this reason, τ is set equal to zero. For similar reasons, given the medium-long distance of the routes, the road gradient of the road ϕ could be assumed equal to zero, since the ups and downs compensate each other.
Secondly, the U-shape of the curve allows the calculation of the optimal speed at which vehicles consume the least amount of fuel and so produce the least amount of carbon emissions. The value of optimal speed is very vehicle-dependent, and it is in the neighbourhood of the 40 km/h. Some papers, as Cheng et al. (2017), set the vehicle's speed as a decision variable of the problem, allowing the model to choose the best value that minimise the objective function of the problem, in this specific example equal to 45 km/h. However, these values of speed are too low to reflect properly the reality of the medium-long distribution routes. For these reasons, following the model proposed by Soysal et al. (2016), the speed is set equal to 80 km/h for all the vehicle types. This value is aligned with the majority of the European countries driving regulations that set the maximum speed limit for heavy goods vehicles over 3.5 tonnes on motorways equal to 80 - 100 km/h (European Commission (a), ec.europa.eu, last accessed on: 3.11.2017). The 80 km/h speed value, according to vehicle characteristics chosen to describe the fuel consumption curve, causes a 37% increment of fuel consumption with respect to the optimal value of 40 km/h, which leads to a fuel consumption equal to 2,26 km/litre against the optimal value of 3,06 km/litre. However, since the purpose of this thesis is to show the effect of different carbon control policies on the classic decision variables of the inventory routing problem, namely the vehicle routing and the quantity of product delivered to each customer, the speed will be treated as a constant input data of the problem.
Finally, it is possible to estimate the carbon emissions generated in a given travelled distance, expressed in $kgCO_2e$, simply multiplying the fuel consumption by a proper fuel-dependent conversion factor indicated as u, and expressed in $kgCO_2e$/litre.

$$E_{CO_2} = \lambda\left(y\left(\frac{a_{i,j}}{f}\right) + \gamma^k\beta^k a_{i,j}f^2 + \gamma^k s\left(\mu^k + F_{i,j,k,p,t}\right)a_{i,j}\right)u, \qquad (11)$$

From a purely syntactic point of view, the heterogenous fleet implementation proposed in this thesis is identical to those proposed in the cited works of Cheng et al. (2017) and Koc et al. (2014), and found in other heterogeneous fleet environmentally-extended inventory routing problems analysed in literature (Niakan and Rahimi (2015), Rahimi et al. (2016), Franco et al. (2016)). All of these papers implement a heterogenous fleet model using a set $K = \{1, 2 \dots, |K|\}$, where the k-index refers to the vehicle type. This notation, together with the use of the Boolean decision variable

$X_{i,j,k,t}$ to indicate if a vehicle of type k travels the arc (i, j) in period t, fundamentally prevents two or more vehicles of the same type travelling the same arc at the same period. This because the decision variable $X_{i,j,k,t}$, which cannot assume values higher than one, does not refer to the specific single vehicle, but to an entire class of vehicles. This contradiction is resolved by the cited papers with the introduction of a constraint that prohibits the split delivery of quantities. This means that each customer (or each supplier, in a many-to-one network) can be visited only by one vehicle in each time period t. There is another factor to take into consideration when dealing with this k-index notation, which is the network structure. In fact, the distribution network of the cited papers is characterized by a supplier's site which coincide with the starting point of the vehicle routing. This structure leads to a situation where there are no common arcs among the vehicles, because each single vehicle is assigned to a specific set of customers, and starts the routing already loaded.

Instead, the model proposed by Soysal et al. (2016) presents some differences. First, split deliveries are allowed, which it means that two or more vehicles can visit the same customer in the same period. Secondly, the network structure presents a depot, that represents the starting point of the vehicles routing, which does not coincide with the supplier's site. This means that, in each period, different vehicles have to travel the same arc between the depot and the supplier, in order to pick-up the products before the customers routing. In this framework, the authors model a homogeneous fleet of vehicles using the set $K = \{1, 2 \ldots, |K|\}$, where the k-index refers to the specific single vehicle.

Given these assumptions, this thesis proposes a model that features a mix between the two approaches shown above, and in particular implements a heterogeneous fleet of vehicles where the k-index does not refer to the vehicle type, but to the specific single vehicle.

3.4. Base case model

Based on the reference model of Soysal et al. (2016), it is now proposed the mathematical formulation of the model for the base case denoted as Z_{BC}, where no carbon control policy is applied. The reference model addresses the uncertainty of the customers demand, employing service level constraints expressed in the form of chance constraints, while the comprehensive fuel consumption function is incorporated in the objective function. In addition to these two features, the model proposed in this thesis takes into account a heterogeneous fleet of vehicles, taking as a reference the works of Cheng et al. (2017) and Koc et al. (2014). The objective function of the model is shown below.

$$Z_{BC} = Minimise \sum_{i\in V_c}\sum_{p\in P}\sum_{t\in T} I^{+}_{i,p,t} h_{i,p} \qquad (12.i)$$

$$+ \sum_{(i,j)\in A}\sum_{k\in K}\sum_{t\in T} \lambda \left(y\left(\frac{a_{i,j}}{f}\right) X_{i,j,k,t} + \gamma^k \beta^k a_{i,j} f^2 X_{i,j,k,t} \right.$$

$$\left. + \gamma^k s \left(\mu^k X_{i,j,k,t} + \sum_{p\in P} F_{i,j,k,p,t} \right) a_{i,j} \right) l \qquad (12.ii)$$

$$+ \sum_{(i,j)\in A}\sum_{k\in K}\sum_{t\in T} \left(\frac{a_{ij}}{f}\right) X_{i,j,k,t} w. \qquad (12.iii)$$

The objective function is composed by three parts. The first part $(12.i)$ calculates the overall expected inventory holding cost at the customers over the entire planning horizon. The second part $(12.ii)$ calculates the fuel cost from the transportation operations, employing the comprehensive emissions model specifically modified in order to take into account a heterogeneous fleet of vehicles. The third part $(12.iii)$ calculates the drivers cost based on the driven hours of the vehicles. The sum of the fuel cost and drivers cost is indicated as the routing cost.

The objective function of the model is computed at the beginning of the planning horizon. For this reason, the first component related to inventory holding cost substantially differs from the others two components. As shown in the constraints description, the values of the inventory levels at each customer are estimated based on the data of the expected demand, so they could differ from the actual values associated with the actual values of demand. Differently, the expected routing cost coincides with the actual routing cost, since it is associated with the routing and delivery decisions, which are no dependent on uncertain data.

The proposed objective function is subjected to the following inventory constraints:

$$E\left[I_{i,p,t}\right] = \sum_{s=1}^{t}\sum_{k\in K} Q_{i,k,p,s} - \sum_{s=1}^{t} E\left[d_{i,p,s}\right], \qquad \forall i \in V_C, p \in P, t \in T \qquad (13)$$

$$I^{+}_{i,p,t} \geq E\left[I_{i,p,t}\right], \qquad \forall i \in V_C, p \in P, t \in T \qquad (14)$$

$$\Pr\left(I_{i,p,t} \geq 0\right) \geq \alpha, \qquad \forall i \in V_C, p \in P, t \in T \qquad (15)$$

Constraints $(13) - (15)$ concern the inventory decisions. Constraint (13) calculates the expected level of inventory at each customer's site for each time period of the planning horizon, based on difference between the cumulated value of deliveries and the cumulated value of expected demand. As assumption, the inventory level at time zero is set equal to zero, so $I_{i,p,0} = 0, \forall i \in V_C, p \in P$. Constraint (14) calculates the positive level of inventory stored in the warehouse, necessary for the calculation of the inventory holding cost. The additional positive-defined decision variable $I^{+}_{i,p,t}$ is required, since the model is designed to consider shortages by allowing the decision variable $I_{i,p,t}$ to assume also negative values. Constraint (15) is the service-level constraint on the stock-out probability at the end of each time period. It states that the inventory level at each customer measured at the end of each time period, must be positive with a probability higher than α. The deterministic approximation of this chance constraint is explained in the linearization section.

$$\sum_{i \in V, i \neq j} X_{i,j,k,t} = \sum_{i \in V, i \neq j} X_{j,i,k,t}, \qquad \forall j \in V \backslash \{0\}, k \in K, t \in T \qquad (16)$$

$$\sum_{i \in V, i \neq j} X_{j,i,k,t} \leq 1, \qquad \forall i \in V, k \in K, t \in T \qquad (17)$$

$$X_{i,0,k,t} = 0, \qquad \forall i \in V_S, k \in K, t \in T \qquad (18)$$

$$X_{0,j,k,t} = 0, \qquad \forall i \in V_C, k \in K, t \in T \qquad (19)$$

$$F_{0,j,k,p,t} = 0, \qquad \forall j \in V_S, k \in K, p \in P, t \in T \qquad (20)$$

$$\sum_{j \in V, i \neq j} F_{i,j,k,p,t} = \sum_{j \in V, i \neq j} F_{j,i,k,p,t} + B_{i,k,p,t}, \qquad \forall i \in V_S, k \in K, p \in P, t \in T \qquad (21)$$

$$\sum_{j \in V, i \neq j} F_{i,j,k,p,t} = \sum_{j \in V, i \neq j} F_{j,i,k,p,t} - Q_{i,k,p,t}, \qquad \forall i \in V_c, k \in K, p \in P, t \in T \qquad (22)$$

$$\sum_{p \in P} F_{i,j,k,p,t} \leq c^k X_{i,j,k,t}, \qquad \forall (i,j) \in A, k \in K, p \in P, t \in T \qquad (23)$$

$$\sum_{k \in K} B_{i,k,p,t} \leq q_{i,p,t}, \qquad \forall\, i \in V_S, p \in P, t \in T \qquad (24)$$

$$U_{i,k,t} + 1 \leq U_{j,k,t} + |V|\left(1 - X_{i,j,k,t}\right), \qquad \forall (i,j) \in A(V \backslash \{0\}), k \in K, t \in T \qquad (25)$$

Constraints $(16) - (25)$ concern the routing decisions. Constraint (16) concerns the conservation of flow of vehicles. It assures that, if a vehicle k enters a node j during period t, the same vehicle has to leave the same node in the same period. This is valid

for each node, except for the depot represented by node $\{0\}$. Constraint (17) assures that each vehicle can perform at most one route per time period, since the Boolean decision variable $X_{i,j,k,t}$ cannot assume values higher than one.
Constraint (18), eliminating the direct flows from the suppliers to the depot, assures that no vehicle comes back to the depot without visiting any customer. Similarly, constraint (19), eliminating the direct flows from the depot to the customers, assures that no vehicle, after leaving the depot, goes directly to the customers without visiting the supplier to pick-up the products. Constraint (20) states that a vehicle that exits the depot to start its routing must be empty. Constraint (21) and (22) are similar to constraint (16) since they concern the conservation of flow of products. Specifically, constraint (21) states that if a vehicle k, that brings an initial product quantity of $F_{i,j,k.p,t}$, visits a supplier i, the same vehicle has to leave the supplier with the same initial product quantity plus the quantity $B_{i,k,p,t}$ picked-up at the supplier. Similarly, constraint (22) assures that if a vehicle k, that brings an initial product quantity of $F_{i,j,k,p,t}$, visits a customer i, the same vehicle has to leave the supplier with the same initial product quantity minus the quantity $Q_{i,k,p,t}$ delivered to the customer. Constraint (23) concerns the vehicle capacity and it assures that on each arc (i,j) the total load of product on the vehicle k does not exceed the total capacity c^k. Constraint (24) ensures that the sum of product quantities picked-up at a supplier i in period t does not exceed the total available quantity at the supplier's site. Finally, constraint (25) eliminates sub-tours.
The remaining following constraints represents the restriction imposed on the decision variables:

$$X_{i,j,k,t} \in \{0,1\}, \qquad \forall (i,j) \in A, k \in K, t \in T \qquad (26)$$

$$F_{i,j,k,p,t} \geq 0, \qquad \forall (i,j) \in A, k \in K, p \in P, t \in T \qquad (27)$$

$$-\infty < I_{i,p,t} < +\infty, \qquad \forall i \in V_C, p \in P, t \in T \qquad (28)$$

$$I^{+}_{i,p,t} \geq 0, \qquad \forall i \in V_C, p \in P, t \in T \qquad (29)$$

$$U_{i,k,t} \geq 0, \qquad \forall i \in V \backslash \{0\}, k \in K, t \in T \qquad (30)$$

$$Q_{i,k,p,t}, B_{i,k,p,t} \geq 0, \qquad \forall i \in V_C, k \in K, p \in P, t \in T \qquad (31)$$

The proposed model can be strengthened by including the following valid inequalities, representing respectively the relationships between the routing decision variables and the decision variables on the picked-up and delivered quantities:

$$\sum_{j\in V_S}\sum_{k\in K} X_{0,j,k,t} \geq \sum_{i\in V_S}\sum_{k\in K}\sum_{p\in P}\frac{B_{i,k,p,t}}{c^k}, \qquad \forall t \in T \qquad (32)$$

$$\sum_{j\in V_C}\sum_{k\in K} X_{i,0,k,t} \geq \sum_{i\in V_S}\sum_{k\in K}\sum_{p\in P}\frac{Q_{i,k,p,t}}{c^k}, \qquad \forall t \in T \qquad (33)$$

Constraint (32) states that the sum of vehicles departing from the depot in each time period has to be higher than or equal to the ratio between the overall picked-up quantity of product and the vehicles capacity. Similarly, constraint (33) states that the sum of the vehicles coming back to the depot at the end of the routing in each time period has to be higher than or equal to the ratio between the overall delivered quantity of products and the vehicles capacity. However, as shown by the reference paper of Soysal et al. (2016) and by preliminary tests run on the proposed model, from a time-computational effort point of view is better to include only the first valid inequality in the model formulation, since the inclusion of both the constraints leads to higher computational times to find the optimal solution. For this reason, only constraint (32) is included in the final formulation of the model.
The proposed model is not linear since it presents the constraint on the desired service-level which is a chance-constraint. However, this constraint can be linearized following the approach adopted by the reference model of Soysal et al. (2016) which in turn follows the linearization method proposed by Bookbinder and Tan (1988). The authors, dealing with stochastic optimization problems, show three main resolution strategies, namely the static uncertainty, the dynamic uncertainty and the mixed "static-dynamic" strategy. The reference model and the model proposed in this thesis apply the static uncertainty approach since the values of all the decision variables must be determined at the beginning of the planning horizon. This means that the variable $Q_{i,k,p,t}$ concerning the delivery quantities must be decided before the real value of demand $d_{i,p,t}$ of each customer becomes known. As assumptions of the proposed model, the customer demand at each time period is not known with certainty, while the probability density function of the demand is assumed to be known with certainty.

3.4.1. Linearization of base case model

As explained in the constraints description, constraint (15) states that the inventory level at each customer must be positive with a probability higher than a certain threshold α.

$$\Pr\left(I_{i,p,t} \geq 0\right) \geq \alpha, \qquad \forall i \in V_c, p \in P, t \in T \qquad (15)$$

The terms in brackets state that the measured level of inventory at the end of time period t must be positive for each customer i. This is equivalent to say that the sum of the measured level of inventory at the end of period $t-1$ and the overall delivered quantity of products at period t must be higher than the customer's demand at period t, for each customer. This can be written as:

$$\Pr\left(I_{i,p,t-1} + \sum_{k \in K} Q_{i,k,p,t} \geq d_{i,p,t}\right) \geq \alpha, \qquad \forall i \in V_c, p \in P, t \in T \qquad (34)$$

The value of the variable $I_{i,t-1}$ can be calculated applying the constraint (13), and it can be substituted in the previous inequality leading to the (35).

$$I_{i,p,t-1} = \sum_{s=1}^{t-1} \sum_{k \in K} Q_{i,k,p,s} - \sum_{s=1}^{t-1} d_{i,p,s}, \qquad \forall i \in V_C, p \in P, t \in T \qquad (13')$$

$$\Pr\left(\sum_{s=1}^{t-1} \sum_{k \in K} Q_{i,k,p,s} - \sum_{s=1}^{t-1} d_{i,p,s} + \sum_{k \in K} Q_{i,k,p,t} \geq d_{i,p,t}\right) \geq \alpha \quad \forall i \in V_C, p \in P, t \in T \;\; (35)$$

The constraint $(13')$ is slightly different by constraint (13) since it does not deal with the expected value of demand, but with the real demand. Consequently, the computed value $I_{i,p,t-1}$ represent the real measured level of inventory at the end of period $t-1$. The resulting constraint (35) could be rearranged as:

$$\Pr\left(\sum_{s=1}^{t} \sum_{k \in K} Q_{i,k,p,s} \geq \sum_{s=1}^{t} d_{i,p,s}\right) \geq \alpha, \qquad \forall i \in V_C, p \in P, t \in T \qquad (36)$$

The term on the right of the inequality inside the brackets could be rewritten as:

$$\sum_{s=1}^{t} d_{i,p,s} = d_{i,p,1} + d_{i,p,2} + \cdots + d_{i,p,t} = D_{i,p}(t), \qquad (37)$$

while the term on the left could be temporarily denoted as $u = \sum_{s=1}^{t} \sum_{k \in K} Q_{i,k,p,s}$. The constraint (34) can be written as:

$$\Pr\left(D_{i,p}(t) \leq u\right) = \alpha. \qquad (38)$$

Introducing the cumulative distribution function of $D_{i,p}(t)$ as $G_{d_{i,p,1}+d_{i,p,2}+\cdots+d_{i,p,t}}(u) = G_{D_{i,p}(t)}(u)$, is possible to express the service level as $\alpha = G_{D_{i,p}(t)}(u)$. Calculating the inverse function of the cumulative distribution as $u = G^{-1}_{D_{i,p}(t)}(\alpha)$, and substituting again the term u, it is possible to obtain the following inequality:

$$\sum_{s=1}^{t}\sum_{k\in K} Q_{i,k,p,s} \geq G^{-1}_{D_{i,p}(t)}(\alpha) \qquad \forall i \in V_C, p \in P, t \in T \qquad (39)$$

The last remaining step to conclude the linearization of the chance-constraint is the estimation of the term on the right of the inequality (39). The procedure consists in relating $G^{-1}_{D_{i,p}(t)}(\alpha)$ to the mean and standard deviation of the demand, based on the assumption of normally-distributed forecast errors. In particular, if demand values $\{d_{i,p,t}\}$ are normally-distributed and pairwise uncorrelated, the resulting sum $d_{i,p,1} + d_{i,p,2} + \cdots + d_{i,p,t} = D_{i,p}(t)$ will be normally distributed. In this way, the variable $d_{i,p,t}$ will be denoted by the expected value $E[d_{i,p,t}]$ and the standard deviation $S_{d_{i,p,t}}$. The expected value and the standard deviation are related to each other by a coefficient of variation C_p assumed constant, which lead to the following equations:

$$S_{d_{i,p,t}} = C_p \cdot E\left[d_{i,p,t}\right], \qquad (40)$$

$$S_{D_{i,p}(t)} = C_p \cdot (\sum_{s=1}^{t} E^2[\, d_{i,p,t}])^{1/2}. \qquad (41)$$

Given a certain value of desired service level α, the related safety factor Z_α, calculated as the inverse of the standard normal cumulative distribution, could be expressed by the following equation:

$$Z_\alpha = \frac{D_{i,p}(t) - E[D_{i,p}(t)]}{S_{D_{i,p}(t)}}, \qquad (42)$$

Rearranging and substituting the terms it is possible to obtain the following equation:

$$G^{-1}_{D_{i,p}(t)}(\alpha) = \sum_{s=1}^{t} E[\, d_{i,p,s}] + C_p Z_\alpha (\sum_{s=1}^{t} E^2[\, d_{i,p,s}])^{1/2}, \qquad \forall i \in V_C, p \in P, t \in T \quad (43)$$

which can be finally substituted in the inequality (39), leading to the linear constraint on the delivered quantities of product to each customer at each time period:

$$\sum_{s=1}^{t}\sum_{k\in K} Q_{i,k,p,s} \geq \sum_{s=1}^{t} E[\,d_{i,p,s}] + \; C_p Z_\alpha (\sum_{s=1}^{t} E^2[\,d_{i,p,s}])^{1/2} \quad \forall i \in V_C, p \in P, t \in T \quad (44)$$

This constraint substitutes constraint (15) transforming the chance-constrained programming model into a deterministic linear programming model. The coefficient of variation C_p could be estimated plotting corresponding pairs of point $(E\left[d_{i,p,t}\right], S_{d_{i,p,t}})$ on a diagram, and calculating the slope of the obtained straight line.

The syntax of constraint (44) concerning the calculation of the delivery quantities, is derived from the constraint (13), which calculates the expected inventory levels at the end of each time period. While the majority of papers analysed in literature calculates these two values (I and Q) referring solely on the value of demand at time t, the syntax proposed by the reference model, and employed in the proposed model, computes the value of I and Q, based on the cumulated series of demand values. This syntax properly modelled the shortages as backlogs, transferring the eventual stock-out occurring in a time period to the next period. The proposed model does not consider any shortage cost associated with stock-outs. This assumption is well-motivated by the choice of the proper value of the desired service level α. As explained in Bookbinder and Tan (1988), the value α already incorporates the management' s perception of the cost of backorders, so that shortage cost can be neglected in the objective function of the model.

The final resulting model is composed by the objective function (12), subject to the constraints $(13)-(14)$, $(16)-(25)$, $(26)-(31)$, (32) and (44).

The following section introduces the carbon control policies applied to the proposed problem. First, are outlined the reasons justifying the introduction of these policies and the problem of estimation of the social cost of carbon. Then, each policy is described and modelled, further analysing the relationships between differences policies and models.

In addition to the base case model, two more models are proposed. The first, denoted as Z_{env}, is the emissions-minimising model, where the objective function is composed only by the minimisation of the carbon emissions and reflect the solely environmental concern. The second, denoted as Z_{const}, corresponds to the base case model where the fuel consumption and the related emissions are calculated using a constant approach based simply on the travelled distance, without using the comprehensive emissions model.

3.5. Emissions-minimising model

The proposed emissions-minimising model is needed to compute the maximum feasible emissions reduction that the base case model can achieve, without the application of any carbon control policy. In addition, the results of this model can be compared with the results of the policies application, in order to highlight the different economic and operational implications of a purely environmental objective function against the cost-minimising objective function. The emissions-minimising model is denoted as Z_{env}, where the suffix env stands for "environmental".

$$\begin{aligned} min\ Z_{env} \ = \sum_{(i,j)\in A} \sum_{k\in K} \sum_{t\in T} \lambda \Bigg(y\left(\frac{a_{i,j}}{f}\right) X_{i,j,k,t} + \gamma^k \beta^k a_{i,j} f^2 X_{i,j,k,t} \\ + \gamma^k s \left(\mu^k X_{i,j,k,t} + \sum_{p\in P} F_{i,j,k,p,t} \right) a_{i,j} \Bigg) u \qquad (45) \end{aligned}$$

subject to constraints $(13) - (14)$, $(16) - (25)$, $(26) - (31)$, (32) and (44).
Based on the results of the emissions-minimising model, it is possible to determine the maximum value of emissions reduction that can be imposed to the base model with the application of the cap policy.

3.6. Constant emissions model

The constant emissions model is developed to highlight and quantify the difference in the fuel consumption and emissions estimation when it is not employed the comprehensive emissions model. As shown in the related section, the comprehensive emission model takes into account numerous parameters that have to be precisely estimated. Moreover, the higher complexity of the formulation, that depends on two decision variables, namely the routing and the deliveries decisions, leads to higher computational effort that, in theory, can be avoided adopting a constant emissions model based only on the travelled distance. The constant emissions model is described by the following equations, where the suffix $const$ stands for "constant":

$$min\ Z_{const} = \sum_{i\in V_C} \sum_{p\in P} \sum_{t\in T} I^{+}_{i,p,t} h_{i,p} + \sum_{i\in V} \sum_{j\in V} \sum_{k\in K} \sum_{t\in T} uc_k \cdot \frac{a_{i,j}}{1000} \cdot X_{i,j,k,t} \qquad (46)$$

The constant emissions model is subject to the same set of constraints of the base case model, namely constraints $(13) - (14)$, $(16) - (25)$, $(26) - (31)$, (32) and (44).

Since there is no fuel consumption calculation, necessary to precisely estimate the related carbon emissions, in this constant model, emissions are estimated in the following way:

$$E_{CO_2}^{const} = \sum_{i\in V}\sum_{j\in V}\sum_{k\in K}\sum_{t\in T}\frac{1}{ac_k}\cdot\frac{a_{i,j}}{1000}\cdot X_{i,j,k,t}\cdot u \qquad (47)$$

The parameter uc_k denotes the unitary cost of routing per kilometre expressed in €/km, while the parameter ac_k denotes average fuel consumption per kilometre, expressed in km/litre. These parameters are dependent only on the type of vehicle, and they are obtained running the base case model with only one type of vehicle at time. In this way, the base case model is used only one time, in order to estimate these two parameters, while the constant emissions model is used to schedule the operational activities for each planning horizon. The two introduced parameters are calculated in the following way:

$$uc_k = \left(\frac{total\ routing\ cost\ [€]}{total\ driven\ kilometres\ [km]}\right)_{base\ case_k} \qquad (48)$$

$$ac_k = \left(\frac{total\ driven\ kilometres\ [km]}{total\ fuel\ consumed\ [litre]}\right)_{base\ case_k}, \qquad (49)$$

where the total driven kilometres and the total fuel consumed are obtained through the following equations:

$$tot\ driven\ km = \sum_{(i,j)\in A}\sum_{k\in K}\sum_{t\in T}\frac{a_{i,j}}{1000}\cdot X_{i,j,k,t} \qquad (50)$$

$$tot\ fuel\ cons = \sum_{(i,j)\in A}\sum_{k\in K}\sum_{t\in T}\lambda\left(y\left(\frac{a_{i,j}}{f}\right)X_{i,j,k,t} + \gamma^k\beta^k a_{i,j}f^2X_{i,j,k,t} + \gamma^k s\left(\mu^k X_{i,j,k,t} + \sum_{p\in P}F_{i,j,k,p,t}\right)a_{i,j}\right) \qquad (51)$$

4. Carbon control policies

Carbon control policies can be defined as the set of tools, measures, and rules that a subject with legislative autonomy puts in place in order to reduce emissions, or mitigate their damaging effects. Given the extreme variety of the subjects involved in the climate change problem, the mitigation solutions developed over the years are many and diversified. The variety of these solutions is mainly dependent on the country and on the economic sector interested by those measures. In fact, the potential negative effect of the climate change is differently perceived by country to country. Moreover, the commitment needed to mitigate climate change can be differently recognized, based on the self-responsibility of each country towards the actual environmental situation. Mitigation solutions of developed countries, which already went across all the industrial revolutions and are the major responsible of climate change, are naturally different from those adopted by developing countries, which in principle should avoid the unsustainable development of the former.

Concerning the economic sectors, given the unevenly application of policies among the different countries, but considering the global competitiveness of companies, policies are specifically tailored to give an incentive to companies to move towards low-carbon solutions, without heavily impact on their economic results. This aspect is strictly linked with the so called “carbon-leakage”, that refers to a particular situation where companies subjected to highly expensive carbon control measures, prefer to transfer their activities to other countries which have softer (or none) constraints on carbon emissions. This is typical for example of the energy intensive sector (European Commission (b), 2016). In order to prevent carbon leakages, which may negatively affect the internal economy of a country, the most exposed economic sectors are carefully addressed, for example allocating for free emissions credit (or allowances) in the first phase of introduction of a control policy. One other aspect that affect the inhomogeneous application of mitigation measures sectors is the precise estimation of the carbon emissions of each emitter. For some sectors, such as the power production sector, is relatively simple to know the actual emissions, consequently it is easier to develop targeted policies. Other sectors, such as the transportation sector addressed in this thesis, present intrinsic difficulties in measuring exactly the carbon emission, which leads to the development of more strategic solutions.

The wide range of existing policies leads to the impossibility of giving a comprehensive and exhaustive representation of all of them. The aim of the classification proposed in this section is to provide a general framework, where to identify the characteristics of the analysed policies, in order to highlight the conceptual differences and purposes. The following classification is partially based on the classification proposed by the cited “State and trends of carbon pricing, 2015”, developed by Kossoy et al., in 2015. First of

all, carbon control policies are divided in two groups: those that explicitly price carbon emissions, and those that implicitly put a price on emissions.
The former group is further subdivided in two groups: carbon control policies that puts a fixed price on carbon emissions, imposed by a regulator authority, and those characterized by a variable price, determined by the difference between supply and demand of emissions credits in a specific emissions trading system. The most common fixed-price carbon control policy is the imposition of a carbon tax based on the registered emission. Among the variable-price carbon control policies, the emission trading systems, the offset mechanism and the results-based finance are the most diffused mitigation measures. Differently, the implicit-price carbon control policies include removal of fossil fuel subsidies, energy taxation, support for renewable energy, energy efficiency certificate trading and the imposition of maximum allowed emissions cap. A similar classification of the carbon control policies can be found in Benjafaar et al. (2013), which distinguish between price-based policy instruments (for example the imposition of a tax on emissions) and quantity-based policy instruments (for example the imposition of a cap). The following diagram represent the classification of carbon control policies explained above (**Figure 16**).

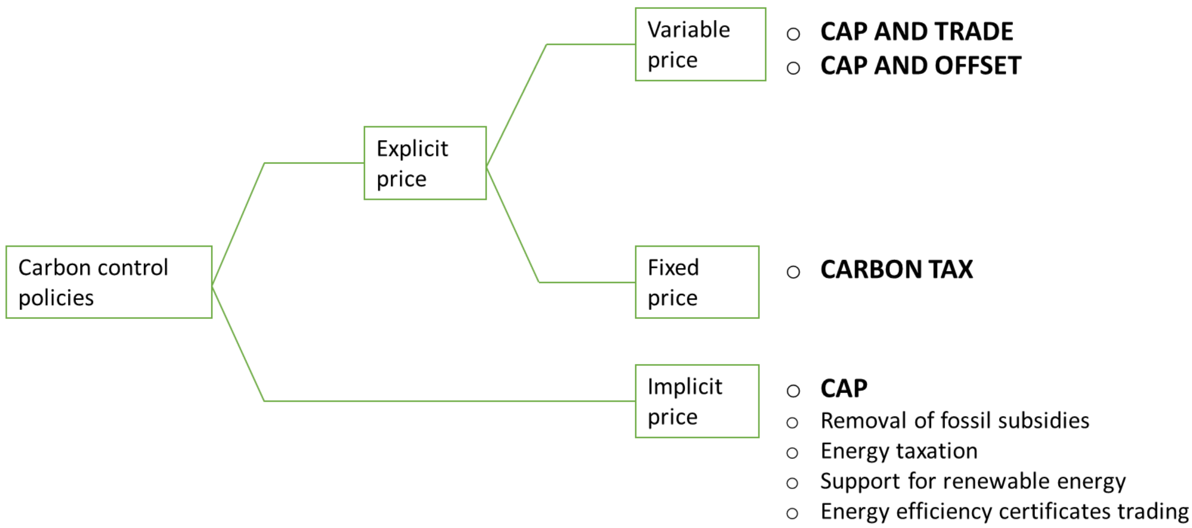


Figure 16 - Schematic classification of the main carbon control policies (in bold the policies analysed in this thesis).

As shown below, the introduction of a specific policy does not necessarily exclude the implementation of an additional policy, given the same region and the same economic sector. Often, a mix of diverse measures is implemented in order to properly address all the economic and environmental implications of a mitigation policy. The

combination of a cap with a carbon tax analysed by Treitl et al. (2014) can be considered as an example specifically applied to the inventory routing problem.
Based on the suggestions of He et al. (2016b), that study how regulatory policies affect carbon emissions mitigation and operations adaption in supply chains, the model proposed in this thesis will be analysed under the imposition of four different policies: (i) the cap, (ii) the carbon tax, (iii) the cap-and-trade, (iv) the cap-and-offset. These latter two respectively belong to the emissions trading mechanisms and to the offset mechanisms. The following table briefly describe the four considered carbon control policies (**Table 5**).

Policy	Short description
Cap	The overall carbon emissions of a company in a given period cannot exceed an imposed maximum limit.
Carbon tax	The carbon emissions of a company are priced proportionally to the volume of emissions.
Cap-and-trade	Emissions allowances are freely allocated to companies. Companies that emit more than the allocated allowances, can purchase extra allowances from those companies that emit less than the allocated allowances.
Cap-and-offset	The overall carbon emissions of a company in a given period can exceed an imposed maximum limit, only buying extra emissions credits by investing in emissions reduction projects in other companies, or in a developing country.

Table 5 - Carbon control policies analysed in this thesis.

These four carbon control policies have been already embedded into operational management models. Benjafaar et al. (2013), develop a mathematical formulation to incorporate policy settings in a classic lot-sizing model for single and multiple firms, further suggesting addressing other common operations management models, such as the multi-location news-vendor models, economic order quantity models, multi-period stochastic inventory models and supply chain coordination and contracting models.
Cheng et al. (2016) applied these four policies to an inventory routing problem which, differently from this thesis, analyse the many-to-one network with deterministic demand and a homogeneous fleet of vehicles. The work of Cheng et al. is set as a reference to modify the proposed base case model in order to account for the four considered policies. Concerning the environmental and economic implication of these addressed policies, Cheng et al. (2016) and Benjafaar et al. (2013) provide a set of propositions and observations which will be verified in this thesis.

4.1. Estimation of the social cost of carbon emissions

The main problem concerning the implementation of fixed-price carbon control policy, such as the carbon tax, is the correct determination of the price related to a carbon emissions unit. The same problem is indirectly tackled also by the variable-price policies, since the price of the corresponding emission credits is not completely market-dependent, but each regulator authority can intervene to modify the price with different measures, as further explained in each policy description. More in general, each implemented policy affecting an economic sector, also those apparently characterized by no economic considerations such as the imposition of a cap, have to face the economic implications of the policy application. This leads to a key-question: which is the cost of emitting one unit of CO_2, namely one metric tonne of CO_2, in the atmosphere, in terms of contribution to the climate change? This cost, defined as "social cost", is the sum of direct (private) and indirect (externalities) losses sustained by a third subject as a result of unrestrained economic activities. Given the global nature of the climate change problem, the correct estimation of the externalities related with the carbon emissions are still a great challenge.
In the specific context of this thesis, the considered carbon emissions are generated by the freight transportation activities. As shown by the report on the external cost of transport in Europe (van Essen et al., 2008), the climate change factor is not the only externality involved in the transportation activities. The accidents, the air pollution, the noise and the congestion represent the other main cost categories that determined the overall external social cost of transport. However, as illustrated in the report, the climate change cost factor represents the largest component of the overall cost after the accidents, accounting for the 29% of the total share (**Figure 17**).

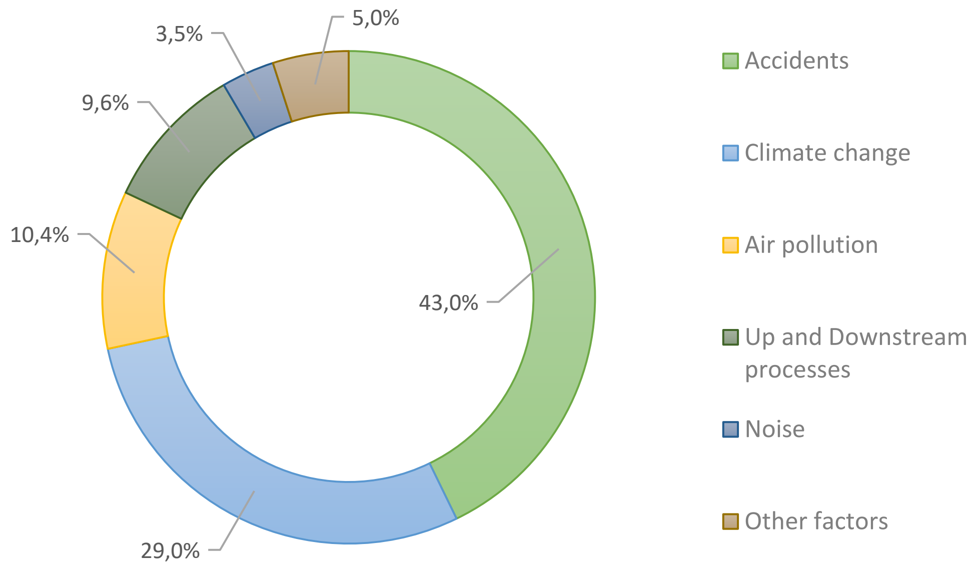


Figure 17 - Share of cost categories of the total external cost of transport in 2008 for the EU 27. Source: Van Essen et al., 2008.

The represented total share is strongly network-dependent. In fact, urban areas are mainly dominated by the accidents cost, while in the non-urban areas the cost of climate change related to emissions is dominant. Given the assumptions of setting the problem outside the urban context, it is well-justified the choice of focusing only on the climate change cost component, neglecting the remaining components.
In general, there are two main different methodological approaches to estimate the social cost of carbon emissions: the *damage cost approach* and the *abatement cost approach* (or avoidance cost).
The damage cost approach evaluates the damage caused by the emission of one tonne of CO_2 under the assumption that no efforts are taken to reduce the progress of climate change. This evaluation takes into consideration various effect of the climate change, both negative effects (sea level rise, increase of extreme weather effects, spread of diseases, etc.) and positive effects (new cultivable areas in northern regions). Instead, the avoidance cost approach is based on a specific target level of emissions reduction to achieve, and it estimate the most cost-effective solution to reach that result. These target levels depend on the time horizon considered and on the specific country. Given the European case, with respect to the baseline carbon emissions of 1990, the objectives consist in a 20% emissions reduction to achieve by 2020, a 30% reduction by 2030 and a 50% reduction by 2050. These targets are based on the overall global target to stabilise global warming at 2°C above the average temperature of the pre-industrialised era.

There are three main aspects that make the avoidance cost approach more suitable in correctly estimating the social cost of carbon emissions:

- The damage cost estimation is very complex since it is based on the evaluation of uncertain long-term risks, and on the very interrelated phenomena.
- In the damage cost approach some risks could be underestimated or not taken into consideration, due to risk-aversion of people.
- Reduction target are already set. Avoidance cost approach provide simpler and more transparent estimation of the climate change cost.

Despite these assumptions, many studies try to give an estimation of a plausible range of carbon emissions social cost, employing both the damage cost and the avoidance cost approaches. In 2005 Tol et al., reviewed 28 papers for a total of 103 estimates of the marginal damage cost of carbon emissions, finding a mean value of 93 \$/tonCO_2. The study on the external cost of transport in Europe previously cited, in 2008 came up with an estimate of 25€/tonCO_2 (low value based on the 2020 target) and 146 €/tonCO_2 (high value based on the 2°C target), using the avoidance cost approach applied to the transport sector. In 2012, Ackerman and Stanton revised the 21\$/tonCO_2e carbon social cost estimated by a U.S. government working group, coming up with a pessimistic estimate of 900\$/tonCO_2e for 2010 and 1550\$/tonCO_2e for 2050 (Ackerman et al., 2012). These represent the higher values of the estimated ranges, obtained combining the three pessimistic values of uncertainty related to carbon social cost estimation, which are:

- **Climate sensitivity**: the long-term temperature increase expected due to a double CO_2 concentration in the atmosphere, comprised between 0°C and 10°C.
- **Damage function estimates:** calculated based on the relationships between the temperature increases and the economic damage.
- **Discount rates:** the risk-free rate of return applied to the estimation of economic events in the future.

The "Handbook on external costs of transport" developed for the European Commission in 2014, using the avoidance cost approach based on the 2°C target, estimate a range comprised between 48€/tonCO_2 and 168€/tonCO_2 with a central value of 90€/tonCO_2 (Korzhenevych et al., 2014). Finally, the recent report of the Interagency Working Group on social cost of greenhouses gases developed in 2016 (www.epa.gov, last accessed on: 3.11.2017) provides a wide range of values, considering three different percent discount rates and the 2010-2050 timespan (**Figure 18**).

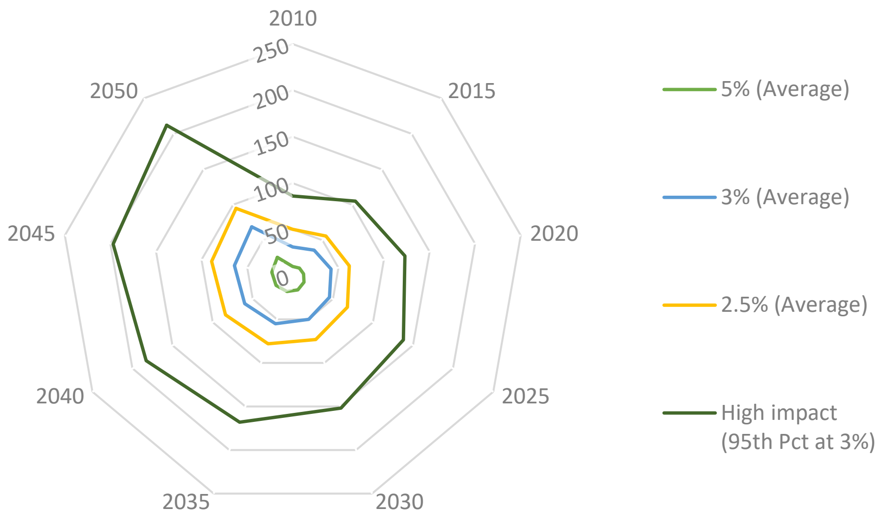


Figure 18 - Estimates of CO_2 Social cost in \$/tonCO_2e in 2010-2050 - Source: Interagency Working Group on social cost of greenhouses gases (2016).

The values exposed above outline a very heterogeneous framework, where it is possible to further contextualize the results of the policies application to the proposed environmentally-extended routing problem. Given all those social cost of CO_2 estimations, the "Handbook on external costs of transport" of 2014, is chosen as a reference, for the following reasons:

- the environmental part of the inventory routing problem under analysis in completely dominated by the carbon emissions produced by vehicles during the transportation activities. The considered work specifically addresses the climate change cost of transportation.
- It adopts the avoidance cost approach, which has been shown to be preferred to the marginal damage approach, especially when dealing with precise set environmental target, in this case the 2°C climate stabilization target.
- It provides a wide range of CO_2 social cost, depending on the type of vehicle and on the type of network.

The following sections report the formulation of the models for each addressed carbon control policy.

4.2. Cap policy

Under the cap policy, the carbon emissions generated by the activities of a company in a specific period of time, cannot mandatorily exceed a given threshold determined by a regulator authority. The non-compliance with this constraint is sanctioned with fines, that can be proportional to the excess or emissions or can be uniform. Uniformity of the sanction results in a heavy burden perceived by small company compared to larger companies. However, in the analysis of the cap policy the non-compliance with the regulation will be not taken into consideration, setting an ideal very high cost of fines, that automatically excludes the non-compliance decision.
The cap policy can be considered as a *command and control* regulation (CAC), since it presents quality standards that must be complied with (Command), and negative sanctions resulting from non-compliance (Control). As shown by the policy classification in **Figure 16**, the cap policy is an implicit-price since there is not an explicit definition of the cost of emissions. However, monetary implications are taken into account when dealing with the estimation of the efficiency (in term of cost-effectiveness) of the cap policy compared with other policies.
The *command and control* regulations are widely employed in the environmental sector, in particular concerning the emissions of pollutants, that address the local dimension of the environmental problem. With regards of climate change, which tackles a global-dimension problem, the implementation of comprehensive, transparent and coordinated cap policy is almost impossible. The restrictive nature of the cap policy makes difficult its implementation also at a national level. This leads to the development of other types of mitigation measures that incorporate the cap, such as the cap-and-trade or the cap-and-offset, analysed in the following sections. However, from an operational point of view, the theoretical implementation of the cap policy leads to very interesting insights, since it mandatorily forces the system to reorganize itself in order to meet the imposed limits. Moreover, it is interesting investigate which are the intrinsic limits of the system, defined as the values of cap that provide no feasible solutions of the inventory routing problem.

4.2.1. The model formulation

Here below it is presented the model that features the cap policy. Having denoted the solution of the base case with no policy as Z_{BC}, the cap policy model can be defined as:

$$minimise\ Z_{cap} = Z_{BC} \qquad (52),$$

subject to constraints $(13)-(14)$, $(16)-(25)$, $(26)-(31)$, (32) and (44), plus the additional constraint that set the maximum allowed level of carbon emissions, denoted as Cap, positive-defined and expressed in kgCO₂e:

$$\sum_{(i,j)\in A}\sum_{k\in K}\sum_{t\in T}\lambda\left(y\left(\frac{a_{i,j}}{f}\right)X_{i,j,k,t}+\gamma^k\beta^k a_{i,j}f^2X_{i,j,k,t}\right.$$
$$\left.+\gamma^k s\left(\mu^k X_{i,j,k,t}+\sum_{p\in P}F_{i,j,k,p,t}\right)a_{i,j}\right)u\ \leq Cap \qquad (53).$$

Differently from the formulation of Cheng et al. (2016), that defined a Cap_t for every time period of the planning horizon, in the proposed formulation the cap is applied on the overall planning horizon. The same authors suggest analysing the case with the overall cap. This formulation in fact, provides more degrees of freedom to the model, that can better arrange routing and deliveries to meet the set target. Preliminary analysis carried on the model with the cap imposed on each period (Cap_t) provided no feasible solutions, even for high values of maximum allowed emissions, since there was no possibility to emit more in a period, in order to emit less in one other.

4.2.2. Expected impact

The modifications in the routing and deliveries decisions with respect to the base case, depends only on the value of the imposed cap. A cap greater than or equal to the carbon emissions generated by the base case model would provide no modifications, since the solution already satisfies the constraint of the cap. Differently, a cap lower than the base case carbon emissions, surely provides some types of modifications in order to reduce the emissions. Since the base case model provides the cost-minimising solution, the imposition of a cap that does not modify the objective function, necessarily implicates the increase of the total cost. In this framework, the reduction in the carbon emissions can be achieved reducing the number of trips ($X_{i,j,k,t}$) or reducing the payload of the vehicle ($F_{i,j,k,p,t}$). A reduction of number of trips would lead to lower drivers cost and higher inventory holding cost, since higher quantities are delivered in the same periods. On the other hand, a payload reduction determines a higher number of trips, so higher drivers cost and lower inventory holding cost. It is finally expected to reach the limit of the problem, when the value of the imposed cap provides no feasible configuration of routing and deliveries that allows to meet the customers' demand.

4.3. Carbon tax policy

The carbon tax is defined as "*the fee imposed on the burning of carbon-based fuels (coal, oil, gas)*" (Carbon Tax Center (b) www.carbontax.org, last accessed on 3.11.2017). The carbon tax is paid at the source of the productive chain, namely at the extraction phase of carbon-based fuels. In this way, the carbon tax is transferred to all the step of productive chain, affecting the final price of the product consumed. Under a carbon tax policy, the CO_2 emitted in the atmosphere due to the fuel combustion, is priced. The assigned price should reflect the externalities related to the marginal damage caused by the emissions of one tonne of CO_2e. Therefore, the marginal damage cost of climate change is internalized in the product, along all the fuel-consuming related activities such as production and distribution. The carbon tax is based on the "polluters pay" principle, and it should act as an incentive to move to more convenient low-carbon solution. In most of the countries the revenues from the carbon tax go to finance low-carbon investments. As shown by the following figure (**Figure 19**) carbon tax policies are successfully implemented in many countries (Kossoy et al., 2015). Countries that have already implemented emissions trading system, usually introduce carbon tax policies to cover those economic sectors not covered by the ETSs.

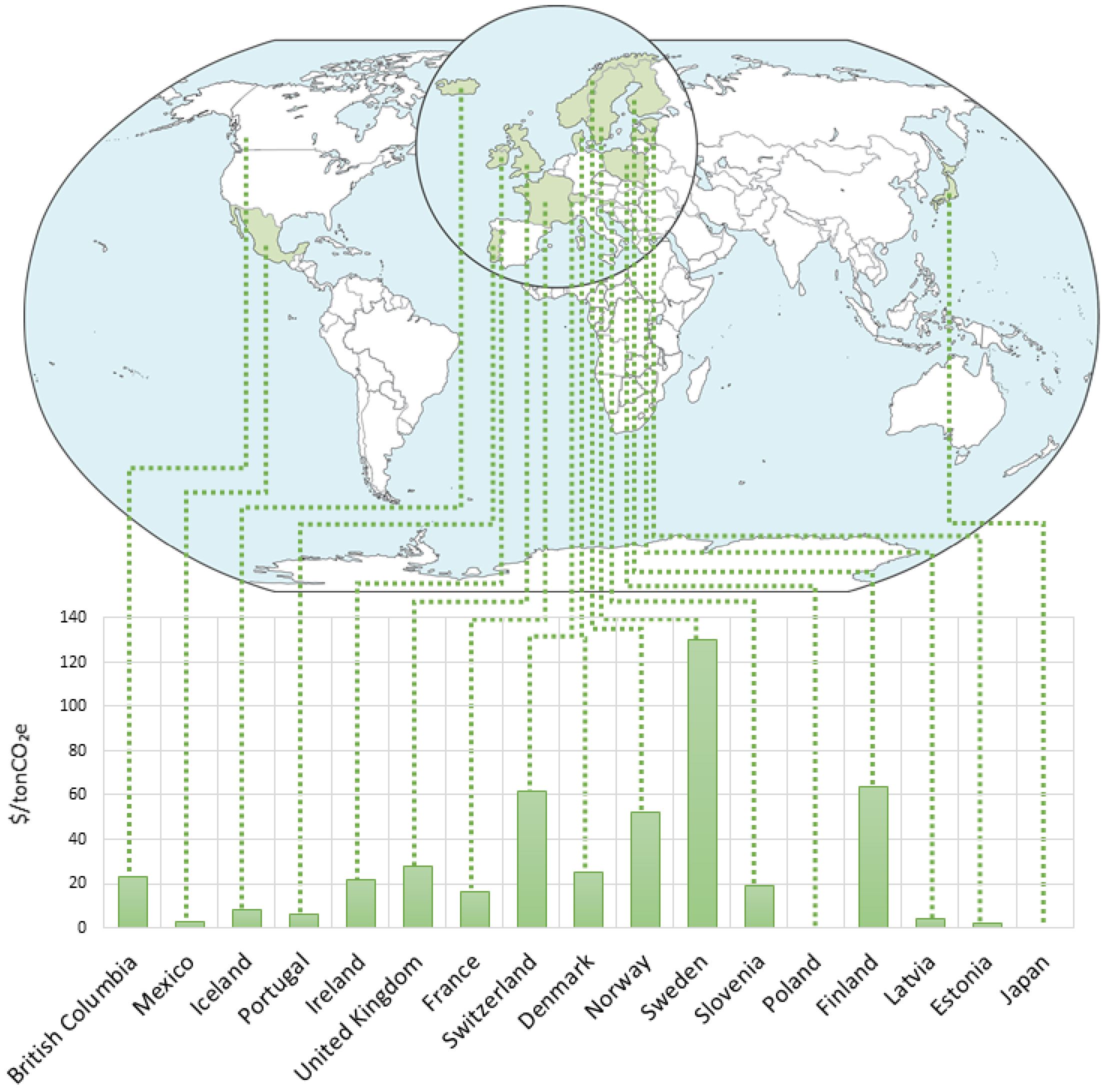


Figure 19 - Carbon taxing systems in the world and relative carbon price in $/tonCO_2e$. Source: Kossoy et al., 2015.

Given the relative simplicity of the implementation of a carbon taxing system, usually this type of carbon control policy is adopted as the first step of a two-stage set of regulatory environmental policy mechanisms, where the second step corresponds to the implementation of an emissions trading system, which is traditionally more complex to set.

The main problem associated with carbon tax is the uncertainty in the achieved carbon emissions reduction, given by the fact the registered emissions reductions are dependent on many other factor, for example on the natural economic cycles of a country. This lead to the difficulty in estimating correctly the cost-effectiveness of the carbon tax policy.

4.3.1. The model formulation

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 €/kgCO_2e. Referring to the base case model, the carbon tax model is the following:

$$Z_{carbon\,tax} = Minimise \sum_{i \in V_c} \sum_{p \in P} \sum_{t \in T} I^{+}_{i,p,t} h_{i,p} \qquad (54.i)$$

$$+ \sum_{(i,j) \in A} \sum_{k \in K} \sum_{t \in T} \lambda \left(y \left(\frac{a_{i,j}}{f} \right) X_{i,j,k,t} + \gamma^k \beta^k a_{i,j} f^2 X_{i,j,k,t} \right.$$

$$\left. + \gamma^k s \left(\mu^k X_{i,j,k,t} + \sum_{p \in P} F_{i,j,k,p,t} \right) a_{i,j} \right) (l + u \cdot tax) \qquad (54.ii)$$

$$+ \sum_{(i,j) \in A} \sum_{k \in K} \sum_{t \in T} \left(\frac{a_{ij}}{f} \right) X_{i,j,k,t} w, \qquad (54.iii)$$

subject to constraints $(13) - (14)$, $(16) - (25)$, $(26) - (31)$, (32) and (44). In this case there is no modification in the constraints of the base case model, while the objective function is modified in order to incorporate the carbon tax associated with the fuel consumption. The term u convert the litres of fuel consumed into carbon emissions that are multiplied by the carbon tax.

4.3.2. Expected impact

The modification in the base case configuration of routing and deliveries will depend exclusively on the imposed value of the variable tax. A relative low value of tax will provide no modifications, so no emissions reduction: the system simply incurs in an extra cost represented by the carbon tax. Conversely, a relatively high value of tax will force the model to change its configuration and reduce emissions, since the achieved cost savings due to the emission reduction offsets the increase in the operational cost caused by the non-optimal routing and deliveries configuration. The system reduces the carbon emissions from transportation acting on the decision variables $X_{i,j,k,t}$ and $F_{i,j,k,p,t}$. The considerations made for cap policy case concerning these decision variables, are still valid for the carbon tax policy. Since the variable tax is positive defined, the term $(54.ii)$ of the objective function will be always greater than or equal to the corresponding term of the base case model $(12.ii)$. This means that any value of tax will provide a more expensive solution with respect to the base case solution, since the system incurs in the carbon tax extra cost.

4.4. Cap-and-trade policy

The cap-and-trade is an emission trading system, which is one of the three basic systems proposed by the Kyoto Protocol to curb emissions of industrialised countries with binding greenhouse gas emissions targets (Carbon Trust, 2009). The other two mechanisms are the Clean Development Mechanism (CDM) and the Joint Implementation (JI). The former allows companies in developed countries to meet their emissions cap purchasing Certified Emissions Credits (CERs), financing carbon reduction projects in developing countries. The cap-and-offset policy further analysed belong to the CDMs. The Joint Implementation is very similar to the Clean Development Mechanism, but it involves the trading of credits (called Emission Reduction Units, ERUs) between developed (or industrialised) countries.

In a cap-and-trade system, a cap that represent the overall amount of allowed carbon emissions in a given period, is imposed to the companies of a certain economic sector, at a national or regional-level. The emissions allowances of the overall cap are then allocated to the single company. A company that cannot meet the imposed cap, can purchase extra allowances from those companies that, emitting less than the imposed cap, sell the extra allowances gained. From this point view, the cap-and-trade policy acts as an incentive to move toward 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 allowed, because of the extra cost incurred. Companies that are unable to meet the imposed cap, even with the purchasing of extra credits, incur in severe fines.

The strong point of cap-and-trade systems is that the overall amount of allowed emissions in a given period is fixed and known. This value is proportionally reduced year by year, to meet the carbon emissions reduction targets. The other side of the coin is represented by the uncertainty in the emissions allowance price, which is variable, because determined by the market laws of supply and demand. From the point of view of companies, this price volatility is a disincentive to invest in low-carbon solutions because it is difficult to precisely forecast the economic results linked with the trading of extra allowances. The following figure show the price variation of the emission allowance in the European Emission Trading System (EU ETS), based on the data of the European Energy Exchange (European Emission Allowance Auction, www.eex.com, last accessed on: 3.11.2017):

Figure 20 - Price of one emissions allowance equal to one tonne of CO_2e in the European Emissions Trading Systems, considering the timespan from 2008 to 2017. Source: www.eex.com, last accessed on: 3.11.2017.

A possible solution to mitigate the allowances price volatility is represented by the introduction of a price floor and/or a price ceiling to prevent the allowance from assuming values under and/or over certain thresholds. In particular an extremely low allowance price would compromise the correct functioning of the emissions trading systems since there would be no economic incentives in reducing emissions.

Cap-and-trade systems, as shown by the following figure are implemented all over the world, at different regional levels.

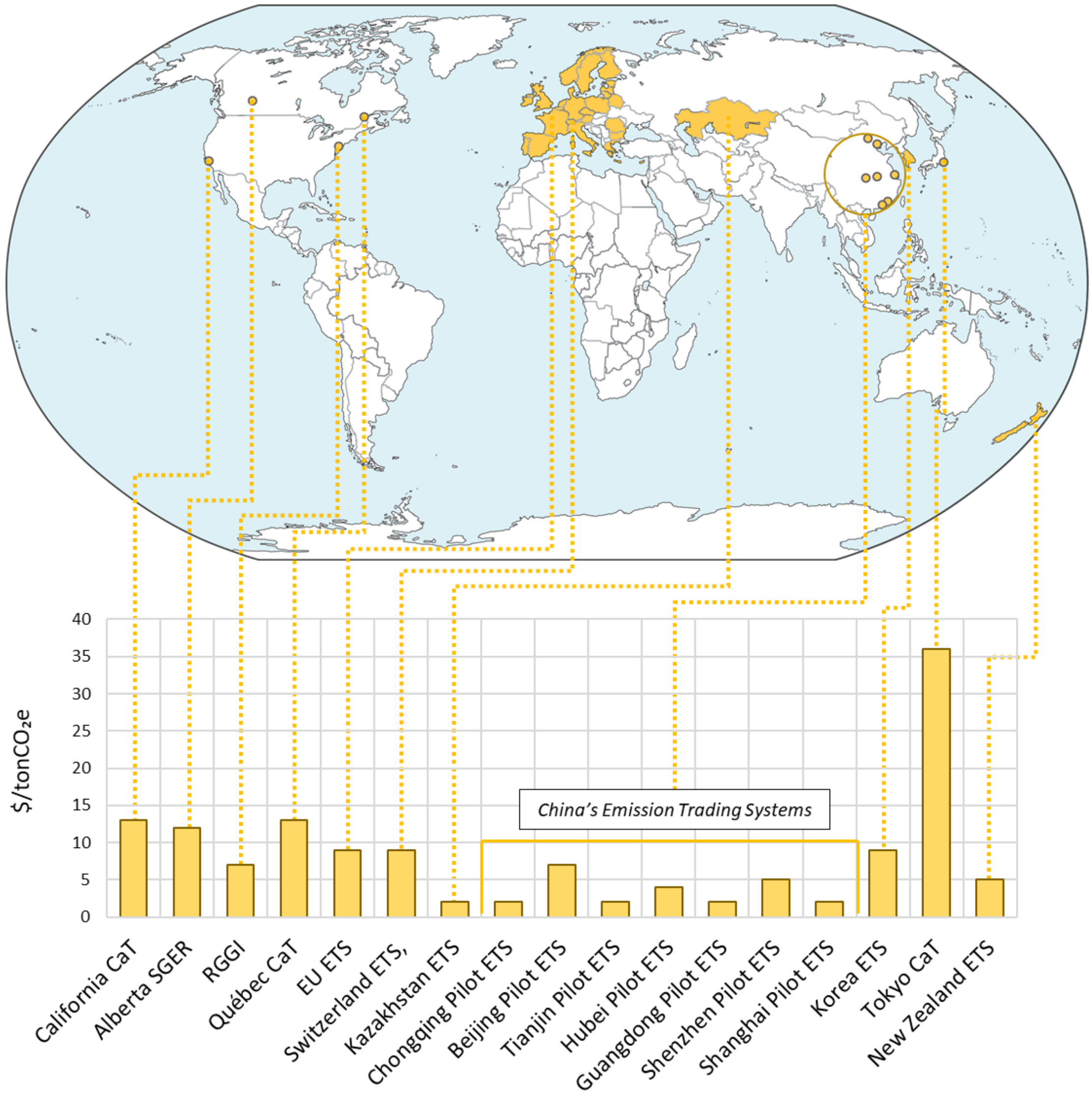


Figure 21 - Carbon trading systems in the world and relative emissions allowance price in $/tonCO_2e$.
Source: Kossoy et al., 2015.

In particular, the European cap-and-trade (EU ETS), represents the most important pillar of the European climate policy (Kossoy et al., 2015). In terms of covered carbon emissions, it is the biggest greenhouse gas emissions trading system in the world, accounting for about 11'000 installations in the 28 EU members states plus Iceland, Norway and Liechtenstein, that cover around the 45% of the total EU greenhouse gas emissions (European Commission (b), 2016). Specifically concerning the carbon dioxide emissions, the covered economic sectors are the power and heat generation, the energy-intensive industries (oil refineries, steel works and production of iron, aluminium, metals, cement, lime, glass, ceramics, pulp, paper) and the civil aviation. However, as shown in the introduction of the thesis, the inclusion of the transportation sector is currently under analysis. Given these assumptions, the

European Emissions Trading System is taken as a reference to contextualize the results obtained from the application of the cap-and-trade to the base case model. As reported in the European Emissions Allowances Auction (EUA) online database, the value of the single emission allowance, traded on the 2nd of October 2017, is equal to 7.00€/tonCO_2e (www.eex.com, last accessed on: 3.11.2017).

4.4.1. The model formulation

The solution of cap-and-trade model is denoted as $Z_{cap\ and\ trade}$. The maximum allowed level of carbon emissions all over the planning horizon is denoted as Cap expressed in kgCO_2e. Each bought allowance to emit one kgCO_2e is denoted as e^+, while the sold allowance is indicated as e^-, and both are positive-defined and expressed in kgCO_2e. The monetary value of the bought/sold emission allowances is indicated as χ^{trade}, expressed in €/kgCO_2e. Referring to the base case model, the cap-and-trade model is the following:

$$Z_{cap\ and\ trade} = Minimise \sum_{i\in V_c}\sum_{p\in P}\sum_{t\in T} I^+_{i,p,t} h_{i,p} \qquad (55.i)$$

$$+ \sum_{(i,j)\in A}\sum_{k\in K}\sum_{t\in T} \lambda \left(y\left(\frac{a_{i,j}}{f}\right) X_{i,j,k,t} + \gamma^k \beta^k a_{i,j} f^2 X_{i,j,k,t} + \gamma^k s \left(\mu^k X_{i,j,k,t} + \sum_{p\in P} F_{i,j,k,p,t} \right) a_{i,j} \right) l \qquad (55.ii)$$

$$+ \sum_{(i,j)\in A}\sum_{k\in K}\sum_{t\in T} \left(\frac{a_{ij}}{f}\right) X_{i,j,k,t} w \qquad (55.iii)$$

$$+ \chi^{trade} \cdot (e^+ - e^-), \qquad (55.iv)$$

subject to constraints $(13)-(14)$, $(16)-(25)$, $(26)-(31)$, (32) and (44), plus the additional constraint that set the maximum allowed level of carbon emissions:

$$\sum_{(i,j)\in A}\sum_{k\in K}\sum_{t\in T}\lambda\left(y\left(\frac{a_{i,j}}{f}\right)X_{i,j,k,t}+\gamma^k\beta^k a_{i,j}f^2X_{i,j,k,t}\right.$$
$$\left.+\gamma^k s\left(\mu^k X_{i,j,k,t}+\sum_{p\in P}F_{i,j,k,p,t}\right)a_{i,j}\right)u+e^- \leq Cap+ e^+. \qquad (56)$$

Differently from the paper of Cheng et al. (2016), in this case the cap is applied on the entire planning horizon, as shown in the description of the cap policy. The assumptions that justify this choice are the same of the cap policy case and are valid for the cap-and-trade case, too. Differently from the previous two policies, the cap-and-trade model modifies both the objective function and the constraints of the base case model. In particular it introduces two additional decision variables, namely $e^+$and e^-.

4.4.2. Expected impact

Differently from the previous two policies, the modifications to the base case configuration caused by the introduction of the cap-and-trade policy depend on two variables, namely the imposed cap (Cap) and the price of traded emissions allowances (χ^{trade}). Concerning the cap, it is expected that the system configuration is independent on the cap value, but the changes in the base case are exclusively driven by the price of the emission allowances. In particular, if the price is sufficiently high, the system will modify the routing/deliveries configuration in order to reduce the emissions. At this step, based on the value of the cap, the achieved emissions reduction will alternatively lower the emissions cost buying less emission allowances, or generating revenues selling the surplus of emission allowances. Differently from the carbon tax case, under the cap-and-trade policy is theoretically possible to obtain a cost-minimising solution lower than the solution of the base case with no policy applied. This is obtained due to the introduction in the objective function of the positive-defined decision variable e^-, that represent the number of sold allowances that generate revenues. Also under the cap-and-trade policy, the emissions reduction is achieved by acting on the decision variables $X_{i,j,k,t}$ and $F_{i,j,k,p,t}$, as for the two previous policies.

4.5. Cap-and-offset policy

Under a cap-and-offset policy, if the business-as-usual carbon emissions of a company are greater than the allocate cap for a given period, the company has two possibilities to meet the regulation: (i) modifying the existing configuration, thus reducing its emissions with energy efficiency and low-carbon fuels investments (domestic reduction), or (ii) buying carbon offsets investing in low-carbon projects in developing countries (foreign reduction) (Carbon Tax Center (a), www.carbontax.org, last accessed on: 3.11.2017). In the second case, the reduction of carbon emissions is not achieved at regional-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. Very often the carbon offsets are a feature of the 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. For example, the cap-and-trade system implemented in California allows companies to offset their emissions for a total of 8% of their compliance obligations (California Air Resources Board, www.arb.ca.gov, last accessed on: 3.11.2017). As shown in the description of the cap-and-trade policy, the cap-and-offset policy can be referred to the Clean Development Mechanism (CDM) administered by the United Nations Framework Convention on Climate Change (UNFCCC). On the CDM online platform it is possible the buy carbon offsets, financing different kind of projects concerning agriculture, biomass energy, energy efficiency, hydropower, N_2O gas reduction, solar power, transport, waste handling and disposal and wind power (**Figure 22**).

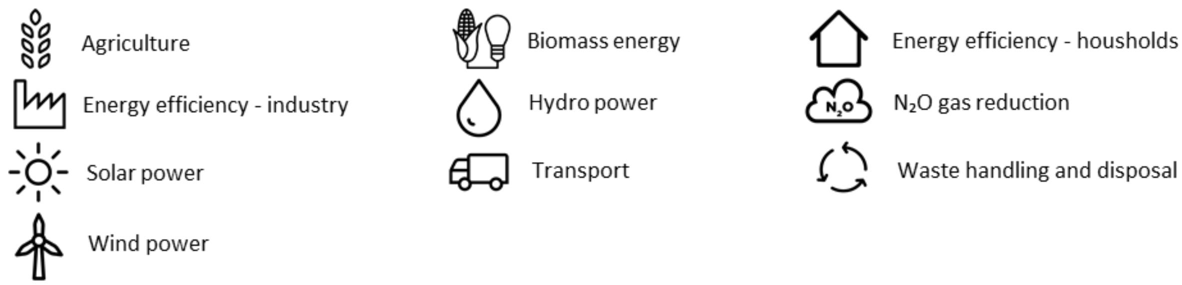


Figure 22 - Representation of the different type of projects included in the Clean Development Mechanism

The cost of the carbon offsets related to the projects present in UNFCC database updated to 2017 ranges from a minimum of 0.40$/ton$CO_2$e to a maximum of 8.50$/

tonCO₂e (UNFCCC, offset.climateneutralnow.org, last accessed on: 3.11.2017). The following figure show the distribution of these project all around the world (**Figure 23**).

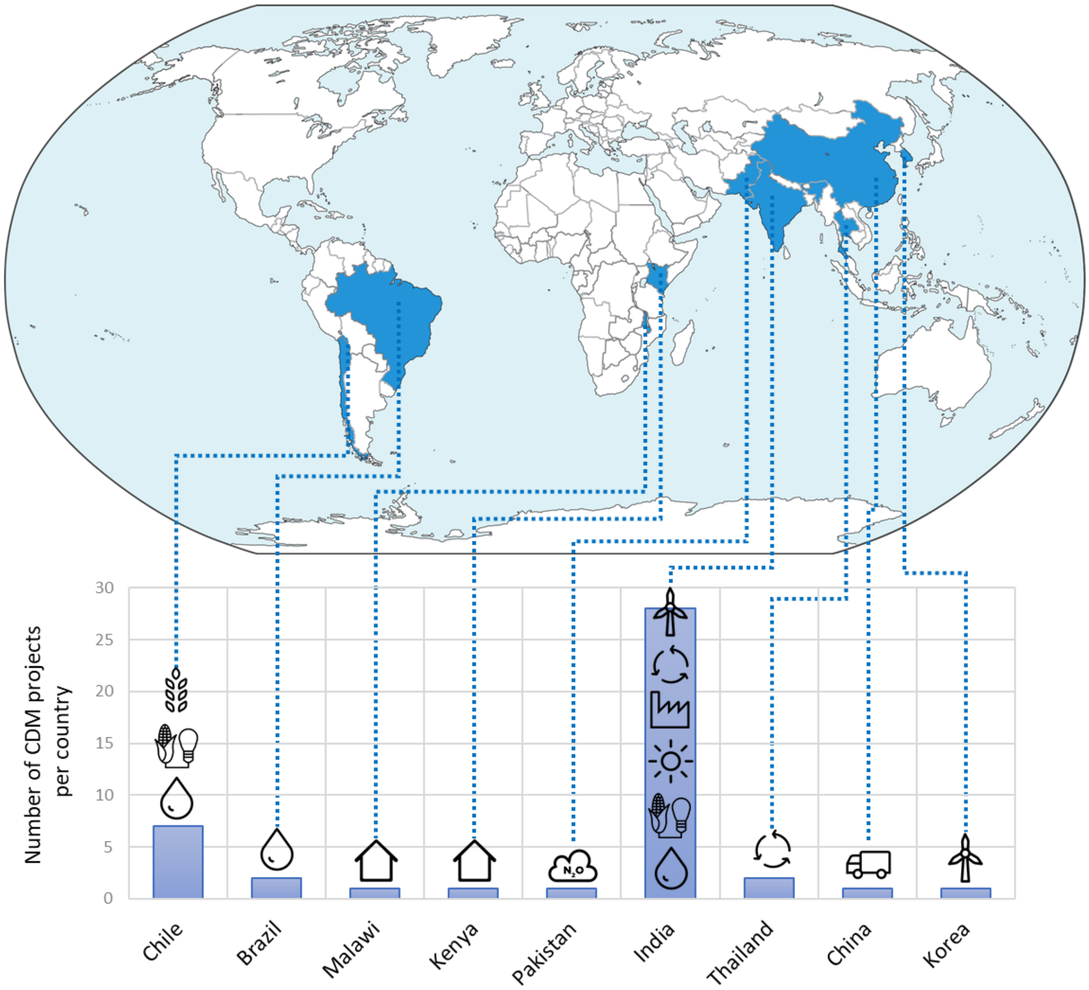


Figure 23 - Countries and related number and type of Clean Development Mechanism projects hosted. Source: UNFCCC, offset.climateneutralnow.org, last accessed on: 3.11.2017.

Besides the positive effect of improving cost-effectiveness of carbon reduction in developed countries, offset mechanisms have two positive collateral effects: (i) they help to reduce carbon leakage in industrialised countries and (ii) they accelerate the transfer of clean, zero-carbon technologies to developing countries.

4.5.1. The model formulation

The formulation of the cap-and-offset model is similar to the cap-and-trade model. Having denoted the solution of the cap-and-offset model as $Z_{cap\ and\ offset}$, the decision variable on the number of emission credits bought is indicated as e^+, positive-defined and expressed in $kgCO_2e$, as in the cap-and-trade case, while the cost of each emission credit is denoted as χ^{offset}, expressed in €/kgCO_2e. Referring to the base case model, the model for the cap-and-offset policy is the following:

$$Z_{cap\ and\ offset} = Minimise \sum_{i \in V_c} \sum_{p \in P} \sum_{t \in T} I_{i,p,t}^{+} h_{i,p} \qquad (57.i)$$

$$+ \sum_{(i,j) \in A} \sum_{k \in K} \sum_{t \in T} \lambda \left(y \left(\frac{a_{i,j}}{f} \right) X_{i,j,k,t} + \gamma^k \beta^k a_{i,j} f^2 X_{i,j,k,t} \right.$$

$$\left. + \gamma^k s \left(\mu^k X_{i,j,k,t} + \sum_{p \in P} F_{i,j,k,p,t} \right) a_{i,j} \right) l \qquad (57.ii)$$

$$+ \sum_{(i,j) \in A} \sum_{k \in K} \sum_{t \in T} \left(\frac{a_{ij}}{f} \right) X_{i,j,k,t} w \qquad (57.iii)$$

$$+ \chi^{offset} \cdot e^{+}, \qquad (57.iv)$$

subject to constraints $(13) - (14)$, $(16) - (25)$, $(26) - (31)$, (32) and (44), plus the additional constraint that set the maximum allowed level of carbon emissions:

$$\sum_{(i,j) \in A} \sum_{k \in K} \sum_{t \in T} \lambda \left(y \left(\frac{a_{i,j}}{f} \right) X_{i,j,k,t} + \gamma^k \beta^k a_{i,j} f^2 X_{i,j,k,t} \right.$$

$$\left. + \gamma^k s \left(\mu^k X_{i,j,k,t} + \sum_{p \in P} F_{i,j,k,p,t} \right) a_{i,j} \right) u \leq Cap + e^{+}. \qquad (58)$$

The assumption that justifies the choice of analysing the cap imposed on the overall planning horizon made for the cap and for the cap-and-trade models is still valid for the cap-and-offset model.

4.5.2. Expected impact

The model formulation of the cap-and-offset policy is similar to the cap-and-trade formulation. The only difference is the absence of the decision variable e^{-}. In this way the cap-and-offset model has no possibility of generating revenues by the trading of emission allowances. The only degree of freedom in this case is represented by the possibility to offset part of the generated emissions in order to meet the imposed cap. This means that under the cap-and-offset policy the model will always provide cost-minimising solutions higher than or equal to the base case solution. As in the previous policy, the achieved emissions reduction is expected to be independent on the value of the cap, but driven only by the value of the emission credit χ^{offset}. As in the previous three policies, the emissions reduction under the cap-and-offset policy is achieved by acting on the decision variables $X_{i,j,k,t}$ and $F_{i,j,k,p,t}$.

4.6. Propositions and observations on the carbon control policies

Cheng et al. (2016) formulate four propositions concerning the relations among the carbon control policy models implemented, specifically addressing a deterministic demand, homogeneous fleet, many-to-one network environmentally-extended inventory routing problem. These propositions are reported below, adapted with the current mathematical notation, described, and the results obtained by the models proposed in this thesis are analysed taking them into account.

Benjafaar et al. (2013), analysing the implications of these four carbon control policies on the operational decisions of a set of companies, propose a total of 13 observations tackling different aspects of the problem, in particular: 5 observations deal with the environmental and economic impacts of the policies, 3 observations deal with the comparison between the results obtained with adjustments of the operational decisions and those obtained with energy-efficient technology investments, 5 observations deal with the relations between the carbon control policies, the emissions reduction achieved and the collaboration between multiple companies, in terms of sharing of costs. Concerning the aspects addressed in this thesis, only the first set of observations are considered. These 5 observations are reported below, and the results obtained by the models proposed in this thesis are analysed taking them into account.

4.6.1. Propositions on the carbon control policies

Proposition 1. *The carbon cap model is a special case of the cap and offset model.*

$$Z^*_{cap\ and\ offset} \leq Z^*_{cap} \qquad (59)$$

The notation Z^* denotes the optimal value of the related model. In particular if the value of the emission credit χ^{offset} is sufficiently high, the choice of meeting the cap by purchasing extra emission credits will be not convenient, and the model prefers to modify the routing/deliveries configuration in order to reduce the emissions without credits purchase. The resulting decision variable e^+ will be equal to zero, and the cap and offset model acts as a cap policy model.

Proposition 2. *The cap and offset model is a special case of the cap-and-trade model.*

$$Z^*_{cap\ and\ trade} \leq Z^*_{cap\ and\ offset} \qquad (60)$$

Under the cap-and-trade policy, when the decision variable on the number of sold emissions allowance e^- is equal to zero, the model is the same as the cap and offset model. For this reason, the cap-and-trade model has more flexibility than the offset policy.

Proposition 3. *The cap model is a special case of the cap-and-trade model.*

$$Z^*_{cap\ and\ trade} \leq Z^*_{cap\ and\ offset} \leq Z^*_{cap} \qquad (61)$$

Under the cap-and-trade policy, when the decision variables on the number of sold emissions allowance e^- and on the number of bought emissions allowances e^+ are equal to zero, the model degrades to the cap policy model. However, a situation where both the sold and bought allowances are equal to zero is very singular. In the cap-and-trade expectations section it has been stated that the decisions on the selling or purchasing of emissions allowances should depend on the monetary value of the allowance χ^{trade}. Under this assumption the situation characterised by null sold and bought allowances would correspond to the case where the baseline emissions of a company meet exactly the imposed cap (namely $E_{CO_2} = Cap$) and the value of the allowance χ^{trade} makes not profitable to shift towards a lower-carbon emissions configuration in order to sell the surplus of allowances.

Proposition 4. *The feasible region of the base case model is the same of the carbon tax policy model.*

$$Z_{no\ policy} = Z_{carbon\ tax} \qquad (62)$$

The carbon tax policy simply adds an extra term to the objective function of the base case model, and therefore if the term tax is positive-defined the feasible regions of the two models would coincide.

4.6.2. Observations on the carbon control policies

The following observations are reported keeping the numeration adopted by the paper of Benjafaar et al. (2013).

Observation 1. *It is possible to impose significant caps on emissions with relatively limited impact on total cost.*

The impact on total cost will be quantified with respect to the distribution problem analysed in this thesis, highlighting the range of imposed cap values that leads to significant emissions reduction without excessively hurt the economic result.

Observation 4. *Tighter caps on emissions can paradoxically lead to higher total emissions.*

This observation is based on a cap policy where the limit on emissions is imposed on each single period of the planning horizon. As explained in the cap policy description, in this thesis the cap is imposed on the overall planning horizon, thus the results will be analysed keeping in consideration this aspect.

Observation 5. *Carbon offsets enable tighter emission caps by mitigating the impact of lowering caps on costs.*

Observation 6. *Under cap-and-trade when the price is fixed (and there are no limits on the number of emission credits that can be traded), emission levels are not affected by emission caps and are affected only by the price for carbon.*

This observation tackles one of the assumptions that characterise the cap-and-trade policy implementation in these operational models. Real emissions trading systems in fact are characterised by variations in the price of the emissions allowances caused by the difference between supply and the demand of allowances inside a close market. Each year, governments or regulator authorities tight the cap reducing the total available number of emissions allowance. This reduction should in theory lead to an increment in the allowance price that in turn should incentive companies to reduce their carbon emissions. Thus, there is a relation between the value of the cap, the total number of emissions allowances and the price of the latter. For the purposes of this thesis, and following the approach of the analysed papers that tackled the cap-and-trade policy, the price of emissions is assumed to be independent of the value of cap imposed.

Observation 7. *Under cap-and-trade, a higher carbon price can lead to lower total cost.*

4.7. Qualitative analysis and comparisons of the policies

The proposed policies show distinctive approaches in curbing the carbon emissions of a designated subject. In this section, these different approaches will be compared, highlighting the advantages and disadvantages of each policy, principally in terms of: (i) effectiveness of emissions reduction, defined as the degree of certainty in achieving a set target, given a determined environmental objective; (ii) the implementation and operational costs of the policy, intended as all the expenses needed to set up the policy system, and to measure, control and verify the compliance with the set policy; (iii) the economic impact on the economic sector subjected to carbon control policies.

In terms of effectiveness of emissions reduction, the cap policy, and more in general the implementation of a command and control regulation, represents the best available option among the proposed policies. The regulator authority set a maximum allowed quantity of emissions that has to be mandatorily met. In most of the cases, the authority agrees the minimum required standards with the interested economic sector, in order to meet the environmental goal without excessively hurt the companies' businesses. For example, concerning the regulation of greenhouse gases emissions from transportation, the European Commission agreed with car and van manufactures a maximum limit on the exhaust gases equal to 175 grams of CO_2 per kilometre (European Commission (c), ec.europa.eu, last accessed on: 3.11.2017). The non-compliance with the regulation will lead to the payment of fines, which ensures the strict observance of the set regulation. Referring to the previous example, each gram of CO_2 emitted over the threshold, causes a penalty ranging from 5 €/gCO_2 to 95 €/gCO_2. On the contrary, the explicit price policies, namely the cap-and trade, the cap-and-offset and the carbon tax, are not straightforward in achieving successfully a determined emissions target. The main concern with the effectiveness in emissions reduction with trading systems is the allocation of allowances. In emissions trading systems in fact, there are two way of allocating emission allowances: by auctioning or by grandfathering. As reported by Zakeri et al. (2015), the most widely diffused method is the latter. In a grandfathering emissions allocation method, part of the allowances is freely assigned to each company on the basis of historical data of emissions: in this sense the grandfathering does not incentive companies to reduce emissions, since it simply leads to a smaller number of grandfathered allowances in the next period. From the point of view of the regulator authority, the auctioning method could be an additional source of revenues that can be reinvested. However, the grandfathering allocation is preferred, especially in carbon-leakage sensitive economic sectors, because its minor impact on the economic results of the companies. In general, these two methods are used in combination, but as shown by the following figure (**Figure 24**), that represents the share of the two methods in the European Emissions Trading System, the grandfathering allocation is predominant (European Commission (d), 2017).

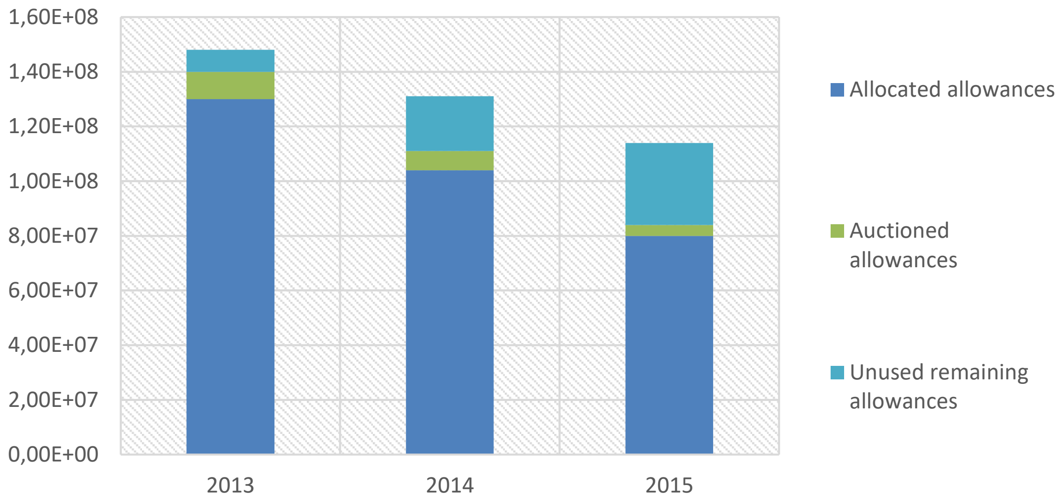


Figure 24 - Share of allocation allowances in EU ETS 2013-2015. Source: European Commission (d), (2017).

The above figure shows the other main problem that affects the effectiveness in achieving the reduction emissions target in trading system, representing by the unused remaining allowances. An imprecise setting of overall cap in fact, would results in a surplus of emission allowances that in turn drives down the allowances prices, decreasing the overall emissions reduction.

Concerning the cap-and-offset policy, the issue in the effectiveness of emission reduction mainly lies in the definition of additionality of a project. This require a precise estimation of the baseline emissions, namely the level of carbon emissions that would occur without the implementation of that specific carbon-free project. This estimation is intrinsically arbitrary, and this leads to a difficult evaluation of the effective positive consequences of the offsets mechanisms (Carbon Tax Center, www.carbontax.org (a), last accessed: 3.11.2017).

The carbon taxing mechanisms, by definition, imply the uncertainty in the precise estimation of the effect of the implementation of this policy, in terms of environmental results. The setting of fixed price would in theory forces carbon-

intensive companies to move towards cleaner technologies and efficient solutions. In practice, the carbon tax, if not well-defined would results in an additional burden for companies that are not economically able to modify their configuration. In this case, the company can decide to simply pay the additional taxes, without reducing the environmental impact, thus resulting in a null net emissions reduction, or can decide to transfer its business in a country with soften environmental regulation, thus resulting in an increment of overall global emissions (carbon leakage phenomenon).
Concerning the implementation and operational cost of the analysed policies, the taxing mechanisms are those that require less effort on both implementation and operational side. As reported by Akerfeldt and Hammar, that analyse the carbon emissions taxation in Sweden, if the carbon tax is collected concurrently with the other taxes collection (for example energy taxes), it results in low administrative costs for the tax authorities and for the operators (Akerfeldt and Hammar, 2015). In general carbon taxes can be applied easier and sooner than the other policies, especially compared to the cap-and-trade policy. The latter is more complex to implement and to manage, since it needs the implementation of a carbon emissions market, and of an authority that monitors and controls the correct functioning of it. The operational costs of trading systems are much larger than those of carbon taxing mechanisms, and a considerable percentage of the revenues of auctioning the allowances is spent for the management of the entire system. Finally, concerning the cap policy, as in the majority of the command and control regulations, the considerable share of cost is represented by the monitoring and verification of compliance to the implemented regulation.
In general, with regards of the economic impact on the economic sectors subjected to policies, as reported by the Center on Budget Policy Priorities, the market-based approaches, such as the cap-and-trade and cap-and-offset mechanisms, are more cost-effective than the traditional "command and control" regulations, since they create incentives for companies to conserve energy, improve energy efficiency, and adopt clean-energy technologies, without prescribing the precise action they should take (Center on Budget Policy Priorities, 2015). As previously shown, the non-compliance with the command-and-control regulations will result in a considerable economic impact caused by the payment of fines, whereas the compliance with too strict regulations would leads to similar consequences. For example, a company can decide to lower the production in order to meet a target level of emissions. Conversely, the market-based mechanisms offer a wider range of solutions to meet the set environmental targets, thus leading to more flexibility and a small economic burden carried by companies. The possibility to offset part of the emissions in a country where the same net emissions reduction is achieved at a lower price is a clear example of this aspect. In the end, the impact of the taxing policies lies in the middle, since it heavily depends on the value of the tax, and on the responses of the taxed economic sectors.

The following table qualitatively summarizes the considerations explained above (**Table 6**).

		Effectiveness in CO_2 reduction	Implementation, operational cost	Economic impact on businesses
Command-and-control regulations	Cap	●	◒	●
Trading mechanisms	Cap-and-trade	◒	●	○
Trading mechanisms	Cap-and-offset	◒	◒	○
Taxing policies	Carbon tax	◒	○	◒
Legend: ○ = low;	◒ = moderate;	● = high;		

Table 6 - Summary of the main characteristics of the analysed carbon control policies

4.8. Corporate carbon pricing

Up to this point, carbon control policies have been considered as regulatory measures imposed by an external authority, usually governments or international organizations. As shown in the introduction of this thesis, also companies started to take consciousness of the potentially disastrous effect of the climate change, and started to actively operate to contrast it, or at least to mitigate the negative effects of their operations.

With regards of the implementation of specific carbon emissions mitigation policies, the Carbon Disclosure Project, in its last report titled "Disclosure Project - Embedding a carbon price into business", presents a list of 1249 companies that voluntarily have decided to put a price on their carbon emissions. It also shows the steep increment with respect to the previous year, represents by +23% of companies that have decided to disclose their practice of pricing carbon emissions, or have already planned to do it (Carbon Disclosure Project, 2016). Internalizing the carbon emissions price in the company's view today implies the creation of prudent buffers to adapt the company strategies to a carbon-constrained future. The data on the rapid increment of climate-sensitive companies, in terms of business decisions, is a symptom of the strong perception that the short and medium-term effects of climate change are economically tangible, and must be taken into account in the analysis of future investments of a company.

A more restrict group composed by 147 companies take the carbon disclosure practice to a next level, incorporating the carbon price directly in their business strategies and operations. In the literature review of this thesis, it has been analysed papers that specifically tackles the operational decision-making sphere of companies, with a focus on the economic impacts of including environmental concerns in the business strategies. As shown by some papers (Treitl et al. (2014), Soysal et al. (2015)), in many cases the correct embedding of the environmental concerns would results in a win-win situation characterised by lower overall costs and lower carbon emissions. With specific regard of the carbon price practice, companies in the Carbon Disclosure Project reports that the internal carbon price is used:

- as an incentive for the reallocation of resources in low-carbon activities;
- as a factor in the business case for R&D investments;
- as a way to reveal hidden risks and opportunities in the operations of the company and in its supply chain.

This last point is particularly crucial, since as shown by the Carbon Disclosure Project's Report on Supply Chains (Carbon Disclosure Project, 2017), the supply chain operations represented the most strategic intervention area in decreasing the carbon emissions of business activities. On average, the indirect carbon emissions from supply chain operations are four times higher than the direct carbon emissions of a company, that leads to a huge potential of reduction, further driven by the fact that the emissions reduction could go in parallel with the improvement of operational efficiency. The potential in carbon emissions reduction of supply chain operations is also represented by the power of procurement decisions. As highlighted in CDP Supply Chain report, companies environmentally-concerned can transfer their own commitment throughout all the steps the supply chain, preferring suppliers which share the same environmental concerns. Obviously, this process is pulled by the final downstream stage of the supply chain, represented by the increasing demand for greener products by the end customers. In fact, carbon label and low-carbon products are the most important climate-related opportunities, along with the possibility to explore emerging opportunities in carbon constrained economies.

The internalization of carbon price in the business strategy of a company has already produced its effect. The CDP report on carbon pricing presents 37 companies that have disclose a tangible impact on their operations, describing a set of tools that directly have shifted the investments toward energy efficiency measures and low-carbon initiatives.

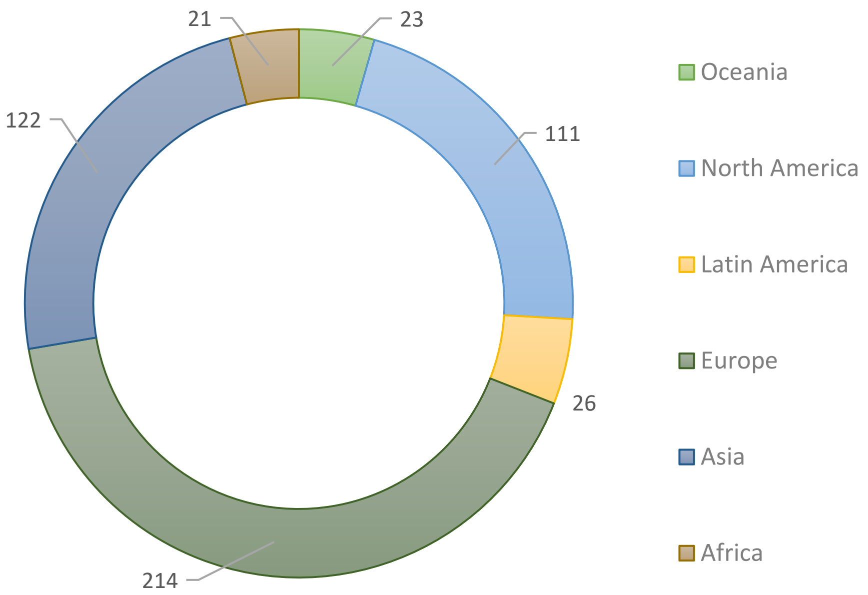
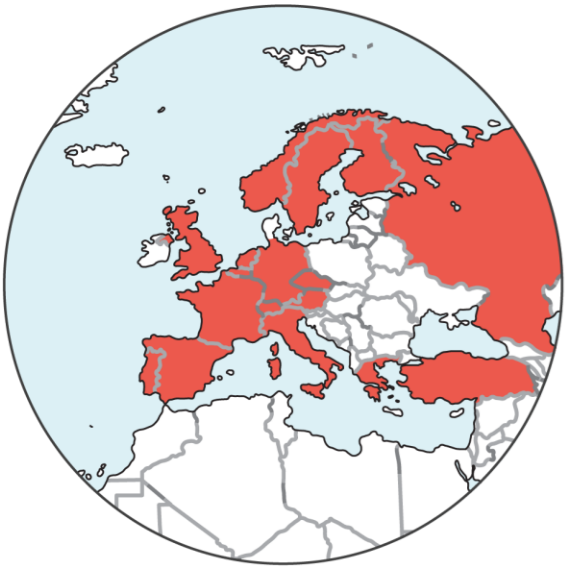


Figure 25 - Number of companies adopting corporate carbon pricing measures. Source: www.cdp.net (a), last accessed on: 3.11.2017.

The choice of focusing only on the European situation is motivated by the fact that European companies represents the forefront of carbon emissions reduction, both in terms of number of companies involved in carbon disclosure projects and in terms of effectiveness of the implemented actions. The **Figure 25** shows that the majority of the considered companies are European. Focusing on the Europe, the CDP report shows a dominance of the British companies in the implementation of corporate carbon practice (almost the 40% of the European companies). The following figure report all the companies that are disclosing their carbon pricing approaches, based on the report of the Carbon Disclosure Project of 2016 (**Figure 26**). This data confirms the climate-sensitivity of United Kingdom, which is the most important country in the world in terms of funds destined to the climate-sustainable development of developing countries (Climate Funds Update, www.climatefundsupdate.org, last accessed on: 3.11.2017).



UNITED KINGDOM

Domino's Pizza Group plc	24,64
Jaguar Land Rover Ltd	11,17
N Brown Group Plc	23,48
Sky plc	23,33
WPP Group	53,15
J Sainsbury Plc	24,64
Unilever plc	10,00
BP	40,00
Big Yellow Group	23,92
Capital & Counties Properties	17,50
Ernst & Young LLP UK	23,92
Unite Students	24,64
Spire Healthcare	24,64
Balfour Beatty	24,64
Go-Ahead Group	23,33
Senior Plc	27,71
Anglo American	3,27 - 8,17
BHP Billiton	24,00
GPS PE Products	17,50
Mondi PLC	33,51
BT Group	24,64
TalkTalk Telecom Group	25,08
Centrica	32,08
National Grid PLC	86,04
Pennon Group	75,83 - 291,65
Severn Trent	21,29
United Utilities	23,48

GERMANY

BMW AG	6,70
HeidelbergCement AG	22,34
E,ON SE	22,34 - 44,68

SWITZERLAND

Nestlé	1,02
Novartis	100,00

FRANCE

Kering	69,25
Carrefour	22,34 - 78,18
Total	27,92
Societe Generale	11,17
Bic	12,29 - 22,34
La Poste	7,82
LEGRAND	33,51
Sopra Steria Group	5,58
MMP Packetis	35,74
MMP Premium	35,74

SPAIN

Inditex	30,00
Banco Popular Espanol S,A,	8,94
CaixaBank	5,58
Abengoa	10,05
Obrascon Huarte Lain (OHL)	4,86
ACCIONA S,A,	39,09 - 50,26
Enagas	7,82
Endesa	12,29
Gas Natural SDG SA	23,24 - 37,11
Iberdrola SA	33,51

PORTUGAL

Jerónimo Martins SGPS	5,58
Galp Energia SGPS SA	33,51
Correios de Portugal	39,10
Energias de Portugal	5,58 - 67,01

ITALY

Eni SPA	40,00
Palladio Group SPA	9,24 - 22,34
A2A	6,70 - 13,40
ENEL SPA	12,29
Snam SPA	8,23

NETHERLANDS

Royal Dutch Shell	40,00
Vopak	27,92
AkzoNobel	55,84 - 150,78

NORWAY

Statoil ASA	50,00 - 64,00

SWEDEN

Lundin Petroleum	54,03
Nordea Bank	2,23
Tetra Pak	11,17

GREECE

Piraeus Bank	7,82

TURKEY

Pegasus Hava Taşimaciliği A.Ş.	6,37

BELGIUM

Solvay S.A.	83,77

FINLAND

Metsä Board	11,17

RUSSIA

Arkhangelsk PPM	16,75

AUSTRIA

Verbund AG	5,58 - 7,48

Figure 26 - European companies adopting corporate carbon pricing measures with relative carbon price. Source: Carbon Disclosure Project, (2016).

5. Methods

In this section, the mathematical formulation of the proposed models is applied to a case study, based on real data. The considered case study is adapted from the reference paper of Soysal et al. (2016). In their work the authors consider the distribution of two different perishable products, provided by two distinct suppliers. In this thesis the developed models are applied to a one-many network characterised by one supplier and five distinct customers with time-varying stochastic demand. The numerical data of the reference model are adapted to suit the considered problem. The economic and environmental performance of the models are assessed with respect to a set of KPIs, based on the considered carbon control policy applied.

In the base case model, where no carbon control policy is applied, the performances are assessed with respect to: (i) driving time, (ii) inventory cost, (iii) routing cost comprised of fuel cost and drivers cost, (iv) carbon emissions and (v) total cost. Focusing on the fleet decisions of the problem, the following KPIs are taken into account: (vi) average saturation of the fleet of vehicles, (vii) total number of employed vehicles, $(viii)$ fleet mix composition. The latter parameter is considered only when a heterogeneous fleet is employed. The average saturation of the fleet of vehicles is calculated as the average of the single vehicles saturation per period, which is given by the ratio between the load of the vehicle when it leaves the supplier and the vehicle maximum payload capacity. The same set of KPIs are computed for the emissions-minimising model, while for the constant emissions model, besides the total inventory cost, it is computed (ix) the approximate routing cost and (x) the approximate emissions.

When considering the application of a specific policy the following additional policy-related KPIs are considered: (xi) achieved emissions reduction, (xii) operational cost increment (due to the policy introduction). When considering an explicit-price carbon control policy (carbon tax, cap-and-trade, cap-and-offset) the $(xiii)$ emissions cost KPI, dependent on the considered carbon price, is considered. When specifically considering the cap-and-trade policy, the following KPI is considered: (xiv) emissions revenue (due to the selling of surplus emissions allowances).

In order to gather insights on the economic and environmental effect due to the vehicle fleet choice, the instances for the proposed models will be applied first to a completely heterogeneous fleet, and then to a completely homogeneous fleet of vehicles.

5.1. Parameters of the problem

5.1.1. Vehicle parameters

One of the purpose of this thesis is the implementation of a heterogeneous fleet on the reference model of Soysal et al. (2016), which already takes into account the uncertainty in demand and a comprehensive emissions model.
In this way, the four carbon policies can be analysed with two different fleet configurations, in order to highlight the differences in employing a heterogeneous fleet rather than a homogeneous one. In this section it will be investigated in detail the choice of the vehicle characteristics to be employed in the proposed problems.
The first step consists in the analysis of the choices made by the two papers taken as a reference, respectively the previously cited work by Soysal et al. (2016), and the work by Cheng et al. (2017) where it is analysed the impact of a heterogeneous fleet on an environmentally-extended inventory routing problem. Soysal et al. (2016) employs a homogeneous fleet of medium-duty vehicles with the following characteristics, reported in **Table 7**.

Vehicle parameter	Notation	Value	Unit of measure
Fuel-to-air mass ratio	ξ	1	-
Gravitational constant	g	9.81	[m/s²]
Air density	ρ	1.2041	[kg/m³]
Coefficient of rolling resistance	C_r	0.01	-
Efficiency parameter for diesel engines	ϖ	0.9	-
Heating value of a typical diesel fuel	κ	44	[kJ/g]
Vehicle speed	f	22.2	[m/s]
Conversion factor	ψ	737	[g/l]
Road angle	ϕ	0	-
Curb-weight	μ	6350	[kg]
Maximum payload (Capacity)	c	10000	[kg]
Engine friction factor	k_e	0.2	[kJ/rev/l]
Engine speed	N_e	33	[rev/s]
Engine displacement	V_e	5	[l]
Coefficient of aerodynamic drag	C_d	0.7	-
Frontal surface area	A	3.912	[m²]

Table 7 - Vehicle parameters of Soysal et al. (2016).

The source of the data employed by Soysal et al. (2016) concerning vehicle parameters, is the work by Demir et al. (2012), which investigates heuristics algorithms for pollution routing problems. Given this data, it is possible to plot the fuel consumption function for a vehicle with this characteristics that travels 100 kilometres with a payload of 2500 kg. The choice of this value of payload is made in order to make possible to further compare the fuel consumption of different class of vehicles characterised the same payload. The results are represented in **Figure 27**.

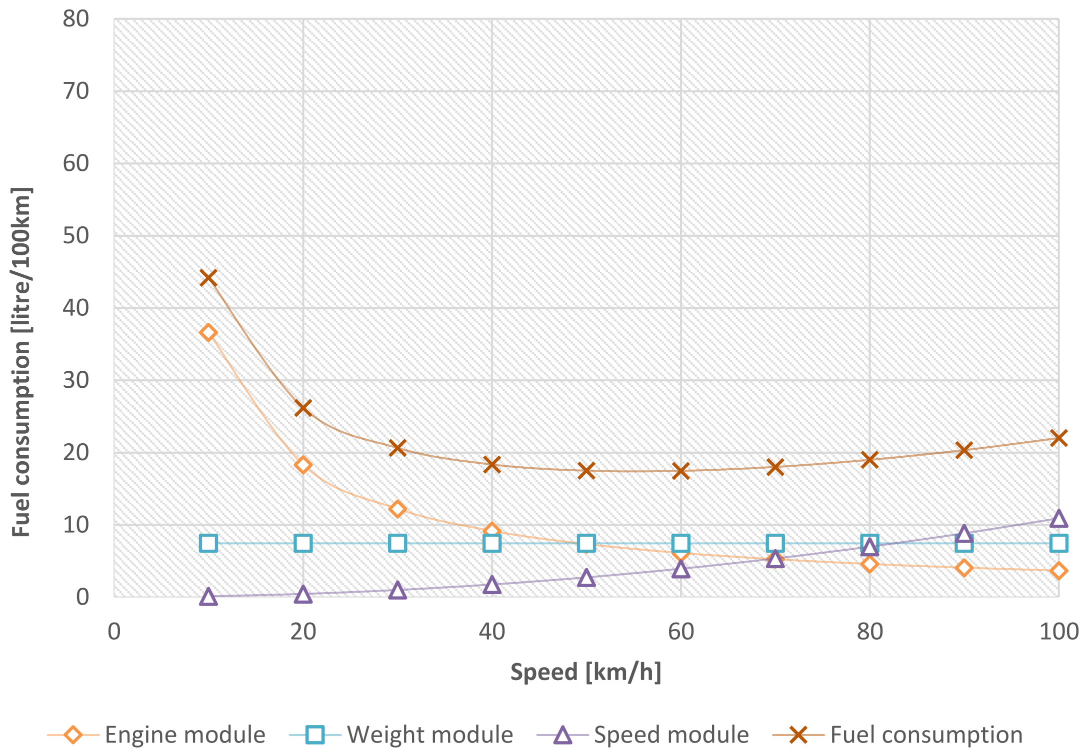


Figure 27 - Fuel consumption in litre/100 km of the medium-duty vehicle used by Soysal et al. (2016), with a payload of 2500 kg.

The same approach can be applied to the work of Cheng et al. (2017). The choice of the vehicles characteristics is shown in the following table (**Table 8**). It is adopted the mathematical notation of Soysal et al. (2016).

Vehicle parameters	Notation	LDV	MDV	HDV	Unit of measure
Vehicle common parameters					
Fuel-to-air mass ratio	$\boldsymbol{\xi}$	1	1	1	-
Gravitational constant	$\boldsymbol{g}$	9.81	9.81	9.81	[m/s²]
Air density	$\boldsymbol{\rho}$	1.2041	1.2041	1.2041	[kg/m³]
Coefficient of rolling resistance	$\boldsymbol{C_r}$	0.01	0.01	0.01	-
Efficiency parameter for diesel engines	$\boldsymbol{\varpi}$	0.45	0.45	0.45	-
Heating value of a typical diesel fuel	$\boldsymbol{\kappa}$	44	44	44	[kJ/g]
Conversion factor	$\boldsymbol{\psi}$	737	737	737	[g/l]
Road angle	$\boldsymbol{\phi}$	0	0	0	-
Vehicle specific parameters					
Curb-weight	$\boldsymbol{\mu^k}$	4672	6328	13154	[kg]
Maximum payload (Capacity)	$\boldsymbol{c^k}$	2585	5080	17236	[kg]
Engine friction factor	$\boldsymbol{k_e^k}$	0.25	0.20	0.15	[kJ/rev/l]
Engine speed	$\boldsymbol{N_e^k}$	39.0	33.0	30.2	[rev/s]
Engine displacement	$\boldsymbol{V_e^k}$	2.77	5.00	6.66	[l]
Coefficient of aerodynamic drag	$\boldsymbol{C_d^k}$	0.6	0.6	0.7	-
Frontal surface area	$\boldsymbol{A^k}$	9.0	9.0	9.8	[m²]
Vehicle drive train efficiency	$\boldsymbol{\varepsilon^k}$	0.40	0.45	0.50	-

Table 8 - Vehicle parameters of Cheng et al. (2017).

The source of the data used by Cheng et al. (2017) is the work of Koc et al. (2014), which in turns employs the MAN trucks online catalogue. Both the papers address a heterogeneous fleet of vehicles composed by three class of vehicles, namely the light-duty vehicles (LDVs), the medium-duty vehicles (MDVs) and the heavy-duty vehicles (HDV). This classification was developed by the United States Federal Highway Administration (FHWA), and, as reported by the work of Koc et al. (2014), the most important truck companies produce almost exclusively these three types of vehicles for distribution. In particular, the MAN company, as shown by the following figure that represents the European market share of truck companies, can be considered representative of the entire sector. In other words, the vehicle characteristics referred to the MAN's trucks, are assumed valid to well describe a generalised heterogeneous fleet of vehicles (**Figure 28**).

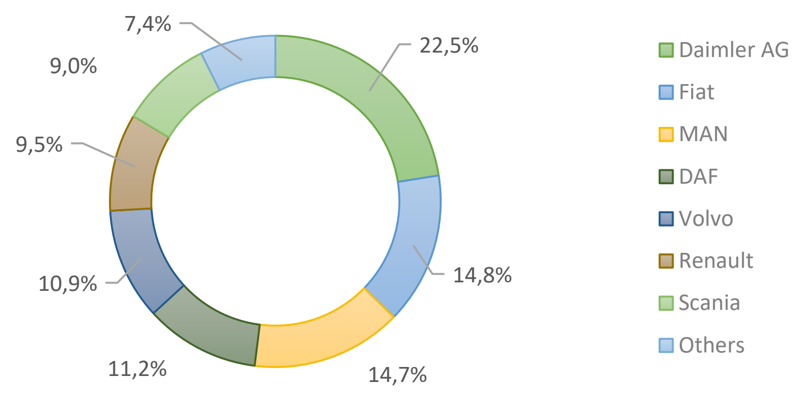


Figure 28 - EU Registrations of all HDVs by manufacturer group in 2008. Source: Hill et al., 2011.

However, the paper by Cheng et al. (2017) modifies some parameters with respect to the source of Koc et al. (2014). In particular the curb-weight, the maximum payload, the engine friction factor, the engine speed, the engine displacement, the coefficient of aerodynamic drag, the frontal surface area and the vehicle drive train efficiency are different in the two considered papers.
With respect to the data proposed by the model of Cheng et al. (2017), it is possible to plot the fuel consumption for the three class of vehicle considered, assuming a payload equal to 2500 kg and a travelled distance of 100 kilometres (**Figure 29**).

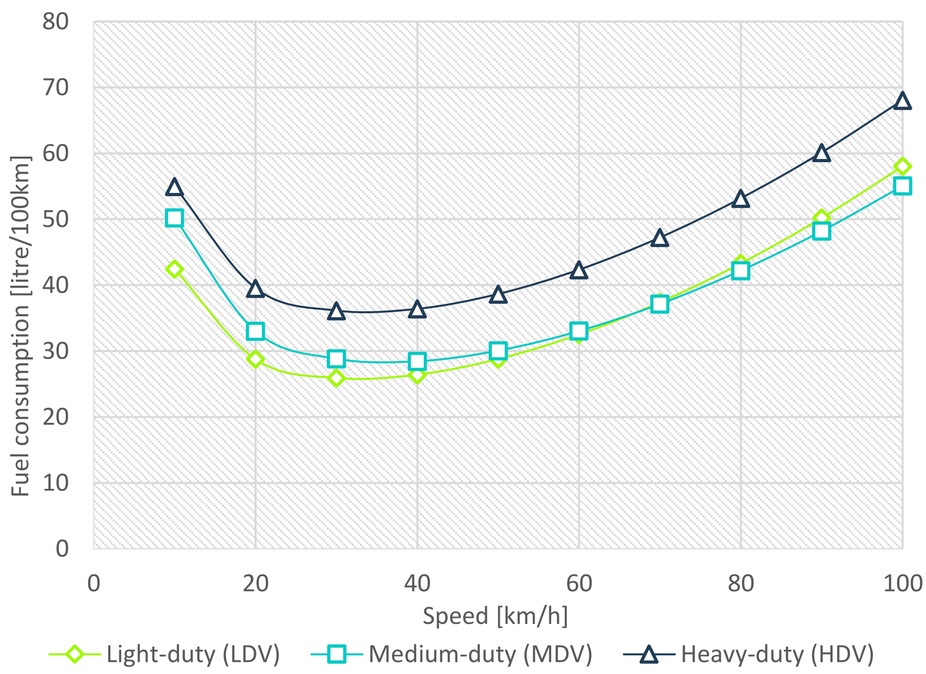


Figure 29 - Fuel consumption in litre/100 km of the heavy-duty, medium-duty and light-duty vehicles used by Cheng et al. (2017), with a payload of 2500 kg.

Furthermore, it is possible to compare the medium-duty vehicle fuel consumption of Cheng et al. with that of Soysal et al., as shown in **Figure 30**.

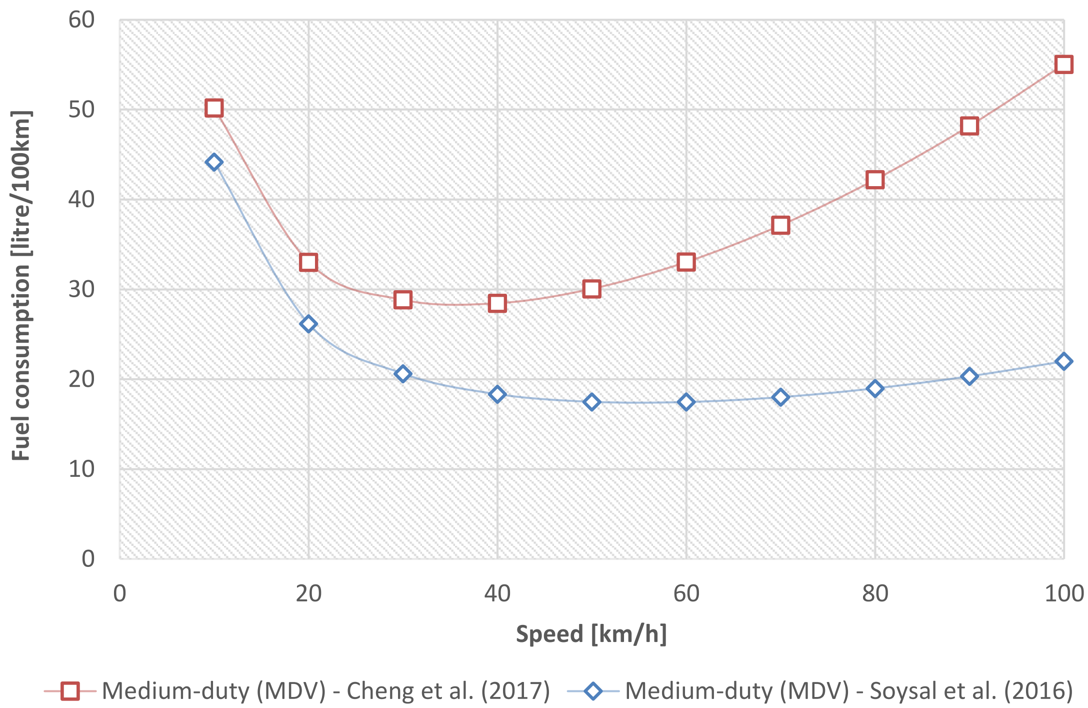


Figure 30 - Comparison between the fuel consumption of the medium-duty vehicle of Soysal et al. (2016) and that of Cheng et al. (2017), given the same payload equal to 2500 km.

The comparison between the two curves show a great difference in the fuel consumption, particularly accentuated with the increment of vehicle speed. In correspondence of the selected vehicle speed for the problem, namely 80 km/h, the vehicle addressed by Cheng et al. (2017) consumes two times the fuel consumed by the vehicle addressed by Soysal et al. (2016). The steadiness of the curve of Soysal et al., among all the different vehicle parameters, is almost exclusively dependent on selected efficiency parameter for diesel engines ϖ. This value is set equal to 0.9, while in the paper by Cheng et al. is set to 0.45, as in the reference paper of Koc et al. (2014). The efficiency parameter for diesel engines, as shown in the comprehensive emissions model section, is inversely proportional to the speed of the vehicles, and affects directly the speed module of the function, driving up the fuel consumption with the increasing of speed.

As shown in the work of Takaishi et al. (2008), that reports the thermal efficiencies of various types of small to medium-sized diesel and gas engines, the value employed by Soysal et al. is highly implausible, since there are no engines with efficiency higher than 0.5÷0.6. For this reason, the values for the vehicle characteristics used by the

reference paper of Soysal et al. (2016) will be not taken into consideration in this thesis.
Focusing on the fuel consumption curves of the vehicles employed by Cheng et al., is possible to draw another interest insight, that helps to choose the right vehicle fleet for the analysis proposed in this thesis. In particular it is useful to focus on the curves of the light-duty and medium-duty vehicles, as shown in **Figure 31**.

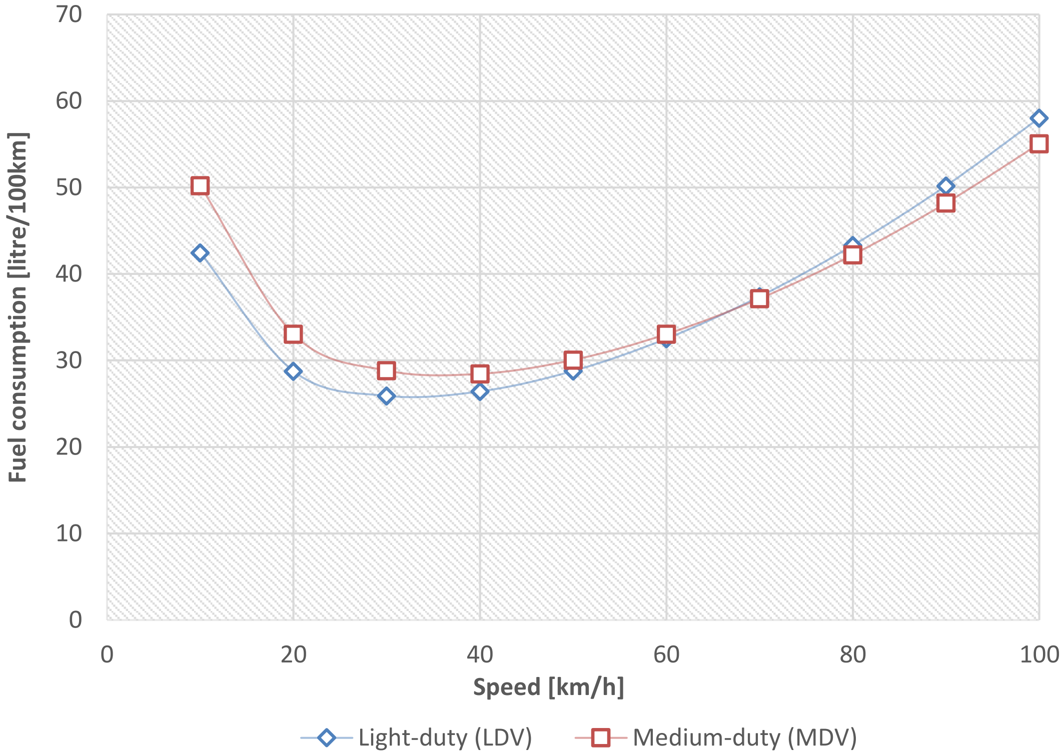


Figure 31 - Comparison between the fuel consumption of the light-duty vehicle and medium-duty vehicles of Cheng et al. (2017), given the same payload equal to 2500 km.

With respect to the comparison between the LDV and MDV fuel consumption curves employed by Cheng et al., it is possible to deduce that the two curves intersect each other in the neighbourhood of 65 km/h. Given those parameters, the intersection happens a lower speed with the increment of the payload, but they still intersect each other. It means that above a certain threshold, in this specific case represented by the 65 km/h value, given the same value of payload, the fuel consumption of a light-duty vehicle results to be higher than the medium-duty one. This implies that the analysis of the problem setting a vehicle speed equal to 80 km/h would always lead the model to neglect the light-duty vehicles, preferring the medium-vehicles that have more payload capacity and less fuel consumption. The choice of employing the fleet used by Cheng et al. would not be significant, since the light-duty vehicles would be excluded a priori.

For this reason, it is now taken into account the set of parameters of the heterogeneous fleet of vehicles employed by Koc et al. (2014). The values are reported in **Table 9** following again the mathematical notation of the reference paper by Soysal et al. (2016).

Vehicle parameters	**Notation**	**LDV**	**MDV**	**HDV**	**Unit of measure**
Vehicle common parameters					
Fuel-to-air mass ratio	$\boldsymbol{\xi}$	1	1	1	-
Gravitational constant	$\boldsymbol{g}$	9.81	9.81	9.81	[m/s²]
Air density	$\boldsymbol{\rho}$	1.2041	1.2041	1.2041	[kg/m³]
Coefficient of rolling resistance	$\boldsymbol{C_r}$	0.01	0.01	0.01	-
Efficiency parameter for diesel engines	$\boldsymbol{\varpi}$	0.45	0.45	0.45	-
Heating value of a typical diesel fuel	$\boldsymbol{\kappa}$	44	44	44	[kJ/g]
Conversion factor	$\boldsymbol{\psi}$	737	737	737	[g/l]
Road angle	$\boldsymbol{\phi}$	0	0	0	-
Vehicle specific parameters					
Curb-weight	$\boldsymbol{\mu^k}$	3500	5500	14000	[kg]
Maximum payload (Capacity)	$\boldsymbol{c^k}$	4000	12500	26000	[kg]
Engine friction factor	$\boldsymbol{k_e^k}$	0.25	0.20	0.15	[kJ/rev/l]
Engine speed	$\boldsymbol{N_e^k}$	38.3	36.7	30.0	[rev/s]
Engine displacement	$\boldsymbol{V_e^k}$	4.50	6.90	10.50	[l]
Coefficient of aerodynamic drag	$\boldsymbol{C_d^k}$	0.6	0.7	0.9	-
Frontal surface area	$\boldsymbol{A^k}$	7.0	8.0	10.0	[m²]
Vehicle drive train efficiency	$\boldsymbol{\varepsilon^k}$	0.45	0.45	0.45	-

Table 9 - Vehicle parameters of Koc et al. (2014).

Again, given these values, it is possible to plot the fuel consumption of the light-duty, medium-duty and heavy-duty vehicles with respect to the speed of the vehicle (**Figure 32**).

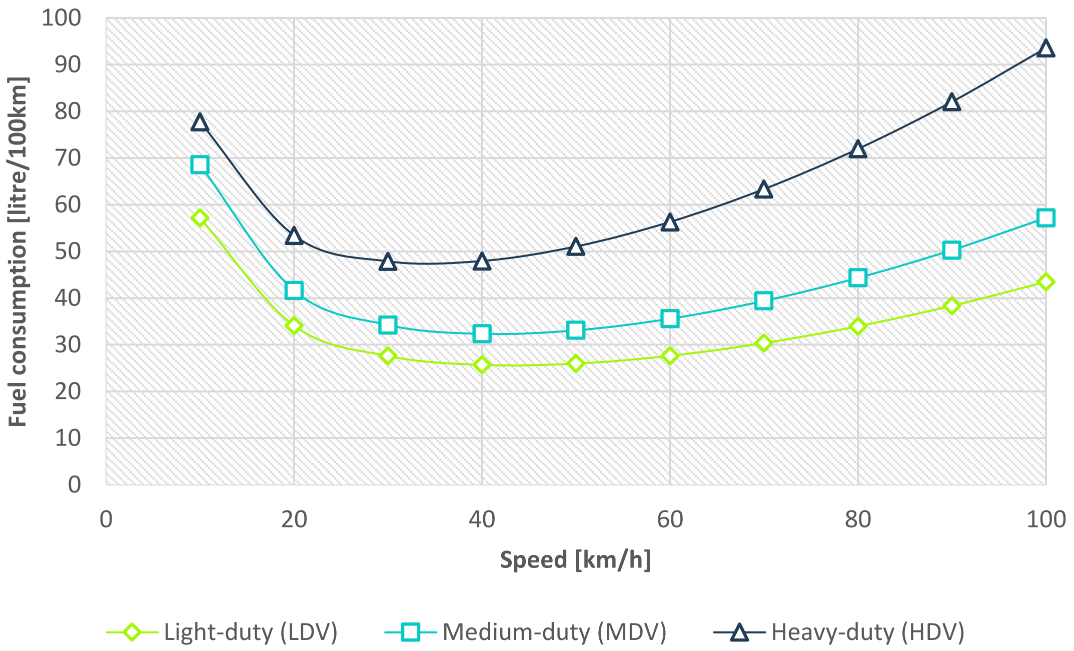


Figure 32 - Fuel consumption in litre/100 km of the heavy-duty, medium-duty and light-duty vehicles used by Koc et al. (2014), with a payload of 2500 kg.

The fleet of Koc et al. (2014) presents an issue concerning the heavy-duty vehicle: the increasing in fuel consumption when shifting from the medium-duty vehicle to the heavy-duty vehicle is twice higher than the shift from the light-duty vehicle to the medium-duty vehicle (62.31% against 30.51% increment calculated with the same payload equal to 2500 kg). This disproportion makes the choice of the heavy-duty vehicle more difficult, since the fuel consumption cost and the related carbon emissions would be considerably higher. In particular, given this configuration, the sum of the fuel consumptions of a light-duty vehicle and a medium-duty vehicle almost equal the fuel consumption of a single heavy-duty vehicle. In this situation, the model could prefer to deliver the same quantity of products using two vehicles rather than one single vehicle. In theory, it always should be better, from an economic and environmental point of view, to use the least number of vehicles. The following figure highlights more clearly the issues in the light-duty and medium-duty vehicles of Cheng et al. (2017) and that in the heavy-duty of Koc et al. (2014), showing the ratio between the capacity and the fuel consumption of each vehicle **Figure 33**.

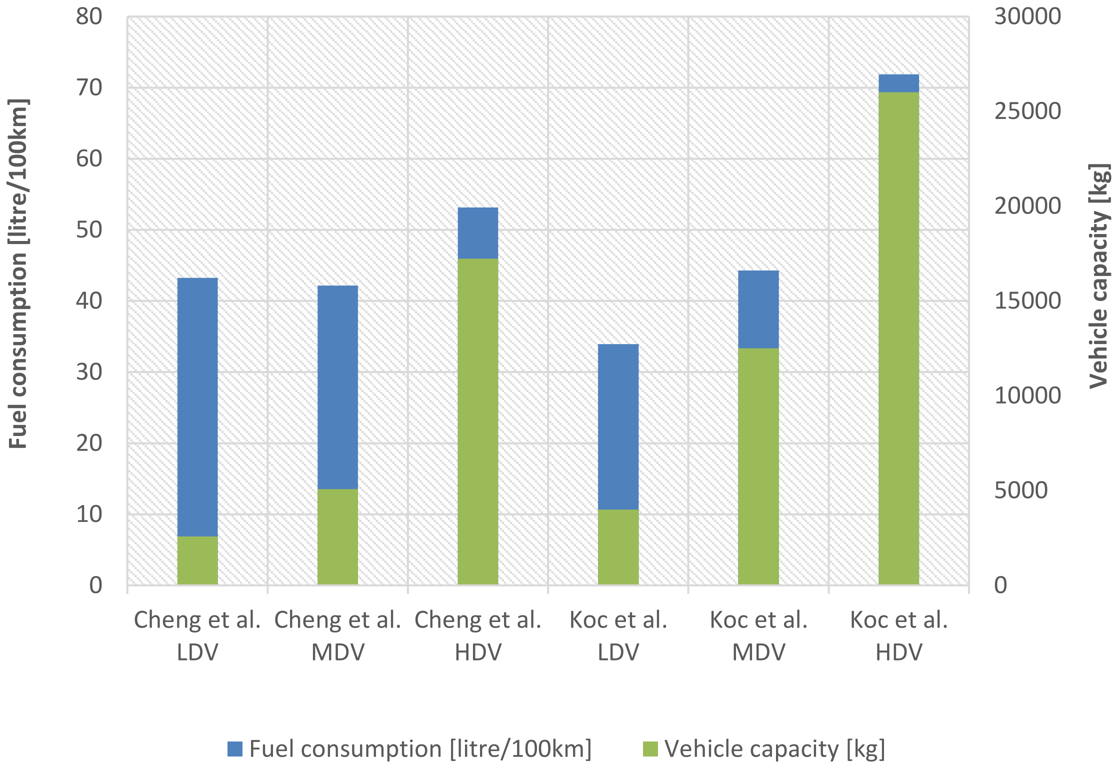


Figure 33 - Comparison between the fuel consumption and the vehicle capacity of the heterogeneous fleet used by Cheng et al. (2017) and that used by Koc et al. (2014).

For all the above cited reasons, the heterogeneous of vehicles used in this thesis will be a mix between the fleets employed by a Cheng et al. (2017) and Koc et al. (2014). In particular it will be employed the heavy-duty vehicle of Cheng et al. (2017) and the medium-duty and light-duty vehicles of Koc et al. (2014). This choice of vehicles is characterised by a proportional increment in fuel consumption when shifting to a higher capacity vehicle, and allows to better highlight the trade-offs implied in the routing and delivery decisions of the environmentally-extended inventory routing problem. The following table shows the resulting choice of the vehicle parameters. From now on, the vehicles will be only denoted by the notation LDV, MDV and HDV, without the reference to the related paper.

In **Table 10** are reported the vehicle parameters for the heterogeneous fleet of vehicles employed in this thesis.

Vehicle parameters	**Notation**	**LDV**	**MDV**	**HDV**	**Unit of measure**
Vehicle common parameters					
Fuel-to-air mass ratio	$\boldsymbol{\xi}$	1	1	1	-
Gravitational constant	$\boldsymbol{g}$	9.81	9.81	9.81	[m/s²]
Air density	$\boldsymbol{\rho}$	1.2041	1.2041	1.2041	[kg/m³]
Coefficient of rolling resistance	$\boldsymbol{C_r}$	0.01	0.01	0.01	-
Efficiency parameter for diesel engines	$\boldsymbol{\varpi}$	0.45	0.45	0.45	-
Heating value of a typical diesel fuel	$\boldsymbol{\kappa}$	44	44	44	[kJ/g]
Vehicle speed	$\boldsymbol{f}$	22.2	22.2	22.2	[m/s]
Conversion factor	$\boldsymbol{\psi}$	737	737	737	[g/l]
Road angle	$\boldsymbol{\phi}$	0	0	0	-
Vehicle specific parameters					
Curb-weight	$\boldsymbol{\mu^k}$	3500	5500	13154	[kg]
Maximum payload (Capacity)	$\boldsymbol{c^k}$	4000	12500	17236	[kg]
Engine friction factor	$\boldsymbol{k_e^k}$	0.25	0.20	0.15	[kJ/rev/l]
Engine speed	$\boldsymbol{N_e^k}$	38.3	36.7	30.2	[rev/s]
Engine displacement	$\boldsymbol{V_e^k}$	4.50	6.90	6.66	[l]
Coefficient of aerodynamic drag	$\boldsymbol{C_d^k}$	0.6	0.7	0.7	-
Frontal surface area	$\boldsymbol{A^k}$	7.0	8.0	9.8	[m²]
Vehicle drive train efficiency	$\boldsymbol{\varepsilon^k}$	0.45	0.45	0.50	-

Table 10 - Vehicle parameters of the heterogeneous fleet employed in this thesis

The resulting curves of fuel consumption with respect to the vehicle's speed are shown in **Figure 34**.

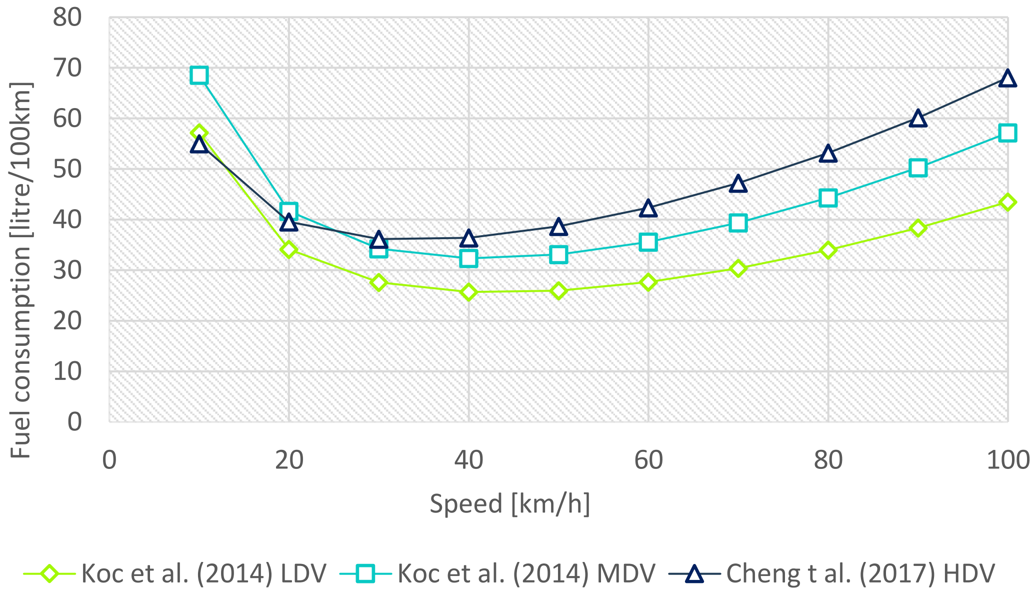


Figure 34 - Fuel consumption in litre/100 km of the heavy-duty, medium-duty and light-duty vehicle of the heterogeneous fleet used in this thesis, with a payload of 2500 kg.

5.1.2. Parameters of the distribution network

The parameters of the distribution network, presented in the model formulation section and reported in **Table 4,** are based on the reference paper by Soysal et al. (2016). The customer's demand for each period is based on the single-product instance of the reference paper. Since the reference paper consider a single-vehicle instance, in the proposed application the reference values of the demand have been doubled in order to address a multi-vehicles case. The expected values of demand are reported in **Table 11**.

	Customers Demand [kg]					
	Weeks					
Customer	**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 11 - Data of expected customers demand per each period

As shown in the linearization of the chance-constrained programming problem, the standard deviation of the stochastic value of the demand is computed based on a coefficient of variation C_p, set equal to 0.1. The customer service level α, corresponding to the probability that customers do not run out of stock, is set equal to 0.95. The distribution network, composed by one supplier, the vehicles depot and five geographically distributed customers, is described by **Table 12** which reports the distances between each node 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 12 - Distances between the nodes of the network

The planning horizon of the problem is set equal to 6 periods, and each time period corresponds to one week. Customers incur in a holding cost equal to 0.12€/kg-week, which correspond to 10% of the selling price of the product. In the reference paper the authors address the distribution of two kind of fruits, namely figs and cherries. This thesis adopts the numerical data referring to the figs product type, but without specifically tackling a perishable type of product. As assumed, the date of expiration of the products are set higher than the planning horizon of the problem, so no considerations on waste and spoiled products are addressed in these analyses. For each period of the planning horizon, the availability of products at the supplier is assumed to be enough to satisfy the related determined deliveries. The drivers of the vehicles are paid hourly, and the wage is set equal to 10.8€/h, corresponding to 0.003 €/s. The fuel price per litre is set equal to 1.7€/litre. Lastly, the conversion factor u, needed to convert the litres of fuel consumed in kilograms of emitted CO_2, is set equal to 2.63kg/litre. This value is provided by the Department for Environment, Food and Rural Affairs of the UK Government, which developed a guideline to greenhouse gases conversion factors for company reporting (Defra, 2007).

5.2. Description of the analysed cases

Based on the chance-constrained programming model presented in the related section, it is first proposed the analysis of the base case, denoted by Z_{BC}, where no carbon control policy is applied, and the solution is given by the minimisation of the overall total cost composed by the inventory holding cost and the routing cost.

Then, it is analysed the results of the emissions-minimising model Z_{env}, where the objective function does not address any considerations on cost, but aims solely on finding the maximum emissions reduction achievable. Successively, the results of the constant emissions model Z_{const} are analysed, quantifying the differences in the routing cost and total emissions between the constant and the comprehensive emissions models.

The distribution problem analysed in the base case model is then analysed under the imposition of the four proposed policies. Based on the specific characteristics of the addressed policy, the objective function and/or the constraints of the base case model are properly modified, as shown in the carbon control policies section of the thesis. For each policy, it is performed a sensitivity analysis on the characterising parameter of that specific policy. In particular:

- The cap policy case is analysed progressively modifying the imposed cap, from 100% of allowed emissions with respect to the base case, to the maximum feasible level of allowed emissions, calculated from the emissions-minimising model, with a decrement progression of 5%.
- The carbon tax policy case is analysed progressively modifying the imposed carbon tax. The analysed range goes from a null value of carbon tax (equal to the base case), to a 500€/tonCO_2e carbon tax, proceeding with a 50€/tonCO_2e increment.
- The cap-and-trade policy, which is characterised both from the value of the imposed cap and the price of the emissions allowance, is analysed first keeping a constant value of cap and varying the allowance price and then varying the former and keeping constant the latter. The sensitivity analysis on the cap is performed from 110% of allowed emissions to 50% of allowed emissions. This is performed on two significant values of associated emissions allowance price, namely the actual price of allowances in the European Emissions Trading System, equal to 7€/tonCO_2 (www.eex.com, last accessed on: 3.11.2017), and the actual highest carbon price adopted worldwide, corresponding to the Sweden carbon tax equal to 137€/tonCO_2e (The World Bank, www.worldbank.org, last accessed on: 3.11.2017). The sensitivity analysis on the emissions allowance price, similarly to the carbon tax policy, is performed from a null value of allowance price to a price of 500€/tonCO_2e. The associated value of cap is first chosen equal to 100% of allowed emissions and then equal to 50%.
- The cap-and-offset policy, differently from the cap-and-trade policy which is characterised by high variance in the emissions credit price, is analysed varying the value of cap from 110% of allowed emissions to 50%, and keeping constant the price of emissions credit. The latter is set equal to 7.27€/tonCO_2e, corresponding to the highest price of certified emissions reductions, among the carbon offset projects on the Clean Development Mechanism online platform (UNFCCC, offset.climateneutralnow.org, last accessed on: 3.11.2017).

All the above proposed cases are first analysed using a completely heterogeneous fleet of vehicles composed by one light-duty vehicle, one medium-duty vehicle and one heavy-duty vehicle. The vehicle characteristics of this fleet are reported in **Table 10**. Then the same cases are analysed using a completely homogeneous fleet of vehicles composed by three identical medium-duty vehicles with the same characteristics of the medium-duty vehicle used in the heterogeneous fleet instances.

5.3. Solution method

The formulations of the proposed problems are developed and solved using the ILOG-OPL development studio and CPLEX 12.6 optimization package. For each problem it is reported the total number of constraints, continuous variables and binary variables. In addition, it is report the total time, in seconds, necessary to reach the optimal solution. The solutions are obtained on a personal computer with the following characteristics:

- Processor: Intel® Core™ i5-3210M, CPU 2.50 GHz.
- RAM: 4.0 Gigabyte.

6. Discussion and analysis of the results

6.1. Base case model

The base case model presents 2700 constraints, 1152 binary variables, 126 integer variables and 1339 continuous variables. The results are shown in **Table 13**. The first row indicates the time needed by the solver to find the optimal solution, expressed in seconds. The last three rows, concerning the mix of vehicles, are computed only for the heterogeneous fleet case and are referred to the entire planning horizon. The percentage differences between the heterogeneous and homogeneous fleet shown in the third column are calculated from the former.

	Heterogeneous fleet	**Homogeneous fleet**	**Difference [%]**
Computer time [s]	508	1392	-63.51%
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%
Emission [$kgCO_2e$]	7635.91	7753.90	-1.52%
Total cost [€]	8948.71	9159.39	-2.30%
Average saturation [%]	86.21%	62.06%	24.15%
Number of vehicles	10	10	0.00%
LDV	4	-	-
MDV	6	-	-
HDV	0	-	-

Table 13 - Comparison of results of base case models with heterogeneous and homogeneous fleet.

The comparison between the results of the base case model with heterogeneous fleet and the base case model with homogeneous fleet shows that the former is better than the latter, in both economic and environmental terms. The results of the heterogenous fleet case are characterised by more frequent deliveries, which drive up the drivers cost. This increment is offset by the decrement of quantity delivered per trip, which lowers the inventory holding cost. In addition, the flexibility of the heterogeneous fleet allows to choose smaller and lighter vehicles, which consume less fuel and produce less carbon emissions. On the contrary, in the homogeneous fleet case, the lower number of deliveries leads to lower drivers cost, but also to higher inventory holding cost because the same quantity of products is delivered in fewer trips. In particular, as shown by **Figure 49** in Annex A, in the homogeneous fleet case the customer C2 is not visited in the last period and the quantity of product to face the related expected demand is delivered in the previous period. **Table 20** and **Table 21** in Annex A, report the quantity delivered to each customer in each period and the related level of inventory at the end of each period. As shown, none of the customers face shortages in the planning horizon, since the inventory levels are always positive. The number of vehicles used in the two cases is the same, which means that the employment of solely medium-duty vehicles leads to higher fuel consumption and higher carbon emissions. Lastly, the heterogeneous fleet arrangement can better saturate the vehicles capacity. The results of the base cases are needed to compare the results obtained from the carbon control policies application. In the base case models in fact, no environmental concerns are tackled, and the operational decisions are taken based only on operational costs considerations.

6.2. Emissions-minimising model

The emissions-minimising model presents 2700 constraints, 1152 binary variables, 126 integer variables and 1339 continuous variables, as the base case model, since no constraints are added, and no decision variables are modified. The **Table 14** and **Table 15** shows the comparison between the results of the emissions-minimising model and the base case model. The third column of each table indicates the percentage difference for each indicator achieved by the emissions-minimising model with respect to the base case model. The last row shows the minimum value of cap that can be imposed on the model, given that specific fleet composition, calculated from the emissions reduction achieved.

	Heterogeneous fleet		
	Emissions-minimising model	**Base case model**	**Difference [%]**
Computer time [s]	90	508	-82.28%
Driving time [h]	37.03	84.63	-56.24%
Inventory cost [€]	16303.08	3098.95	426.08%
Driver cost [€]	399.97	914.00	-56.24%
Fuel cost [€]	2589.71	4935.76	-47.53%
Routing cost [€]	2989.68	5849.76	-48.89%
Emission [kgCO₂e]	4006.43	7635.91	-47.53%
Total cost [€]	19292.76	8948.71	115.59%
Average saturation %	96.89%	86.21%	10.68%
Number of vehicles	6	10	-40.00%
LDV	1	4	
MDV	2	6	
HDV	3	0	
Minimum feasible cap level [%]	52.47%		

Table 14 - Comparison between the results of the emissions-minimising model and the base case model with the heterogeneous fleet

Regarding the heterogeneous fleet case, the emissions-minimising objective function globally leads to a 47.53% reduction in the total emissions and to a 115.59% increment in the total costs. This exponential increment is exclusively driven by the increasing in the inventory holding cost. The model aims at minimising the number of trips and this leads to an exponential increment of the delivered quantity per trip, which causes a 426.08% increment in the inventory holding cost. The total cost increment due to the inventory holding increment is offset by a 56.24% reduction in the drivers cost and by a 47.53% reduction in the fuel cost, which leads to a 48.89% overall reduction in the routing cost. The efforts of the model in minimising the number of trips and maximising the delivered quantity per trip is also highlighted by the analysis of the vehicle-related indicators, namely the average saturation and the fleet composition. The emissions-minimising model tends to always select the heavy-duty vehicle, that is the vehicle with the highest capacity, and tends to achieve the highest feasible saturation of the fleet, aiming at the minimisation of the number of used vehicles, which pass from 10 to 6.
The achieved emissions reduction corresponds to the best routing and deliveries configuration able to meet the constraints of the model, mainly represented by the expected demand of customers and by the agreed customer service level. This latter

parameter is properly determined by the decision maker, who implicitly takes into account the shortage cost related to a 5% possibility of stock-out occurrence. Under these assumptions, the model is forced to deliver at least the 95% of the expected customers demand. The possibility of incurring in a shortage cost and not delivering the demanded product needs the setting of proper shortage costs. However, under those assumptions, the emissions-minimising model would have no sense since it results in no deliveries and the maximum achievable stock-out cost. From this point of view, the formulation adopted in this thesis is particularly suitable for the considerations on the maximum feasible emissions reduction achievable.

	Homogeneous fleet		
	Emissions-minimising model	**Base case model**	**Difference [%]**
Computer time [s]	30	1392	-97.84%
Driving time [h]	42.78	81.20	-47.32%
Inventory cost [€]	17054.04	3270.39	421.47%
Driver cost [€]	462.01	876.97	-47.32%
Fuel cost [€]	2749.24	5012.03	-45.15%
Routing cost [€]	3211.25	5889.00	-45.47%
Emission [kgCO_2e]	4253.23	7753.90	-45.15%
Total cost [€]	20265.29	9159.39	121.25%
Average saturation %	88.66%	62.06%	26.60%
Number of vehicles	7	10	-30.00%
Minimum feasible cap level [%]	54.85%		

Table 15 - Comparison between the results of the emissions-minimising model and the base case model with the homogeneous fleet

The results and the considerations for the homogeneous fleet case are similar to those of the heterogeneous case. It is interesting to show the difference between the results of the emissions-minimising models obtained with the heterogeneous fleet and the homogeneous fleet. The comparison is illustrated in **Figure 35**.

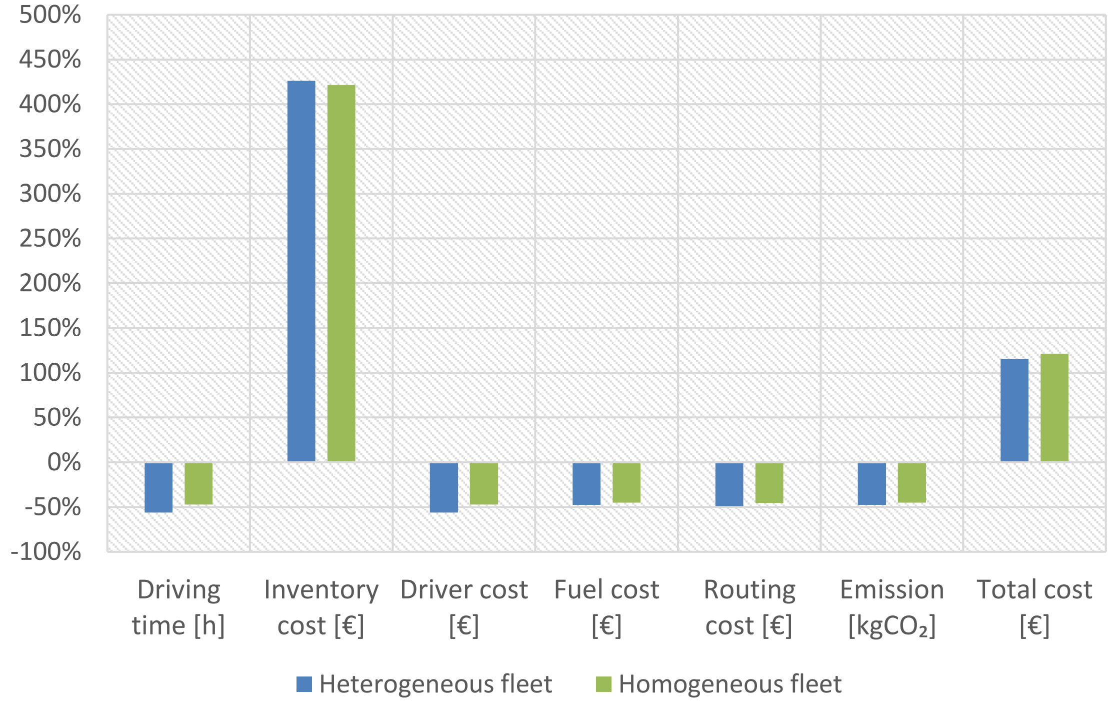


Figure 35 - Comparison of the emissions-minimising models, with a heterogeneous and homogeneous fleet of vehicles.

The comparison of the results of the emissions-minimising model, obtained with a heterogeneous fleet and a homogeneous fleet, presents similarities with the comparison of results of the base case models. The employment of the heterogeneous fleet in fact, leads to a higher emission reduction and to a lower total cost, with respect to the homogeneous fleet case. The analysis of the operational costs shows that the heterogeneous fleet case has higher inventory costs, but lower driver and fuel costs, that leads to a lower total cost. Concerning the further implementation of the cap policy, based on the maximum achieved emissions reductions, the minimum level of cap that can be imposed is equal to 52.47% for the heterogeneous fleet case and to 54.85% for the homogeneous fleet case. In Annex A, **Table 22** and **Table 23** report the values of the decision variables on deliveries and inventory levels, while **Figure 50** and **Figure 51** show the routing of the vehicles of the emissions-minimising model.

6.3. Constant emissions model

The constant emissions model, since it does not imply the introduction of any additional constraint or decision variable, has the same number of constraints of the base case model, namely 2700 constraints, 1152 binary variables, 126 integer variables and 1339 continuous variables. The first step of the analysis is the estimation of the parameter uc_k and ac_k, namely the unitary routing cost expressed in €/km, and the average fuel consumption expressed in km/litre. Since these parameters are dependent on the vehicle-type, three difference instances are considered. First it is run the base case model with only one light-duty vehicle. The data of demand is consequently adjusted to suit the capacity of the single-vehicle problem and thus finding feasible solutions. In particular, it is set equal to one-quarter of the base case demand. For the medium-duty and heavy-duty single-vehicle problems the demand is set equal to half of the base case demand. The results are computed in **Table 16**. The data of the base case demand are shown in **Table 11**.

	Driven distance [km]	Fuel consumption [litre]	Routing cost [€]	Unitary routing cost [€/km]	Average consumption [km/litre]
LDV	4472.37	1455.79	3078.61	**0.69**	**3.07**
MDV	4053.55	1852.26	3696.06	**0.91**	**2.19**
HDV	4053.55	2204.77	4295.35	**1.06**	**1.84**

Table 16 - Constant emissions model - Computation of the unitary routing cost and average fuel consumption per vehicle type

The unitary routing cost and average consumption parameters show that the heavy-duty vehicle is the most expensive in terms of routing cost and it shows the worst performances in terms of driven kilometres per litre. However, this analysis concerns a single-vehicle instance. In a problem characterised by environmental concerns and a multi-vehicles fleet, the emissions are reduced by minimising the number of trips, thus choosing a higher capacity vehicle, able to deliver the same quantity of product in a reduced number of trips. In fact, given the same quantity to deliver and the vehicle parameters of the addressed fleet of vehicles, it is environmentally and economically better to use one heavier vehicle, rather than two smaller ones.
The second step of the analysis consist in running the constant emissions models with the parameters previously computed. The constant emissions model is first run with the heterogenous fleet composed by three different vehicles (light-duty, medium-duty and heavy-duty vehicle), and then with the homogeneous fleet composed by three identical vehicles (medium-duty vehicles). For each case, three data sets of demand are considered:

- **Case 1**: demand equal to 50% of the base case demand (and corresponding to the data of the demand used for the estimation of the unitary routing cost and average consumption parameters of the medium-duty and heavy-duty vehicles).

- **Case 2**: demand equal to the base case demand (corresponding to two times the demand used for the estimation of the unitary routing cost and average consumption parameters of the medium-duty and heavy-duty vehicles).

- **Case 3**: demand equal to 150% of the base case demand (corresponding to three times the demand used for the estimation of the unitary routing cost and average consumption parameters of the medium-duty and heavy-duty vehicles).

The results for the heterogeneous fleet case are computed in **Table 17**. The percentage errors are computed with respect to the results of the comprehensive emissions model used in the base case formulations.

Heterogeneous fleet

Demand instance	Routing cost	Carbon emissions	Approximate routing cost	Approximate emissions	Error on routing cost	Error on emissions
[%]	**[€]**	**[kgCO2e]**	**[€]**	**[kgCO2e]**	**[%]**	**[%]**
Case 1	3548.30	4598.50	3516.00	4551.40	**-0.91%**	**-1.02%**
Case 2	5864.92	7659.37	5717.40	7432.55	**-2.52%**	**-2.96%**
Case 3	7205.89	9709.44	6690.36	8924.82	**-7.15%**	**-8.08%**

Table 17 - Comparison between the results of the base case model and the constant emissions model for the heterogeneous fleet case.

The 50% demand reduction case corresponds to the demand values used to estimate the unit routing cost and average consumption parameters and therefore the error in the estimation of routing cost and emissions is relatively small. The results show that a constant emissions approach can be suitable for static demand contexts, where the operational data of expected demand corresponds to those used to estimate the parameters. In contexts where the demand is subjected to high variation, the constant emissions model would not provide accurate estimation and leads to underestimation of the routing cost and carbon emissions. In particular, concerning **Case 3**, characterised by a high variation of the initial demand used for the parameters estimation (three times the initial demand), the error on routing cost is equal to 515.36€ (-7.15%) and the error on the estimated emissions is equal to 784.62 kgCO_2e (-8.08%). Similar considerations can be done considering the homogeneous fleet case (**Table 18**).

Homogeneous fleet						
Demand	**Routing cost**	**Carbon emissions**	**Approximate routing cost**	**Approximate emissions**	**Error on routing cost**	**Error on emissions**
[-]	**[€]**	**[kgCO2e]**	**[€]**	**[kgCO2e]**	**[%]**	**[%]**
Case 1	3696.06	4871.43	3685.05	4863.10	**-0.30%**	**-0.17%**
Case 2	5917.27	7799.00	5626.90	7425.70	**-4.91%**	**-4.79%**
Case 3	6718.72	8879.04	6192.73	8162.05	**-7.83%**	**-8.08%**

Table 18 - Comparison between the results of the base case model and the constant emissions model for the homogeneous fleet case.

The main difference in estimating the fuel consumption with the constant emissions model is that it does not take into account the decision variable $F_{i,j,p,k,t}$ related to the payload of the vehicles. In this way, the variation of delivered quantity due to the variation of demand would lead to a different payload which in turn implies different fuel consumption and thus different carbon emissions. Therefore, the comprehensive emissions model is particularly suitable for those contexts where it is needed a precise estimation of the emissions due to the distribution activities, for example in business environment characterised by carbon control policies which directly affect the economic result of a company.

6.4. Cap policy

The cap policy model has 2701 constraints, 1152 binary variables, 126 integer variables and 1339 continuous variables, thus one more constraint with respect to the base case model, represented by the constraint on the maximum amount of emissions allowed. In Annex B, **Table 24** and **Table 25** report the results for the cap policy model respectively with a heterogeneous fleet and a homogeneous fleet of vehicles. The operational cost, given by the sum the inventory holding and routing costs, are highlighted in order to express the percentage operational cost increment due to the policy introduction. This increment is caused by the rearrangement of the routing and deliveries configuration, which does not correspond to the optimal operational cost-minimising configuration of the base case. In addition, it is highlighted the achieved emissions reduction, which does not necessarily match the imposed emissions reduction. In particular, since the emissions reduction caused by the rearrangement of the routing and deliveries does not follow a perfect linear pattern, for each decrement of the cap, the real achieved emissions reduction would be slightly higher than or equal to the imposed reduction. The comparison between the total cost and emissions obtained with a heterogeneous and a homogeneous fleet are illustrated in **Figure 36**. Given the results of the emissions-minimising model, the imposed emissions reduction is calculated from 100% to 55% of allowed carbon emissions, with respect to the base case models.

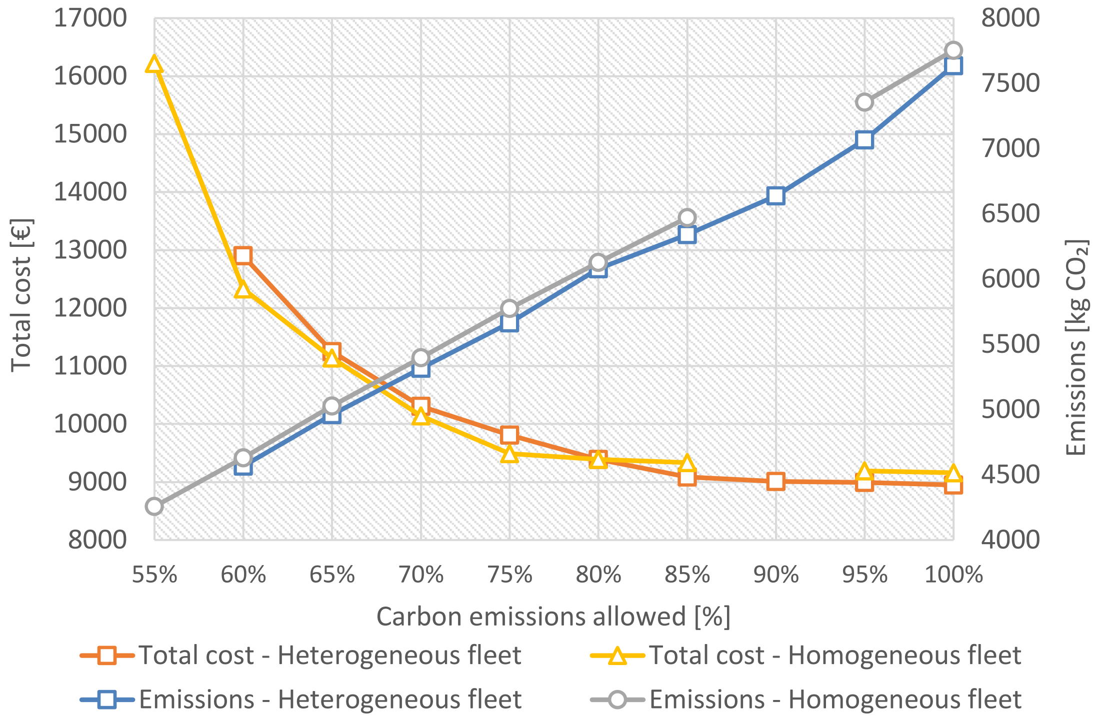


Figure 36 - Comparison of the total cost and emissions between a heterogeneous fleet and a homogeneous fleet model with cap policy

The missing points on the graph (homogeneous fleet case with cap equal to 90%, and heterogeneous fleet case with cap equal to 55%), correspond to those instances for which the CPLEX optimization solver cannot find an optimal solution. The trend of the results of the heterogeneous fleet and homogeneous fleet cases are very similar. In particular, the emissions curves show a decreasing linear pattern, following the linear tightening of the cap, while the total cost curves show an exponential increase, as the value of the cap becomes lower. Concerning the heterogeneous fleet case, it is worthy to notice that during the initial tightening of the cap (from 100% to 85% of allowed emissions with respect to the base case), the model cannot find an optimal solution matching exactly the imposed emissions reduction, and therefore is forced to find optimal solutions corresponding to a higher emissions reduction (+2.45% with the 95% cap, +3.07% with the 90% cap, +1.97% with the 85% cap). In addition, the comparison between the two fleet cases shows that, from an economic perspective, the heterogeneous fleet case is not always the best fleet configuration. In fact, starting from the 80% value of emissions allowed and further tightening the cap, the homogeneous fleet case is characterised by lower total costs results. As shown by **Figure 37**, the increasing in the total cost due to the introduction of the cap policy, is driven only by the inventory holding cost, while the decrement in the driver and fuel costs, leads to the overall decrement of the routing cost. However, the inventory holding cost follows an exponential increasing pattern, while the routing cost reduction is almost linear, which leads to the overall increasing in the total cost.

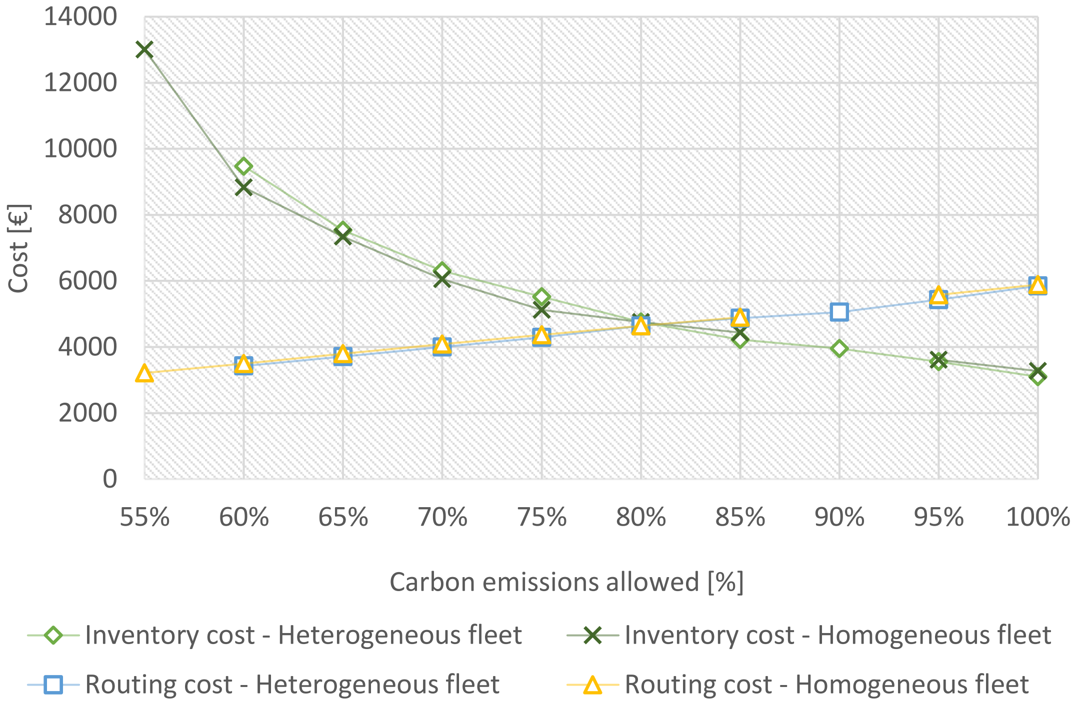


Figure 37 - Inventory and routing costs for cap policy model with a heterogeneous and homogeneous fleet of vehicles

As shown from the insights on the results of the emissions-minimising model, the emissions reduction is achieved modifying the routing and deliveries initial configuration, and in particular, reducing the number of trips and increasing the quantity delivered per trip. Concerning the cap policy results, both the analysed models reduce the number of used vehicles across the planning horizon. In the heterogeneous fleet case, the number of employed vehicles passes from 10 to 6, while in the homogeneous fleet case it passes from 10 to 7. With regards of the homogeneous fleet case, this reduction in the number of used vehicles corresponds to a higher average saturation of the entire fleet, while in the heterogeneous fleet case, as shown by **Figure 38**, the change of vehicle types leads to an almost constant value of average saturation. This because the flexibility provided by the heterogeneous fleet can better achieve higher vehicles saturation, by replacing the light-duty vehicles with the heavy-duty vehicles.

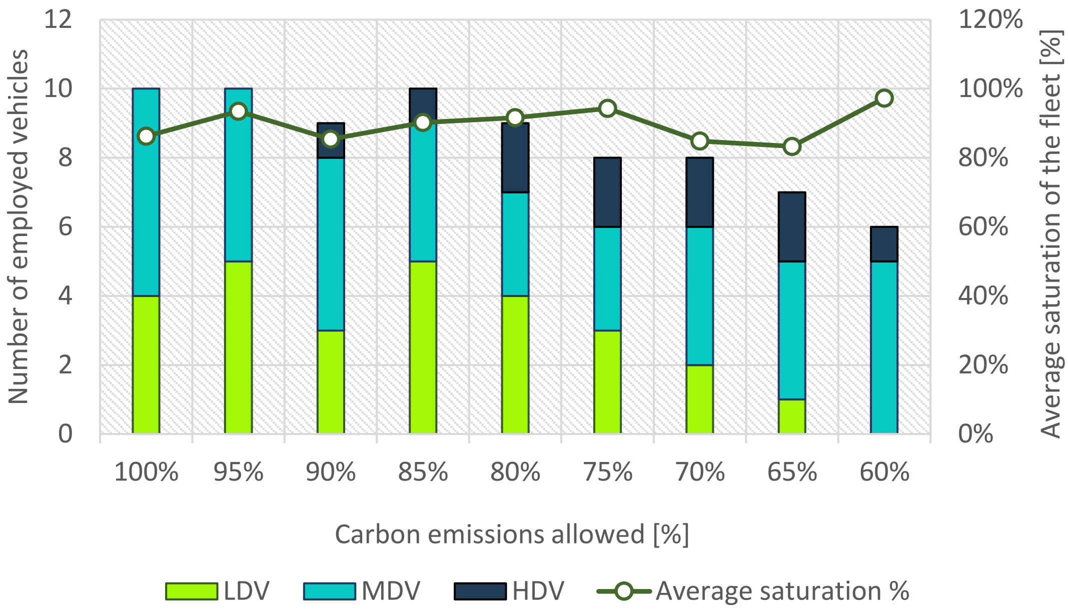


Figure 38 - Number of employed vehicles and average saturation of the fleet, considering the cap policy model with a heterogeneous fleet of vehicles.

With regard of the observations proposed by Benjafaar et al. (2013) and reported in the related section of this thesis, the results of the cap policy model analysed here fully confirm the **Observation 1** concerning the economic implications of the imposed emissions reduction. In particular, as shown in **Figure 36**, it is possible to achieve a great emissions reduction without significant impacts on the economic result of the problem. Considering the heterogeneous fleet case, it is possible to achieve a 16.97% carbon emissions reduction, with only a 1.56% of operational costs increment, while for the homogeneous fleet case, a 16.54% reduction in emissions corresponds to a 1.92% increment in the costs. This because, in the early tightening of the cap, the total cost increment caused by the increasing inventory holding cost is offset by the reduction in the routing cost (driver cost plus fuel cost), caused by the reduced number of driven kilometres. These results show that: (i) a purely cost-minimising approach, represented by the base case models, can hide possible environmental-friendly solutions that can be achieved with almost null cost increments, (ii) when the cap is relatively high (values higher than 80%), the cap policy models have a wide range of possibilities to rearrange the routing and deliveries initial configuration to achieve the imposed target without negatively affecting the economic result.

Lastly, it is worthy to compare the economic and environmental results obtained with the lowest feasible value of cap, equal to 55% of the initial carbon emissions, and the same results obtained with the emissions-minimising model. Since it was not possible to find an optimal solution for the heterogeneous case with a 55% cap value, the comparison address only the homogeneous case. In particular the latter achieves a

45.10% emissions reduction with a 77.10% total cost increment. The emissions-minimising model with the homogeneous fleet shows a total cost equal to 20265.29€ and carbon emissions equal to 4253.23 kg/CO_2e, corresponding to a 121.25% total cost increment and a 45.15% emissions reduction. This result indicates that, similarly to the purely cost-minimising approach, a purely emissions-minimising model would hide possible cost-effective solutions able to achieve exactly the same emissions reduction.

6.5. Carbon tax policy

The carbon tax policy model, since it does not imply the introduction of any additional constraint or decision variable, has the same number of constraints of the base case model, namely 2700 constraints, 1152 binary variables, 126 integer variables and 1339 continuous variables. In Annex B, **Table 26** and **Table 27** report the results for the carbon tax policy models respectively with a heterogeneous fleet and a homogeneous fleet of vehicles. Differently from the cap policy results, the table of results of the tax policy, in addition to the emissions reduction and the operational cost increment indicators, report also the emissions cost, constituted by the tax on emissions paid by the company. In this way, it is highlighted the new cost component, that together with the operational costs constitutes the total cost of the problem. The range of sensitivity analysis on the carbon price goes from a null value to 500€ per one emitted tonne of CO_2e. The null value of carbon price and the 100% value of imposed cap have similar meanings. They both imply no modifications in the routing and deliveries initial configuration, and the results are the same of the base case models. Concerning the choice of analysing the range of carbon prices up to the value of 500€/tonCO_2e, it is worthy to consider the price of the actual implemented carbon tax policies. With regard of the government-based policies, the highest carbon price among the actual policies is that of Sweden, equal to 137€/tonCO_2e (The World Bank, www.worldbank.org, last accessed on: 3.11.2017), while concerning the corporate-based policies, among the European companies, the highest carbon price is that adopted by the Pennon Group, equal to 291.65$/ton$CO_2$e (Carbon Disclosure Project, 2016). Besides these values, the estimation of the social cost of carbon presented in the related section provides other values, and in particular the "Handbook on external costs of transport" by Korzhenevych et al. (2014), sets the upper bound of its cost range equal to 168€/tonCO_2, specifically addressing the climate change-related external costs of transport. Given these assumptions, the choice of analysing a wider range reflects the higher uncertainty that characterises the future evolution of carbon price, and the will of provide insights also on pessimistic evolution of the environmental concerns.

The analysis of the computational time needed to find the optimal solution shows that the carbon tax model is able to find the optimal solution faster than the cap model. This because no additional restrictive constraints are introduced in the model, which has only to face the cost increment due to the carbon tax. The comparison between the total cost and emissions obtained with a heterogeneous and a homogeneous fleet is illustrated in **Figure 39**.

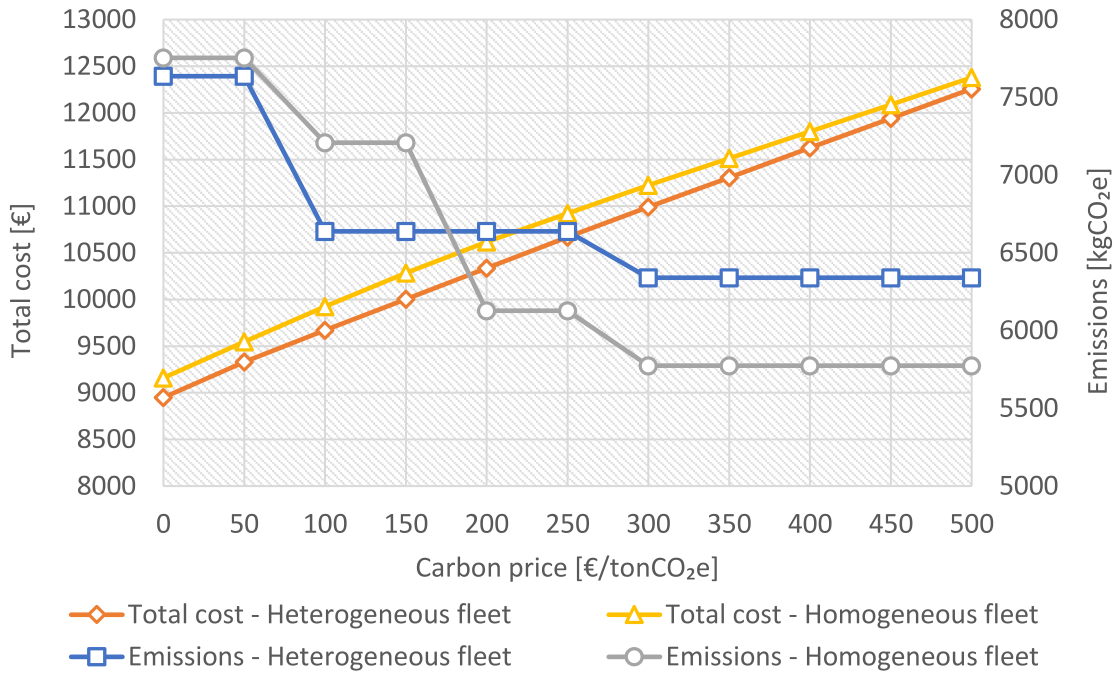


Figure 39 - Comparison of the total cost and emissions between a heterogeneous fleet and a homogeneous fleet model with cap policy

The graph shows a linear increment of total costs, while the emissions curve presents a decreasing staircase pattern, with respect to the increment of carbon price. From a qualitative point of view the heterogeneous and homogeneous fleet cases shows similar results. However, in terms of cost the heterogeneous fleet solution completely dominate the homogeneous fleet one, while concerning the emissions reduction, after a certain value of carbon price (corresponding to a value comprises between 150€/tonCO_2e and 200€/tonCO_2e), the homogeneous fleet case is able to achieve a higher emissions reduction. The staircase pattern that characterise the emissions curve leads to an important insight on the carbon tax policy. For certain ranges of carbon price, the model does not modify the routing and deliveries configuration, and continues to emit the same amount of carbon emissions. In fact, given a certain value of the carbon tax, it is more economically-convenient to pay the emissions cost corresponding to the initial routing and deliveries configuration, rather than modify the latter in order to achieve a lower value of emissions and thus pay less taxes. This because the operational extra cost needed to rearrange the routing and deliveries configuration, and thus achieve an emissions reduction, is higher than the taxes corresponding to the same amount of emissions. For this reason, the increment of the operational cost follows a staircase pattern, and each step corresponds to a different routing and deliveries configuration, while the emissions cost follows the linear increasing trend of the sensitivity analysis. Globally, they lead to an almost linear increase of total cost. This result provides an important insight for policymakers: the economic burden of a carbon tax will be unevenly supported by different companies, based on the flexibility of rearranging an initial business configuration. With respect to case analysed in this thesis for example, a carbon tax higher than 300€/tonCO_2e will not provide any further environmental improvements in terms of emissions reduction, while only contribute to increase the total cost. The **Figure 40** illustrates the evolution pattern of the inventory holding and routing cost with respect to the increasing value of carbon price.

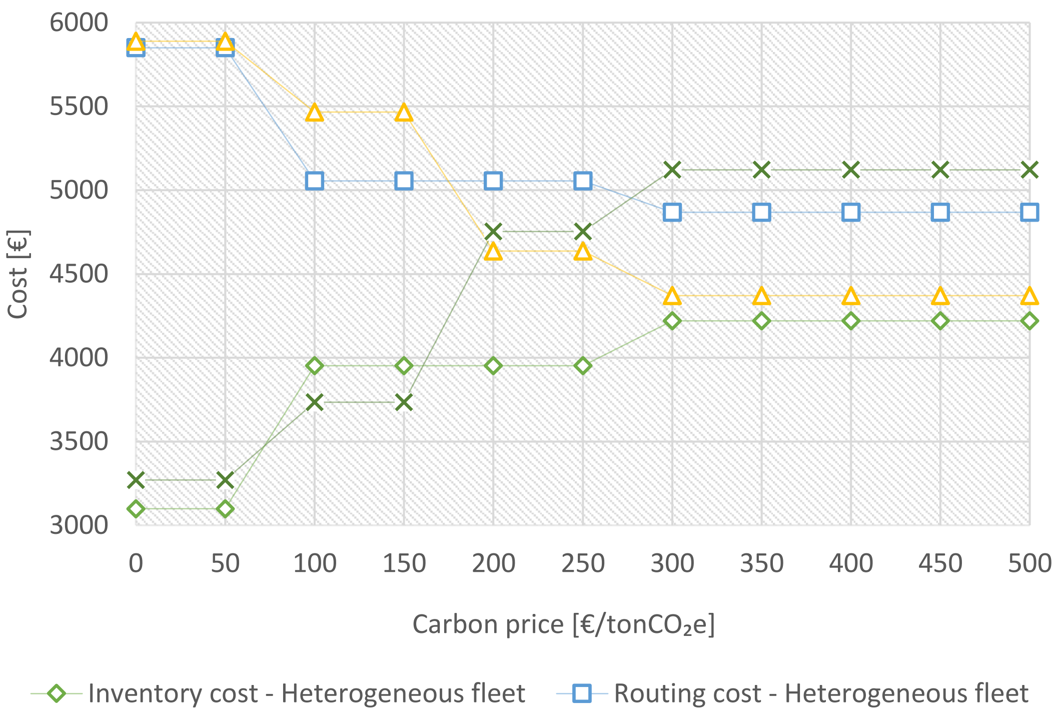


Figure 40 - Inventory and routing costs for cap policy model with a heterogeneous and homogeneous fleet of vehicles

In particular, it shows that the increment of inventory holding cost is almost totally offset by the reduction of routing cost, which leads to a small increment of the operational cost, as reported in **Table 26** and **Table 27**. Linking the operational cost increment with the achieved emissions reduction, it is possible to compare the results of the carbon tax policy with those obtained with the cap policy. Considering the heterogeneous case, a carbon tax equal to 150€/tonCO_2e leads to a 13.07% emissions reduction and a to a 0.66% increment of operational cost. Since the routing and deliveries configuration is the same as the cap policy with a 90% cap, the results are the same. 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 a 11.78% increment in the total cost. Doubling the carbon tax price, from 150€/tonCO_2e to 300€/tonCO_2e, the emissions reduction is slightly improved, from a 13.07% to a 16.97% reduction, but the total cost is doubled from a 11.78% to a 22.82% increment. This aspect is shown in **Figure 41**, which represents the total cost variation with respect to the achieved emissions reduction, for the cap policy and the carbon tax policy.

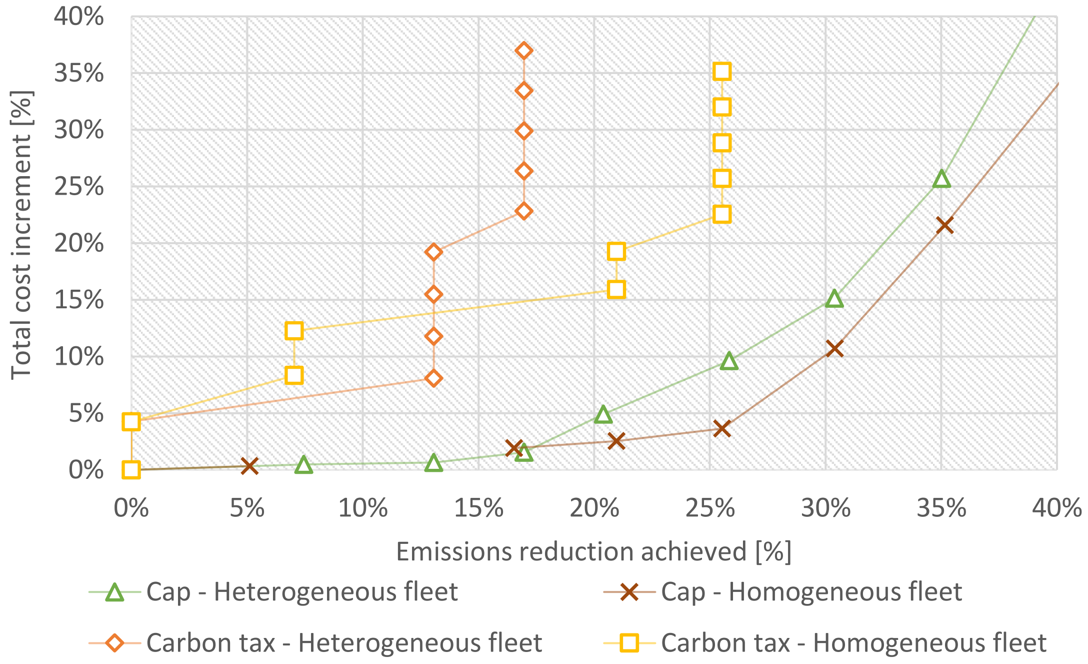


Figure 41 - Comparison between cap policy and carbon tax policy, total cost variation and emissions reduction achieved

The last considerations about the results of the carbon tax policy concerns the contextualisation of the obtained results with the actually implemented policies reported in the policies description section. As shown by **Figure 19**, most of the government-based carbon tax policy adopt carbon prices lower than 50€/tonCO_2e. As shown by the obtained results, these values would not provide any modification in the routing and deliveries configuration, and thus any emissions reduction. With regard of the corporate-based carbon pricing policies, represented in **Figure 26**, the majority of the companies adopt carbon prices lower than 50€/tonCO_2e, that lead to similar considerations. In this sense, the chosen carbon price is not high enough to be perceived as an incentive to move towards lower carbon emissions configuration, thus resulting only as an additional economic burden for the company. Differently, a carbon tax equal to that adopted by Sweden (equal to 137€/tonCO_2e, source: The World Bank, www.worldbank.org, last accessed on: 3.11.2017), given the characteristics of this inventory routing problem, would be effective in providing an emissions reduction (equal to 13.07% for the heterogeneous case and to 7.04% for the homogeneous case).

6.6. Cap-and-trade policy

The cap-and-trade model has 2701 constraints, 1152 binary variables, 126 integer variables and 1341 continuous variables, since it introduced one additional constraint on the maximum allowed level of emissions and two additional decision variables on the number of traded emissions allowances. In Annex B, **Table 28** and **Table 29** report the results for the cap-and-trade policy models respectively with a heterogeneous fleet and a homogeneous fleet of vehicles, analysing the variation of the imposed cap and assuming a price of the emissions allowance equal to 7€/tonCO_2e (actual price of emissions credit in the European Emissions Trading System, source: www.eex.com, last accessed on 3.11.2017). **Table 30** and **Table 31** report the results of the same sensitivity analysis on the cap value, but assuming a price of the emissions allowance equal to 137€/tonCO_2e (Sweden carbon tax, source: The World Bank, www.worldbank.org, last accessed on: 3.11.2017). As shown by the analysis on the actual implemented cap-and-trade systems represented in **Figure 21**, in the majority of the cases the emissions allowance price is lower than 15 $/ton$CO_2$e, but as shown by the price variation of the allowances in the EU ETS represented in **Figure 14**, these prices are highly variable. This aspect is analysed adopting as emissions allowance price the value of the Sweden carbon tax that, from a monetary point of view, represents the highest environmental concern among the actual policies implementation.

Since the cap-and-trade allows the company to sell surplus emissions allowances, the sensitivity analysis on the cap is performed on a wider range, starting from the 110% of emissions allowed with respect to the base case emissions, in order to highlight this particular aspect of the cap-and-trade policy. Besides the previously introduced policy-related indicators (operational cost increment, emissions reduction, emissions cost), the tables of results report the amount of emissions allowances (or emissions credits) bought and sold, expressed in kgCO_2e, and the related costs or revenues due to the trading of these allowances. In particular, the emissions cost corresponds to the monetary value of the emissions allowances that the company has to buy to meet the imposed cap, while the emissions revenues correspond to the sale of the emissions allowance in surplus. The effects of the cap-and-trade policy on the base case models with a heterogeneous and a homogeneous fleet of vehicles, in terms of total cost and emissions, are represented in **Figure 42** and **Figure 43**, respectively for the 7€/tonCO_2e and the 137€/tonCO_2e emissions allowance price case.

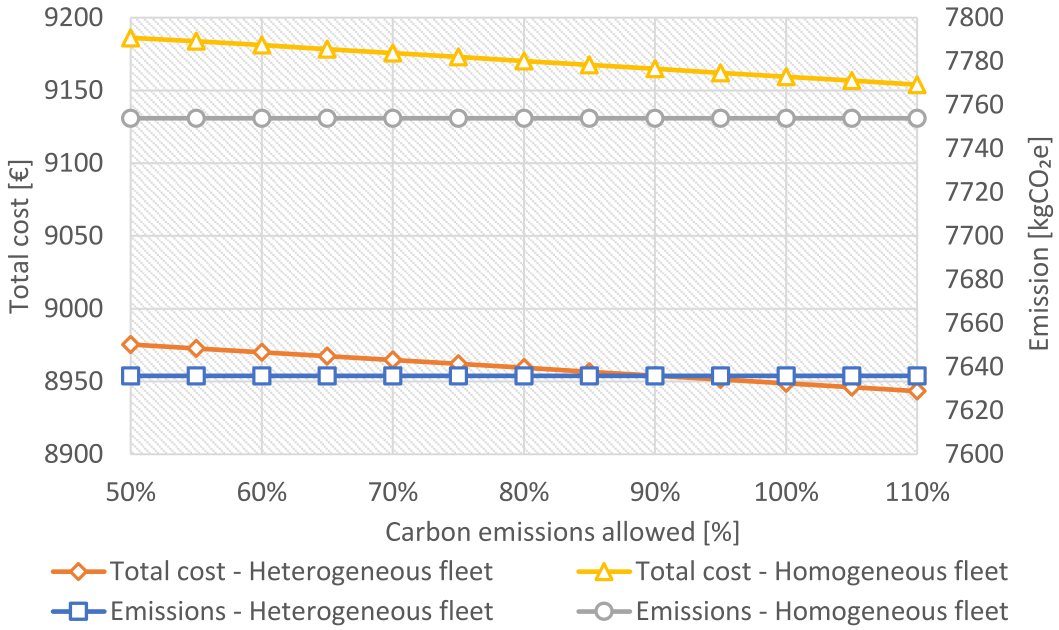


Figure 42 - Comparison of the total cost and emissions between a heterogeneous fleet and a homogeneous fleet model with cap-and-trade policy. Sensitivity analysis on cap with emissions allowance price equal to 7 €/tonCO_2e.

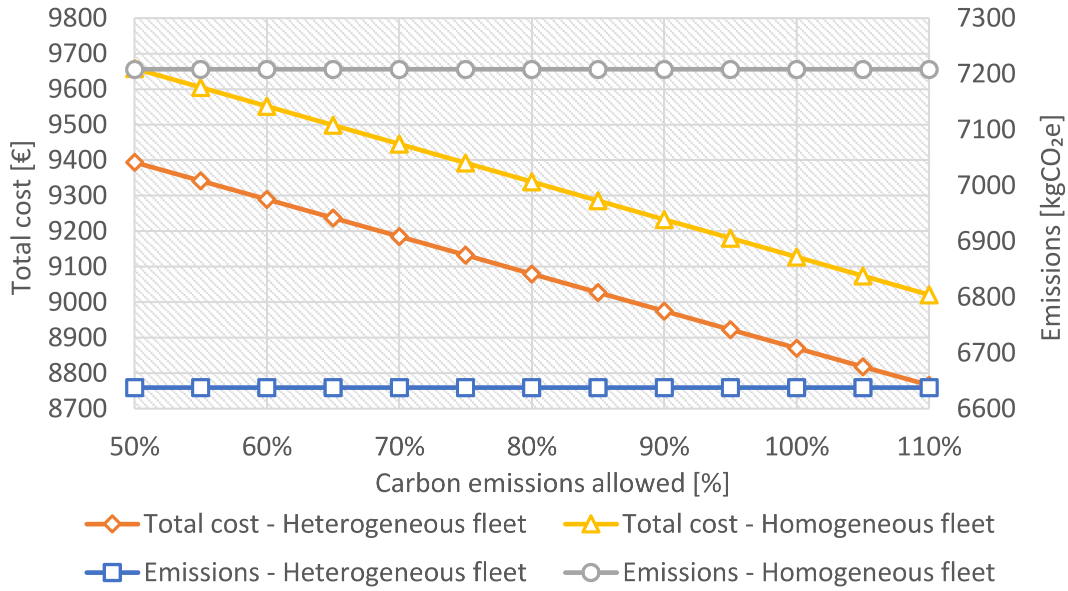


Figure 43 - Comparison of the total cost and emissions between a heterogeneous fleet and a homogeneous fleet model with cap-and-trade policy. Sensitivity analysis on cap with emissions allowance price equal to 137 €/tonCO_2e.

Concerning **Figure 42**, the trend of the total cost and emissions curves of the heterogeneous fleet and homogeneous fleet case is the same. However, as in the base cases and in the minimising-emissions models, the heterogeneous fleet case provides better results in terms of total cost and emissions generated. The total costs, for both the fleet types, show a constant linear increment, with respect to the tightening of the cap. The initial value of total costs, corresponding to the cap equal to 110%, is slightly lower than that of the base cases, since in this situation the company is allowed to emit more than the emissions generated with the cost-minimising optimal solution. In this way, the 10% surplus of allocated emissions allowances can be sold, generating revenues. In this case, given the price equal to 7€/tonCO_2e, the revenues are equal to 5.35€ for the heterogeneous case and 5.43€ for the homogeneous one. In this situation, characterised by a low emissions allowance price, the case where the cap is equal to 100% of the base case emissions the results of the cap-and-trade policy is exactly equal to those of the base case models, both for the heterogeneous and homogeneous fleet. Moreover, the 100% cap value leads to no emissions allowance traded, since there is no need of purchasing extra credits (because the cap is met with the cost-minimising solution), and the low price of the emissions allows does not make profitable the choice to reduce the emissions in order to sell the achieved surplus allowances. This particular case confirms the **Proposition 3** of Cheng et al. (2016), which states that, under the cap-and-trade policy, when the number of traded credits are equal to zero, the model degrades to the cap policy model, in this case with a cap value equal to 100%. Further tightening the cap, since the allocated allowances are lower than the emissions corresponding to the cost-minimising solution, the model is forced to buy extra credits to meet the cap, and thus the emissions cost starts to increase with the decreasing of the cap. The results of the cap-and-trade policy with a fixed emissions allowance price confirms the first part of the **Observation 6** by Benjafaar et al. (2013), which states that when the credit price is fixed (in this case equal to 7€/tonCO_2e), emissions levels are not affected by cap. In fact, the results show no emissions reduction as the cap get tighter. This because the low price of the emissions allowance does not act as an incentive to move towards lower carbon emissions configuration, neither when the cap is high (thus selling surplus emissions allowances), nor when the cap is low (thus buying less emissions allowances to reduce the emissions cost).

The results of the case with an emissions allowance price equal to 137€/tonCO_2e, represented in **Figure 43**, are similar to the previous ones. The difference is that in this case the price is high enough to be perceived as an incentive to modify the routing and deliveries configuration to achieve an emissions reduction. However, this emissions reduction remains constant with respect to the variation of the cap. In particular this emissions reduction is equal to 13.07% in the heterogeneous case and to 7.04% in the homogeneous fleet case. This result confirms the second part of the **Observation 6** by

Benjafaar et al. (2013), which states that, when the emissions allowance price is fixed, the emissions levels are affected only by the price of the allowance. Also in this case it is possible to confirm the **Proposition 3** by Cheng et al. (2016), and in particular, a value of cap comprises between 90% and 85% correspond to that situation where the cap-and-trade policy degrades to a cap policy, and no emissions allowance are traded.
With regard of the cap-and-trade policy with a fixed cap equal to 100% of the base case emissions, the results of the sensitivity analysis on the emissions allowance price are reported in Annex B, respectively in **Table 32** and **Table 33**, while those with the cap equal to 50% are reported in **Table 34** and **Table 35**. These two values are chosen for two specific reason. The cap value equal to 100% in fact, does not mandatorily force the model to reduce the carbon emissions, and thus it is interesting to investigate which are those allowance prices that lead to an emissions reduction. Concerning the cap value equal to 50% of the base case emissions, as shown by the emissions-minimising model, the achievable emissions reduction is equal to 47.53% for the heterogeneous fleet case and to 45.15% for the homogeneous one. This means that in theory, it is not possible to meet a 50% cap without using other policies tools as the emissions allowances trading, thus buying extra emissions allowances. Therefore, the analysis of the cap-and-trade policy with a 50% cap is useful to understand what are the choices of the model when the imposed cap is very low, and it cannot simply be met by reducing the emissions. The effects of the cap-and-trade policy on the base case models with a heterogeneous and a homogeneous fleet of vehicles, in terms of total cost and emissions, are represented in **Figure 44** and **Figure 45**, respectively for the cap equal to 100% and the cap equal to 50%.

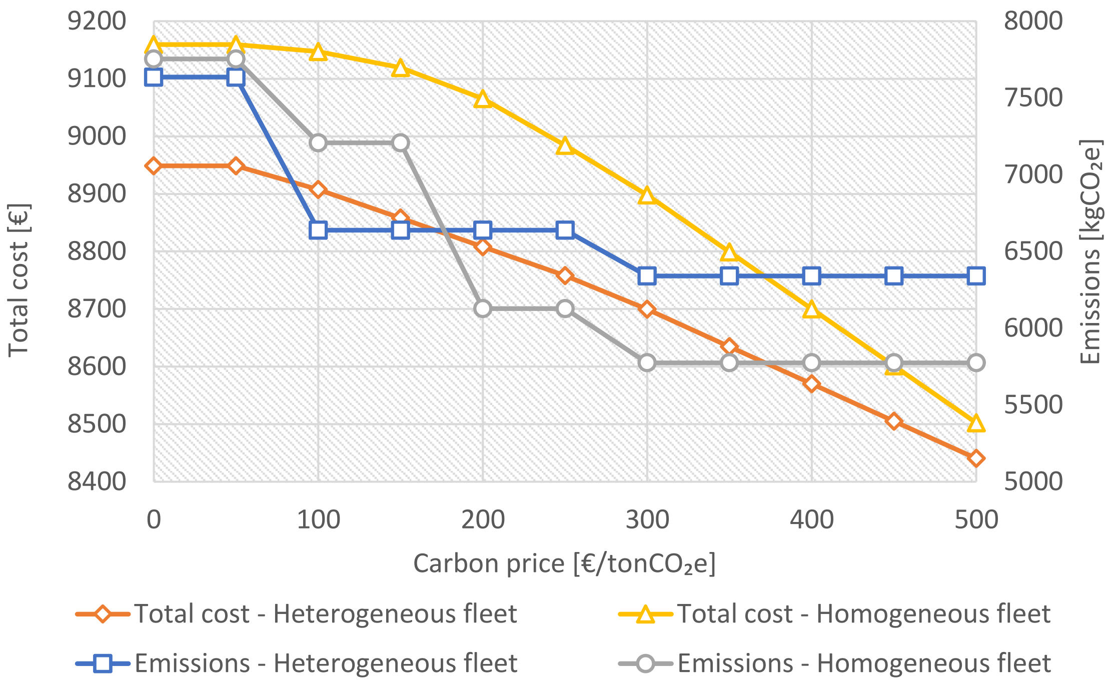


Figure 44 - Comparison of the total cost and emissions between a heterogeneous fleet and a homogeneous fleet model with cap-and-trade policy. Sensitivity analysis on emissions allowance price with cap equal to 100% of the base case emissions.

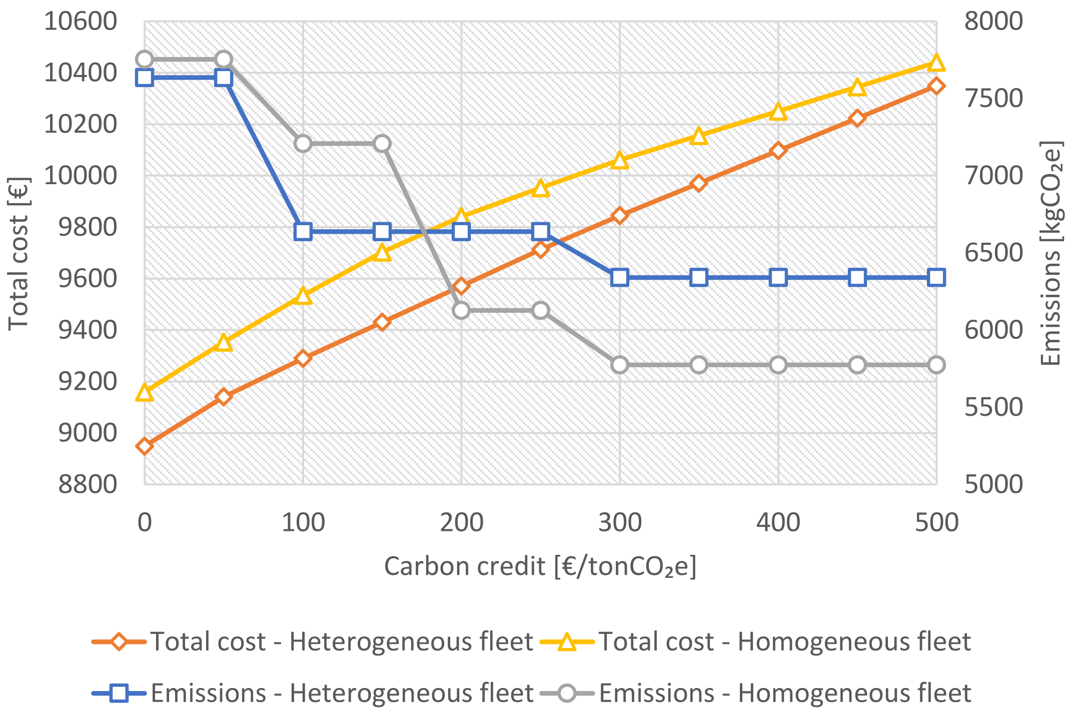


Figure 45 - Comparison of the total cost and emissions between a heterogeneous fleet and a homogeneous fleet model with cap-and-trade policy. Sensitivity analysis on emissions allowance price with cap equal to 50% of the base case emissions.

Figure 44 in particular, shows that, given a value of cap equal to 100% of the base case emissions, there are no traded allowances for low credit prices (0 ÷ 100€/tonCO_2e). This because in that situation, the routing and deliveries configuration already meet the cost-minimising solution and the imposed cap on emissions, and the price of the allowances is too low to make convenient moving towards lower-emissions configuration. Increasing the allowance price, the resulting revenues generated selling the surplus allowances offset the operational cost increment derived from assuming a lower-emissions routing and deliveries configuration. The total cost starts to decrease with an almost linear pattern because, even if the number of sold allowances follows the staircase pattern related to the achieved emissions reduction and thus to the change of routing and deliveries configuration, the allowance price and the related emissions revenues increases. This result confirms the **Observation 7** by Benjafaar et al. (2013) that states that under cap-and-trade, a higher carbon price can lead to lower total cost. In this case in fact, for low values of emission allowance price, the total cost is equal to that obtained in the base case solutions, both for the heterogeneous fleet and homogeneous fleet cases. Increasing the allowance price, the obtained solutions show lower total costs.

From a total cost point of view, **Figure 45** shows an opposite result. In this situation in fact, characterised by an imposed cap equal to 50% of the base case emissions, the model is forced to meet the cap buying emissions allowances. Therefore, the resulting total cost increase as the allowance price increases. From an operational point of view, the decisions of the cap-and-trade model with a 50% cap are exactly the same of those with the 100% cap. This means that, given the same range of allowance price, the modifications in the routing and deliveries configuration occur in the same points. This results further confirm the **Observation 6** by Benjafaar et al. (2013), that state that the achieved emissions reduction under cap-and-trade does not depend on the value of the cap. Moreover, if it is assumed a cap value equal to 0%, corresponding to the null allocation of free allowances, the cap-and-trade model degrades to the carbon tax policy, where the company has to pay a carbon price for each unit of emissions generated. In this case the decision variable on the sold allowance will be always null, and the credit price corresponds to the carbon tax, both expressed in €/tonCO_2e. This means that, given the same carbon price (for the carbon tax policy) or credit price (for the cap-and-trade policy), the operational decisions under the two policies are the same. Therefore, it is interesting to compare the results of the analysed cases of cap-and-trade policy and carbon tax policy, in terms of total cost variation with respect to the achieved emissions reduction. As in the previous cases, the percentage variations are calculated taking as references the total cost and emissions of the base case models. The comparison is illustrated in **Figure 46.**

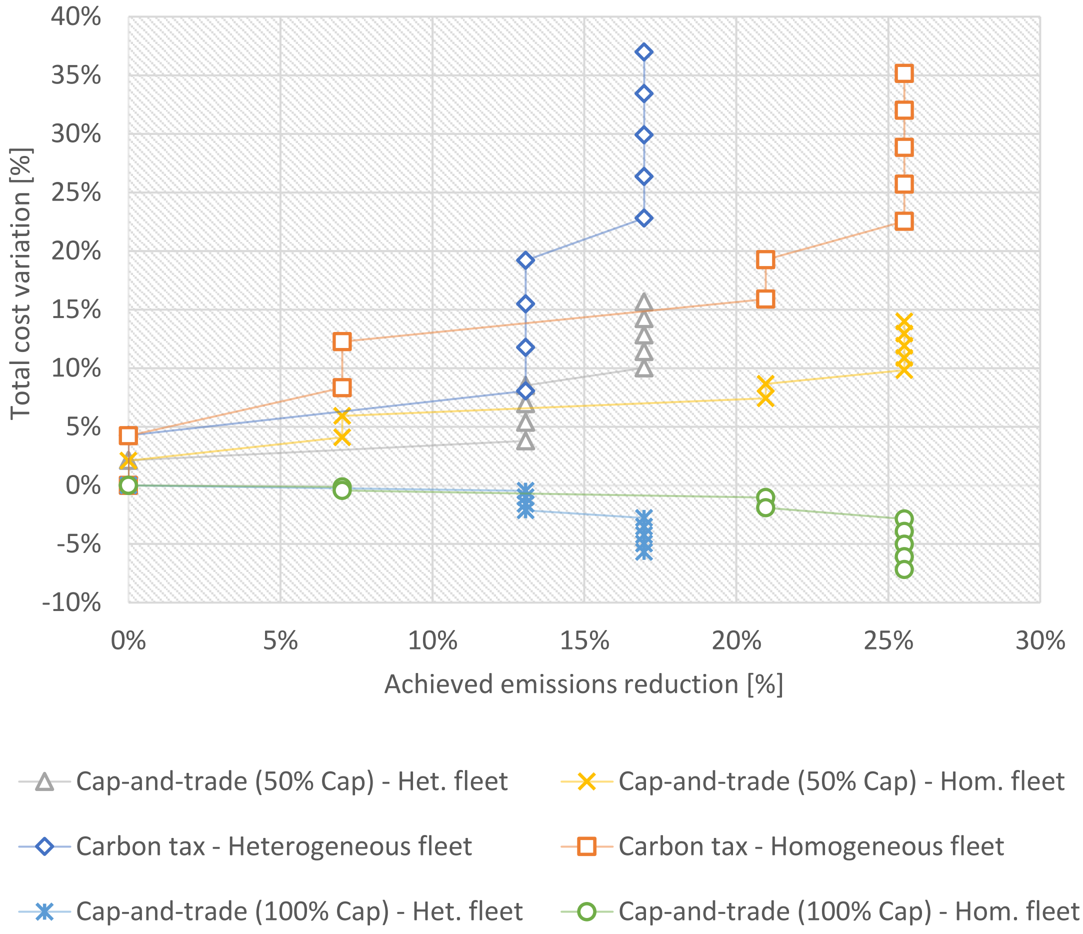


Figure 46 - Comparison between carbon tax policy and cap-an-trade policy with cap equal to 100% and 50% of the base case emissions, in terms of total cost variation and emissions reduction achieved.

The comparison shows how the carbon tax policy, given the same achieved emissions reduction, is that policy that lead to the highest total cost increment. 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.

6.7. Cap-and-offset policy

The cap-and-offset model has 2701 constraints, 1152 binary variables, 126 integer variables and 1340 continuous variables, since it introduces one additional constraint on the maximum allowed level of emissions and one additional decision variables on the number of purchased carbon credits. In Annex B, **Table 36** and **Table 37** report the results of the cap-and-offset model, with a sensitivity analysis on the cap and a fixed carbon credit price equal to 7.27€/tonCO_2e. Since the cap-and-offset mechanisms and the related carbon offset project are monitored and managed by the UNFCCC, the price of the carbon credit is not subject to the market laws, and therefore it is not characterised by high variations. For this reason, it is not performed a sensitivity analysis on the credit price, preferring to analyse the variation of the cap value, given the highest price of certified emissions reductions, among the carbon offset projects actually implemented. As for the cap-and-trade policy, the sensitivity analysis on the cap values is performed starting from a cap equal to 110% of the base case emissions. The **Figure 47** represents the total cost and the emissions of the cap-and-offset with fixed credit price, comparing the curves related to the heterogeneous fleet and the homogeneous fleet case.

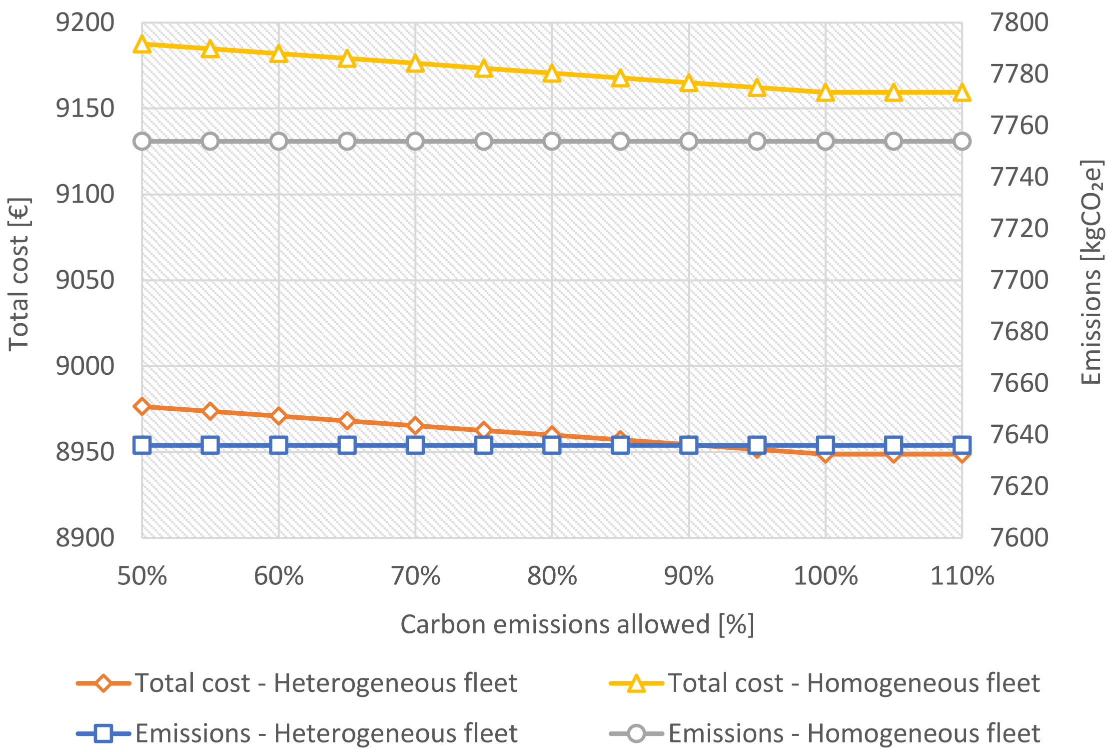


Figure 47 - Comparison of the total cost and emissions between a heterogeneous fleet and a homogeneous fleet model with cap-and-offset policy. Sensitivity analysis on cap with credit price equal to 7.27 €/tonCO_2e.

As shown by the results, under the cap-and-offset policy, since there is no possibility to sell the surplus credits, if the imposed cap is higher than the base case emissions, the total cost and the related emissions remain unvaried. Tightening the cap for values lower than 100%, the total cost starts to increase since the company needs to purchase extra credits to meet the imposed cap. As for the cap-and-trade policy, the emissions reduction does not depend on the value of the imposed cap, but it depends only on the price of the carbon credits. In this case, given the credit price equal to 7.27€/tonCO_2e, it is more convenient to maintain the base case routing and deliveries configuration, thus achieving no emissions reduction, and meet the imposed cap purchasing extra emissions credits. Concerning these results, **Observation 5** by Benjafaar et al. (2013) states that the offset mechanism enables tighter caps by mitigating the impact of lowering cap on costs. In order to correctly address this observation, it is necessary to stress the difference between the achieved emissions reduction and the imposed cap (and thus the imposed emissions reduction). Under the cap policy the imposed emissions reduction and the achieved emissions reduction approximately coincide (it has been shown that the cap policy models, given a determined maximum allowed level of emissions, achieved a smaller additional reduction since they cannot find a routing and deliveries configuration that perfectly matches the imposed cap). Under the cap-and-trade and the cap-and-offset policies, the imposed reduction determined by the value of the cap approximately coincides with the achieved emissions reduction only when the number of purchased extra credits is equal to zero, which means that the model meet the regulation by modifying the routing and deliveries configuration. This means that **Observation 5** can be confirmed only addressing the imposed cap (and not the real achieved emissions reduction). Moreover, from this point of view, it is possible to impose caps lower than the feasible operational limits highlighted from the emissions-minimising models. In this case, imposing a cap equal to 50% leads to no local emissions reduction (focusing on the single addressed company), but leads to a 50% global emissions reduction since, as described in the related section, the 50% cap implies an emissions reduction provided by a financed carbon-free project.

Concerning the results shown in **Figure 47**, the heterogeneous fleet case achieves a global emissions reduction equal to 50% (corresponding to 3817.95 $kgCO_2e$) with a total cost increment equal to 0.31% (corresponding to 8976.46 €). The homogeneous fleet case achieves the same global emissions reduction equal to 50% (corresponding to 3876.95 $kgCO_2e$) with a total cost increment equal to 0.31% (corresponding to 9187.57 €) too. From this point of view, the cap-and-offset policy allows great global emissions reduction without impacting negatively on the economic results of the company. In this sense, the cap-and-offset policy represents an interesting possibility for those companies characterised by environmental concerns over the effects of their activities but that do not have enough degrees of freedom to achieve an effective local emissions reduction by modifying their operational configuration.

With respect to the **Proposition 1** of Cheng et al. (2013), which state that the cap is a special case of the cap-and-offset, the cap-and-offset model proposed in this thesis is run assuming a credit price equal to 10000€/$tonCO_2e$. The **Table 19** reports the obtained results.

Indicator	Result
Driving time [h]	43.75
Inventory cost [€]	9475.02
Driver cost [€]	472.49
Fuel cost [€]	2951.62
Routing cost [€]	3424.10
Emission [kgCO_2e]	4566.33
Total cost [€]	12899.13
Credit bought [kgCO_2e]	0.00
Emission cost [€]	0.00

Table 19 - Cap-and-offset model with heterogeneous fleet, 60% of imposed cap and 10000€/tonCO_2e credit price

The credit price is intentionally set very high in order to demonstrate the **Proposition 1.** In particular, the obtained results are exactly the same of the cap policy model with a 60% cap. This means that when the credit price is sufficiently high, the cap-and-offset model does take into consideration the possibility of meeting the cap by purchasing extra emissions credit, while it modifies the routing and deliveries configuration to achieve an actual local emissions reduction.

7. Conclusions

The purpose of this thesis is to provide a contribution to the topic of the environmentally-extended routing problem. Based on those elements emerged from the related literature review, the model proposed by Soysal et al. (2016), which addresses the uncertainty in the customers demand and explicitly estimates fuel consumption and the related carbon emissions, is modified in order to take into account a heterogeneous fleet of vehicles. In addition, it is developed an emissions minimising model and a constant emissions model. The former reflects the solely environmental concerns of the decision maker, thus neglecting any economic considerations in the objective function, while the latter is useful to highlight the differences in the estimation of the routing cost and the carbon emissions when the comprehensive emissions model is not used. Based on the work of Cheng et al. (2016), the developed base case 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 main contribution of this thesis, thus, consists in analysing how the different carbon control policies affect the economic and environmental results of an inventory routing problem characterised by a stochastic modelling of the customers demand and an explicit estimate of the carbon emissions through the comprehensive emissions model, focusing on the operational decisions and further highlighting the differences in using a heterogeneous fleet of vehicles rather than a homogeneous one.

The base case model, where no carbon control policy is applied, shows that the heterogeneous fleet provides better results than the homogeneous one, both in terms of total cost (2.30% difference) and in terms of carbon emissions (1.52% difference). These results constitute the baselines for the comparisons with the results obtained with the additional proposed models.

The emissions-minimising model provides insights on how the routing and deliveries configuration of the problem is modified to achieve lower carbon emissions. In particular, the model tends to minimise the number of trips, therefore choosing heavier vehicles with higher capacity, able to deliver the same number of products with fewer trips. This leads to lower routing cost and lower emissions (because of lower driver cost and lower fuel consumption), but to higher inventory holding cost. With a heterogeneous fleet is possible to achieve a 47.53% emissions reduction with a 115.59% increment in total cost. Slightly worse results can be achieved with the homogeneous fleet, in particular, a 45.15% emissions reduction with a 121.25% total cost increment.

The results of the constant-emissions model show that a simplified approach for the estimation of the routing cost and the related carbon emissions, based solely on the total travelled distance, can be suitable for those contexts characterised by highly stable demand, and where there is no a strong need of precisely estimate the carbon emissions. In fact, the constant emissions model with a heterogeneous fleet leads to a 0.91% error on routing cost and to a 1.02% error on emissions. The homogeneous fleet case commits a 0.30% error on routing cost and a 0.17% error on emissions. Differently, for those contexts characterised by high variability in the expected values of demand, and where the correct estimation of the carbon emissions can affect the economic results of the company (as in the case of the carbon control policies), a comprehensive emissions model is necessary. Considering a high-variable demand, the constant emissions model with a heterogeneous fleet commits a 7.15% error in estimating the routing cost and an 8.08% error in estimating the related emissions. The homogeneous fleet case provides similar results, in particular, it leads to a 7.83% error concerning the routing cost and an 8.08% error on emissions.

Concerning the introduction of the policies, the results show that in general the heterogeneous fleet provides better results, both in terms of economic and environmental results, due to the possibility of choosing different kind of vehicles based on the needed capacity. However, under some policy conditions, the homogeneous fleet provides better economic results (cap policy with cap lower than 80%), or better environmental results (carbon tax with tax higher than 150€/ tonCO_2e). Specifically, concerning the cap policy, the results show that it is possible to achieve significant emissions reduction with a small increase in the total cost. In particular, with a heterogeneous fleet, the imposition of a cap equal to 85% of the base emissions provides a 16.97% emissions reduction with only a 1.56% total cost increment. Similar results are achieved with the homogeneous fleet (16.54% emissions reduction with a 1.92% cost increment). The results also show that, under the cap policy, the model is not always able to find the routing and deliveries configuration that perfectly matches the imposed cap, thus it is forced to achieve a slightly higher emissions reduction. Therefore, the cap policy is not particularly suitable for those contexts characterised by low flexibility, where it is relatively difficult to modify the business-as-usual configuration. In this case, the rearrangement of the routing and deliveries configuration allows to tight the cap to 55% of the base case emissions. The results obtained with the imposition of the maximum feasible cap highlight the limits of using an exclusively environmentally-concerned objective function, such as that used in the emissions-minimising model. The cap policy model with a homogeneous fleet of vehicles, in fact, characterised by a cost-minimising objective function, is able to achieve a 45.10% emissions reduction with a 77.10% total cost increment, against the 45.15% emissions reduction with 121.25% total cost increment of the emissions-minimising model. In this sense, the cap policy highlights how the base case model, characterised by a cost-minimising objective function with no environmental concerns, hides possible environmental-friendly interesting solution, while the emissions-minimising model hides potential cost-effective solutions.

Given the same achieved emissions reduction, the carbon tax policy provides similar operational cost, corresponding to the rearrangement of the routing and deliveries configuration, but higher total cost with respect to the cap policy. This because the company has to pay the additional emissions cost constituted by the carbon tax. Under this policy, the emissions reduction is not directly proportional to the increasing severity of the policy, namely the carbon tax increment, but it follows a staircase pattern. This means that the carbon tax unevenly affects different companies, based on the operational cost difference in achieving a lower carbon emissions configuration. Furthermore, as for the cap policy, the introduction of a carbon tax regime in a context characterised by low flexibility and expensive possibilities to achieve lower carbon configuration would result in null emissions reductions and in an additional economic burden for the taxed companies. Besides this aspect, the results of the carbon tax policy provide a further insight for policymakers. In fact, the determination of the precise value of the carbon tax is a delicate decision, since, as shown by the application of a carbon tax on the addressed environmentally-extended routing problem, a low value (from 0 to 50 €/tonCO_2e) does not lead to any emissions reduction since it is not perceived as an incentive to move towards lower emissions solutions. Higher values, such as the actual implemented Sweden carbon tax equal to 137€/ tonCO_2e, effectively produce emissions reduction, equal to 13.07% with a heterogeneous fleet and to 7.04% with a homogeneous fleet.

Concerning the cap-and-trade policy, the results confirm the **Observation 6** by Benjafaar et al. (2013). In particular, it is shown that the emissions reduction achieved under the cap-and-trade does not depend on the value of the cap, but it solely depends on the price of the emissions allowance. A low allowance price, as that actually traded in the EU ETS, equal to 7€/tonCO_2e, does not provide any emissions reduction, while a higher price, as the Sweden carbon tax, equal to 137€7tonCO_2e, leads to a modification in the routing and deliveries configuration, thus to an emissions reduction, equal to 13.07% for the heterogeneous fleet case and to 7.04% for the homogeneous fleet case, independently of the cap value. As further shows by the results of the sensitivity analysis on the allowance price with a fixed value of cap, the achieved emissions reductions coincide with those obtained with the carbon tax policy. Since under the cap-and-trade the emissions are not dependent on the cap, the carbon tax policy can be considered a particular case of the cap-and-trade where the value of the cap is equal to 0%. Moreover, the sensitivity analysis on the allowance price when the cap is equal to 100% shows that for sufficiently high allowance prices, the model achieves significant emissions reduction, even if it is not imposed by the cap. This because of the possibility of selling the surplus emissions allowances allocated, which characterises the cap-and-trade policy.

Lastly, concerning the cap-and-offset policy, the results are similar to those obtained with the cap-and-trade policy, but in this case, given an overallocation of free emissions allowance (corresponding to values of cap higher than 100%), there are no economic or environmental improvements as in the cap-and-trade case, since there is no possibility to sell the extra allocated emissions allowances. This result confirms the **Proposition 2** by Cheng et al. (2016) which state that cap-and-trade has more flexibility than the cap-and-offset. An interesting aspect highlighted by the cap-and-offset results concern the difference between the effective achieved emissions reduction and the imposed emissions reduction. As shown, it is possible to impose significant caps (equal to 50% of the base case emissions), and the company can meet those caps incurring very low extra costs. In the heterogeneous fleet case the emissions cost corresponding to a 50% cap is equal to 27.76€, while for the homogeneous fleet case it is equal to 28.19€. In these cases, the emissions reduction 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 emissions credits purchased 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. 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.

As reported by the Carbon Disclosure Project, in its last report titled "Disclosure Project - Embedding a carbon price into business" (Carbon Disclosure Project, 2016), the number of companies that have started to explicitly consider the role of carbon emissions in their activities is rapidly increasing. Besides the environmental concerns, as highlighted by Treitl et al. (2014), one of the main reasons behind this choice is represented by the growing concerns towards the possible implementation of carbon control policies by the governments or regulatory authorities. As shown, these measures can directly impact on the economic results of a company, therefore, an approach that properly addresses this aspect is required. From this point of view, it has been stressed the importance of an approach that directly links the decision variables of the problem with the carbon emissions generated. Specifically, in this thesis, the decision variables regarding the routing of the vehicles and the quantity of product delivered to the customers are linked to the carbon emissions generated by the transportation activities, in the context of a traditional inventory routing problem. These type of logistics problems are particularly suitable for these kinds of considerations since an environmentally-extended approach allows to properly reveal hidden possible environmental friendly and cost-effective solutions that a purely cost-minimising approach neglect.

Moreover, the results obtained due to the introduction of carbon control policies provide useful insights to those companies concerned about their environmental footprint and want to undertake voluntary reduction actions. A self-imposed policy, as a part of a corporate social responsibility commitment, can provide significant reductions at a local level (cap policy), can lead to great emissions reduction on a global scale (cap-and-offset policy), or can lead to low-carbon investments (embedded carbon pricing or carbon tax policy in the business strategy).

As highlighted by the literature review, the topic of the environmentally-extended routing problem is relatively recent and therefore paths for future studies are numerous. First, since the inventory routing problem implies a vendor-managed inventory agreement between the supplier and its customers, it is interesting to quantitatively evaluate, from an economic and environmental perspective, how the introduction of carbon control policies affect the vertical collaboration among the different actors of the supply chain. In particular, it is relevant to analyse how the different costs (inventory holding, driver, fuel, emissions...) are distributed among the different actors, in order to highlight eventual disproportion or inequalities, generated by a supply-chain total cost-minimising approach. In addition, a possible extension of the analysis could address the size of the customers (in terms of volume of demand per period), and how it can influence the diverse distribution of costs of the entire system.

Another interesting path of research is represented by the analysis of the customer service level, in this thesis assumed fixed and equal to 95%. This aspect, in fact, can reveal additional trade-offs, relations and implication between the economic and the environmental performances of an environmentally-extended inventory routing problem. In order to properly address this kind of considerations, the customer service level should be treated as a decision variable of the problem, and a proper shortage cost has to be assumed. In this way, it is possible to highlight eventual effects on the customer service level due to the introduction of carbon control policies.

Finally, it is interesting to analyse how emissions restrictive measures affect a three-echelons supply chain, properly modelling the up-stream stage that represents the availability of products at the supplier's site at each period. The additional stage can be represented by production activities that produce carbon emissions as well, and in this sense, it is relevant to understand what are the different implications along all the supply chain.

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Annex A: Routing and deliveries configurations of the base case and emissions-minimising models

	Customers Demand [kg]						Quantity delivered [kg]						Inventory levels [kg]					
	Weeks						Weeks						Weeks					
Customer	1	2	3	4	5	6	1	2	3	4	5	6	1	2	3	4	5	6
C1	2000	3200	3000	1800	2600	1900	2329	3492	3172	1853	2702	1950	329	621	793	846	948	998
C2	1400	2600	3400	1600	2800	1400	1630	2855	3655	1645	2925	1429	230	486	741	786	911	940
C3	2600	4800	800	7000	400	300	3028	5270	874	7494	702	-	428	898	972	1466	1768	1468
C4	6000	1000	2200	2400	1400	2000	6987	1014	2263	2471	1423	2046	987	1001	1064	1135	1158	1204
C5	1200	2200	1800	2400	4000	1800	1397	2415	1895	2535	4277	1846	197	412	508	643	920	966
Total	13200	13800	11200	15200	11200	7400	15371	15046	11860	15999	12029	7271	2171	3417	4078	4876	5706	5577

	Picked-up Quantity [kg]						Vehicle saturation [%]						Emissions per vehicle [kgCO2e]					
	Weeks						Weeks						Weeks					
Vehicle	1	2	3	4	5	6	1	2	3	4	5	6	1	2	3	4	5	6
LDV	3959	2855	-	3499	-	3892	98,98%	71,39%	-	87,47%	-	97,31%	401,20	380,04	-	400,53	-	508,25
MDV	11412	12190	11860	12500	12029	3379	91,30%	97,52%	94,88%	100,00%	96,23%	27,03%	905,26	1008,66	1259,36	942,27	1300,09	530,25
HDV	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-

Table 20 - Demand, deliveries, inventory levels, picked-up quantities, vehicle saturation and vehicle emissions for the base case model with a heterogeneous fleet.

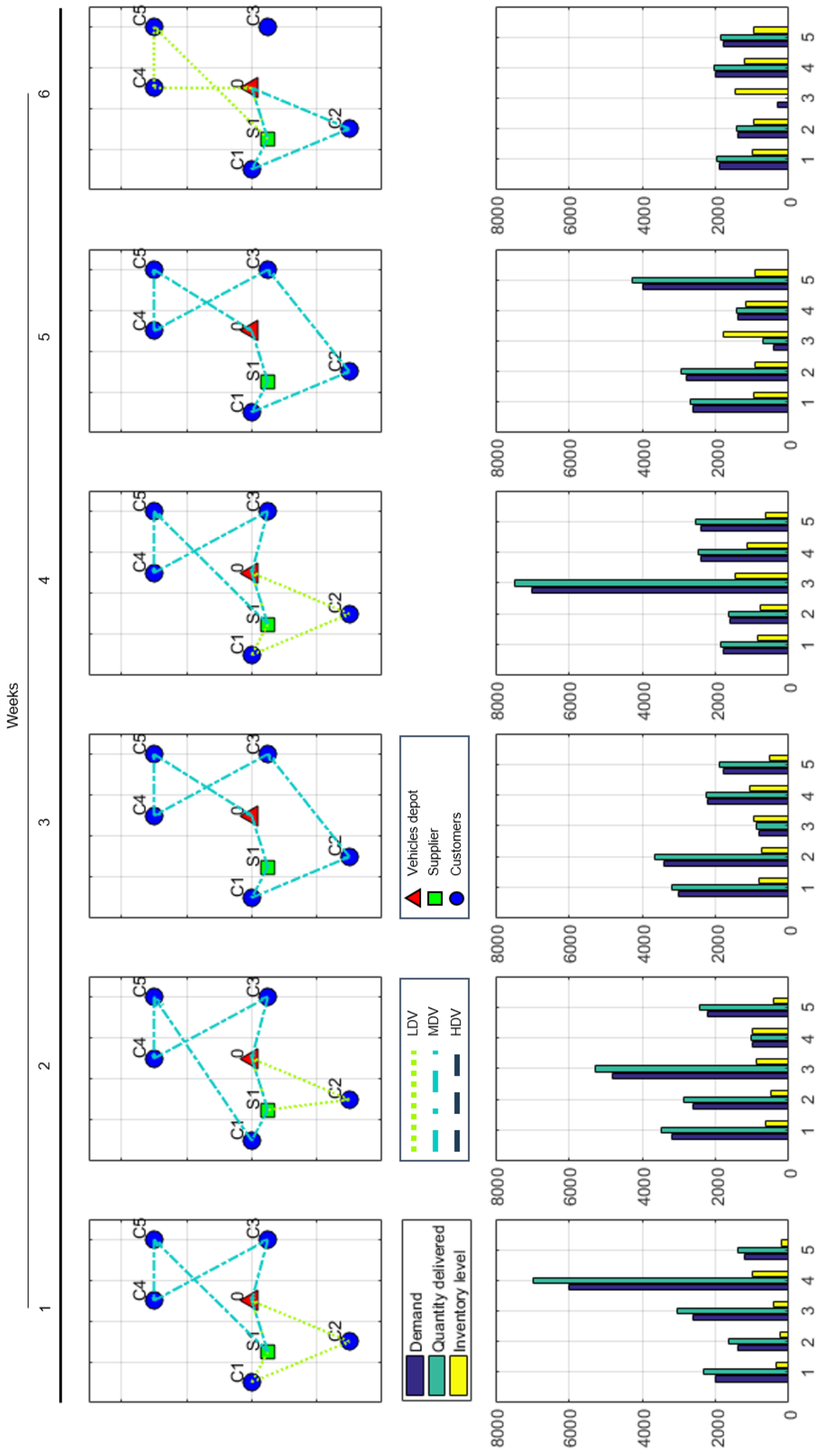

Figure 48 - Vehicles routing and related demand, deliveries and inventory levels for the base case model with a heterogeneous fleet.

	Customers Demand [kg]						Quantity delivered [kg]						Inventory levels [kg]					
	Weeks						Weeks						Weeks					
Customer	1	2	3	4	5	6	1	2	3	4	5	6	1	2	3	4	5	6
C1	2000	3200	3000	1800	2600	1900	2329	3492	3172	1853	2702	1950	329	621	793	846	948	998
C2	1400	2600	3400	1600	2800	1400	1630	2855	3655	1645	4354	-	230	486	741	786	2340	940
C3	2600	4800	800	7000	400	300	3028	5270	874	7494	702	-	428	898	972	1466	1768	1468
C4	6000	1000	2200	2400	1400	2000	6987	1014	2263	2471	1423	2046	987	1001	1064	1135	1158	1204
C5	1200	2200	1800	2400	4000	1800	1397	2415	1895	2535	4277	1846	197	412	508	643	920	966
Total	13200	13800	11200	15200	11200	7400	15371	15046	11860	15999	13458	5842	2171	3417	4078	4876	7134	5577

	Picked-up Quantity [kg]						Vehicle saturation [%]						Emissions per vehicle [kgCO2e]					
	Weeks						Weeks						Weeks					
Vehicle	1	2	3	4	5	6	1	2	3	4	5	6	1	2	3	4	5	6
MDV 1	-	-	11860	12500	-	-	-	-	94,88%	100,00%	-	-	-		1259,36	942,27	-	-
MDV 2	11412	6347	-	0	7056	5842	91,30%	50,78%	-	-	56,44%	46,74%	905,26	545,03	-	-	556,52	775,47
MDV 3	3959	8699	-	3499	6402	-	31,67%	69,59%	-	27,99%	51,22%	-	532,61	885,09	-	531,94	820,35	-

Table 21 - Demand, deliveries, inventory levels, picked-up quantities, vehicle saturation and vehicle emissions for the base case model with a homogeneous fleet.

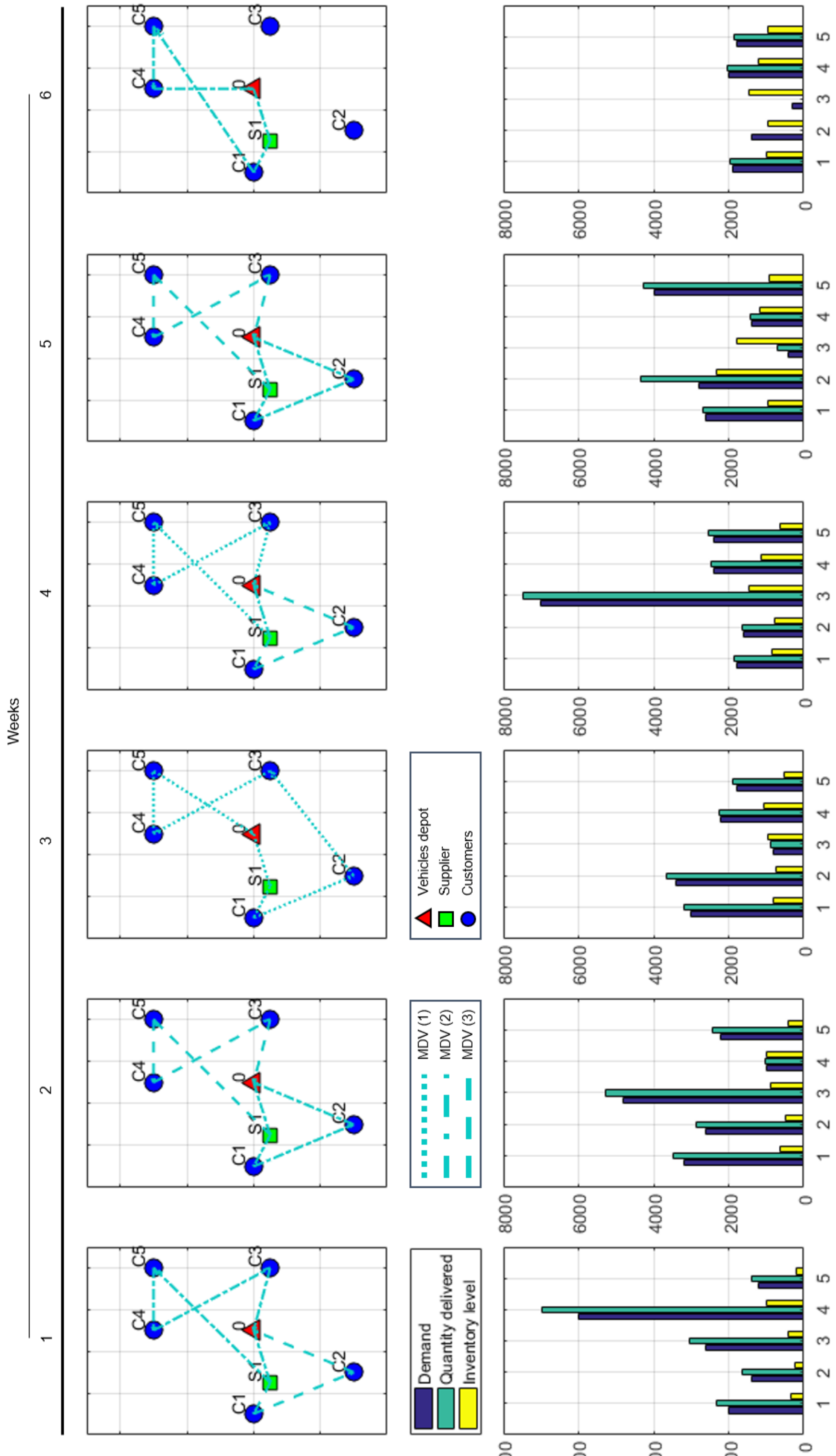

Figure 49 - Vehicles routing and related demand, deliveries and inventory levels for the base case model with a homogeneous fleet.

	Customers Demand [kg]						Quantity delivered [kg]						Inventory levels [kg]					
	Weeks						Weeks						Weeks					
Customer	1	2	3	4	5	6	1	2	3	4	5	6	1	2	3	4	5	6
C1	2000	3200	3000	1800	2600	1900	3096	12402	-	-	-	-	1097	10299	7299	5499	2899	999
C2	1400	2600	3400	1600	2800	1400	14140	-	-	-	-	-	12740	10140	6740	5140	2340	940
C3	2600	4800	800	7000	400	300	3028	14341	-	-	-	-	428	9969	9169	2169	1769	1469
C4	6000	1000	2200	2400	1400	2000	8001	-	8203	-	-	-	2001	1001	7004	4604	3204	1204
C5	1200	2200	1800	2400	4000	1800	5334	-	9033	-	-	-	4134	1934	9167	6767	2767	967
Total	13200	13800	11200	15200	11200	7400	33598	26743	17236	-	-	-	20400	33343	39379	24179	12979	5579

	Picked-up Quantity [kg]						Vehicle saturation [%]						Emissions per vehicle [kgCO2e]					
	Weeks						Weeks						Weeks					
Vehicle	1	2	3	4	5	6	1	2	3	4	5	6	1	2	3	4	5	6
LDV	4000	-	-	-	-	-	100,00%	-	-	-	-	-	352,10	-	-	-	-	-
MDV	12362	12402	-	-	-	-	98,89%	99,22%	-	-	-	-	916,26	292,38	-	-	-	-
HDV	17236	14341	17236	-	-	-	100,00%	83,20%	100,00%	-	-	-	745,34	782,82	917,52	-	-	-

Table 22 - Demand, deliveries, inventory levels, picked-up quantities, vehicle saturation and vehicle emissions for the emissions-minimising model with a heterogeneous fleet.

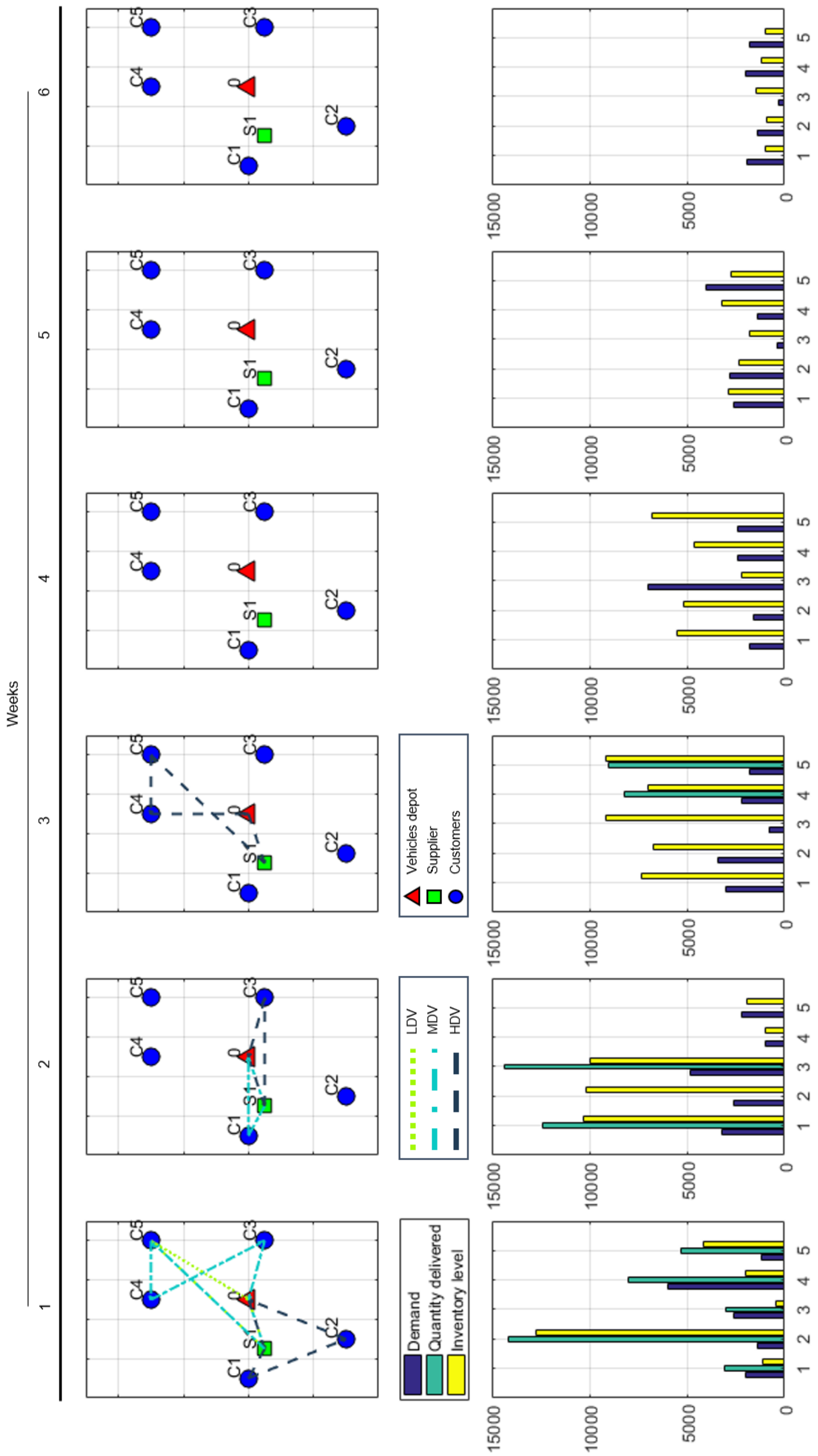

Figure 50 - Vehicles routing and related demand, deliveries and inventory levels for the emissions-minimising model with a heterogeneous fleet.

Customer	Customers Demand [kg]						Quantity delivered [kg]						Inventory levels [kg]					
	Weeks						Weeks						Weeks					
	1	2	3	4	5	6	1	2	3	4	5	6	1	2	3	4	5	6
C1	2000	3200	3000	1800	2600	1900	8993	-	-	6506	-	-	6993	3793	793	5499	2899	999
C2	1400	2600	3400	1600	2800	1400	1640	12500	-	-	-	-	240	10140	6740	5140	2340	940
C3	2600	4800	800	7000	400	300	12500	4868	-	-	-	-	9900	9969	9169	2169	1769	1469
C4	6000	1000	2200	2400	1400	2000	10634	5570	-	-	-	-	4634	9204	7004	4604	3204	1204
C5	1200	2200	1800	2400	4000	1800	1866	12500	-	-	-	-	667	10967	9167	6767	2767	967
Total	13200	13800	11200	15200	11200	7400	35633	35439	-	6506	-	-	22434	44073	32873	24179	12979	5579

Vehicle	Picked-up Quantity [kg]						Vehicle saturation [%]						Emissions per vehicle [kgCO2e]					
	Weeks						Weeks						Weeks					
	1	2	3	4	5	6	1	2	3	4	5	6	1	2	3	4	5	6
MDV 1	12500	10439	-	6506	-	-	100,00%	83,51%	-	52,04%	-	-	656,86	907,55	-	282,51	-	-
MDV 2	12500	12500	-	-	-	-	100,00%	100,00%	-	-	-	-	767,24	521,25	-	-	-	-
MDV 3	10633	12500	-	-	-	-	85,06%	100,00%	-	-	-	-	543,85	573,98	-	-	-	-

Table 23 - Demand, deliveries, inventory levels, picked-up quantities, vehicle saturation and vehicle emissions for the emissions-minimising model with a homogeneous fleet.

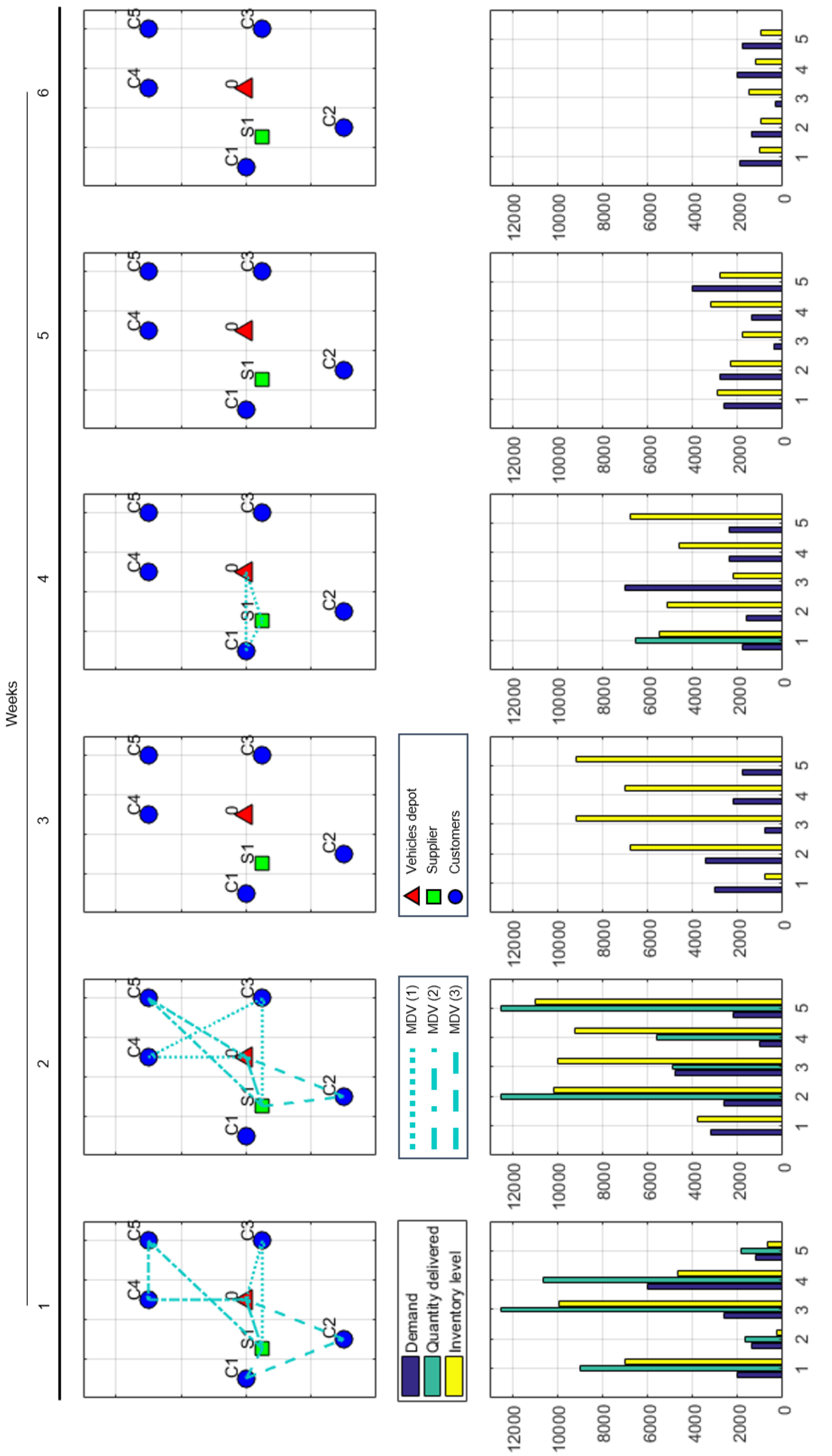

Figure 51 - Vehicles routing and related demand, deliveries and inventory levels for the emissions-minimising model with a heterogeneous fleet.

Annex B: Results of the sensitivity analysis on the parameters characterising carbon control policies

Cap value [%]	100%	95%	90%	85%	80%	75%	70%	65%	60%	55%
Computer time [s]	334	1440	1295	1380	1700	2534	708	1099	1360	OUT*
Driving time [h]	84.63	80.20	70.74	71	65.54	58.76	52.51	46.85	43.75	-
Inventory cost [€]	3098.95	3558.32	3952.93	4220.19	4751.43	5515.64	6301.08	7535.97	9475.02	-
Driver cost [€]	914.00	866.16	763.99	770.00	707.88	634.62	567.05	505.96	472.49	-
Fuel cost [€]	4935.76	4567.90	4290.58	4098.16	3928.82	3660.81	3435.87	3206.88	2951.62	-
Routing cost [€]	5849.76	5434.07	5054.564	4868.16	4636.694	4295.427	4002.92	3712.843	3424.105	-
Emission [kgCO_2e]	7635.91	7066.82	6637.78	6340.10	6078.11	5663.48	5315.49	4961.24	4566.33	-
Total cost [€]	8948.71	8992.39	9007.49	9088.35	9388.13	9811.07	10304.00	11248.81	12899.13	-
Operational cost [€]	8948.71	8992.39	9007.49	9088.35	9388.13	9811.07	10304.00	11248.81	12899.13	-
Operational cost incr. [%]	0.00%	0.49%	0.66%	1.56%	4.91%	9.64%	15.15%	25.70%	44.15%	-
Emission reduction [%]	0.00%	7.45%	13.07%	16.97%	20.40%	25.83%	30.39%	35.03%	40.20%	-
Average saturation [%]	86.21%	93.45%	85.34%	90.17%	91.58%	94.27%	84.86%	83.29%	97.28%	-
Number of vehicles	10	10	9	10	9	8	8	7	6	-
LDV	4	5	3	5	4	3	2	1	0	-
MDV	6	5	5	4	3	3	4	4	5	-
HDV	0	0	1	1	2	2	2	2	1	-

Table 24 - Cap policy with heterogeneous fleet. Sensitivity analysis on the value of the cap.

Cap value [%]	**100%**	**95%**	**90%**	**85%**	**80%**	**75%**	**70%**	**65%**	**60%**	**55%**
Computer time [s]	5040	2760	**OUT***	3960	1140	910	1984	1976	1248	129
Driving time [h]	81.20	76.21	-	66.29	62.56	59.09	56	50.56	46.79	42.78
Inventory cost [€]	3270.39	3613.04	-	4435.77	4753.91	5121.33	6049.04	7340.27	8833.87	13007.64
Driver cost [€]	876.97	823.04	-	715.92	675.65	638.22	602.38	546.04	505.28	462.01
Fuel cost [€]	5012.03	4755.38	-	4183.27	3961.21	3732.45	3488.44	3250.12	2992.46	2751.45
Routing cost [€]	5889.00	5578.42	-	4899.19	4636.85	4370.67	4090.81	3796.16	3497.75	3213.46
Emission [kgCO_2e]	7753.90	7356.86	-	6471.76	6128.219	5774.318	5396.816	5028.127	4629.515	4256.654
Total cost [€]	9159.39	9191.46	-	9334.96	9390.765	9491.997	10139.85	11136.43	12331.62	16221.1
Operational cost [€]	9159.39	9191.46	-	9334.96	9390.77	9492.00	10139.85	11136.43	12331.62	16221.10
Operational cost incr. [%]	0.00%	0.35%	-	1.92%	2.53%	3.63%	10.70%	21.58%	34.63%	77.10%
Emission reduction [%]	0.00%	5.12%	-	16.54%	20.97%	25.53%	30.40%	35.15%	40.29%	45.10%
Average saturation [%]	62.06%	68.96%	-	77.58%	77.58%	77.58%	77.58%	88.66%	88.66%	88.66%
Number of vehicles	10	9	-	8	8	8	8	7	7	7

Table 25 - Cap policy with homogeneous fleet. Sensitivity analysis on the value of the cap.

Carbon tax price [€/tonCO_2e]	0	50	100	150	200	250	300	350	400	450	500
Computer time [s]	494	407	528	374	328	419	232	275	326	195	427
Driving time [h]	84.63	84.63	70.74	70.74	70.74	70.74	71.30	71.30	71.30	71.30	71.30
Inventory cost [€]	3098.95	3098.95	3952.93	3952.93	3952.93	3952.93	4220.19	4220.19	4220.19	4220.19	4220.19
Driver cost [€]	914.00	914.00	763.99	763.99	763.99	763.99	770.00	770.00	770.00	770.00	770.00
Fuel cost [€]	4935.76	4935.76	4290.58	4290.58	4290.58	4290.58	4098.16	4098.16	4098.16	4098.16	4098.16
Routing cost [€]	5849.76	5849.76	5054.56	5054.56	5054.56	5054.56	4868.16	4868.16	4868.16	4868.16	4868.16
Emission [kgCO_2e]	7635.91	7635.91	6637.78	6637.78	6637.78	6637.78	6340.10	6340.10	6340.10	6340.10	6340.10
Total cost [€]	8948.71	9330.50	9671.27	10003.16	10335.05	10666.94	10990.38	11307.39	11624.39	11941.40	12258.40
Emission cost [€]	0.00	381.80	663.78	995.67	1327.56	1659.44	1902.03	2219.04	2536.04	2853.05	3170.05
Operational cost [€]	8948.71	8948.71	9007.49	9007.49	9007.49	9007.49	9088.35	9088.35	9088.35	9088.35	9088.35
Emission reduction [%]	0.00%	0.00%	13.07%	13.07%	13.07%	13.07%	16.97%	16.97%	16.97%	16.97%	16.97%
Operational cost incr. [%]	0.00%	0.00%	0.66%	0.66%	0.66%	0.66%	1.56%	1.56%	1.56%	1.56%	1.56%
Average saturation [%]	86.21%	86.21%	85.34%	85.34%	85.34%	85.34%	90.17%	90.17%	90.17%	90.17%	90.17%
Number of vehicles	10	10	9	9	9	9	10	10	10	10	10
LDV	4	4	3	3	3	3	5	5	5	5	5
MDV	6	6	5	5	5	5	4	4	4	4	4
HDV	0	0	1	1	1	1	1	1	1	1	1

Table 26 - Carbon tax policy with heterogeneous fleet. Sensitivity analysis on carbon tax price.

Carbon tax price [€/tonCO_2e]	0	50	100	150	200	250	300	350	400	450	500
Computer time [s]	1275	2962	3840	4263	6180	1292	1880	859	589	426	454
Driving time [h]	81.20	81.20	74.78	74.78	62.56	62.56	59.09	59.09	59.09	59.09	59.09
Inventory cost [€]	3270.39	3270.39	3734.67	3734.67	4753.91	4753.91	5121.33	5121.33	5121.33	5121.33	5121.33
Driver cost [€]	876.97	876.97	807.64	807.64	675.65	675.65	638.22	638.22	638.22	638.22	638.22
Fuel cost [€]	5012.03	5012.03	4659.39	4659.39	3961.21	3961.21	3732.45	3732.45	3732.45	3732.45	3732.45
Routing cost [€]	5889.00	5889.00	5467.02	5467.02	4636.85	4636.85	4370.67	4370.67	4370.67	4370.67	4370.67
Emission [kgCO_2e]	7753.90	7753.90	7208.35	7208.35	6128.22	6128.22	5774.32	5774.32	5774.32	5774.32	5774.32
Total cost [€]	9159.39	9547.08	9922.53	10282.95	10616.41	10922.82	11224.29	11513.01	11801.72	12090.44	12379.16
Emission cost [€]	0.00	387.70	720.83	1081.25	1225.64	1532.05	1732.30	2021.01	2309.73	2598.44	2887.16
Operational cost [€]	9159.39	9159.39	9201.69	9201.69	9390.77	9390.77	9492.00	9492.00	9492.00	9492.00	9492.00
Emission reduction [%]	0.00%	0.00%	7.04%	7.04%	20.97%	20.97%	25.53%	25.53%	25.53%	25.53%	25.53%
Operational cost incr. [%]	0.00%	0.00%	0.46%	0.46%	2.53%	2.53%	3.63%	3.63%	3.63%	3.63%	3.63%
Average saturation [%]	62.06%	62.06%	68.96%	68.96%	77.58%	77.58%	77.58%	77.58%	77.58%	77.58%	77.58%
Number of vehicles	10	10	9	9	8	8	8	8	8	8	8

Table 27 - Carbon tax policy with homogeneous fleet. Sensitivity analysis on carbon tax price.

Cap value [%]	110%	105%	100%	95%	90%	85%	80%	75%	70%	65%	60%	55%	50%
Computer time [s]	823	407	470	748	748	76	621	78	747	339	938	597	576
Driving time [h]	84.63	84.63	84.63	84.63	84.63	84.63	84.63	84.63	84.63	84.63	84.63	84.63	84.63
Inventory cost [€]	3098.95	3098.95	3098.95	3098.95	3098.95	3098.95	3098.95	3098.95	3098.95	3098.95	3098.95	3098.95	3098.95
Driver cost [€]	914.00	914.00	914.00	914.00	914.00	914.00	914.00	914.00	914.00	914.00	914.00	914.00	914.00
Fuel cost [€]	4935.76	4935.76	4935.76	4935.76	4935.76	4935.76	4935.76	4935.76	4935.76	4935.76	4935.76	4935.76	4935.76
Routing cost [€]	5849.76	5849.76	5849.76	5849.76	5849.76	5849.76	5849.76	5849.76	5849.76	5849.76	5849.76	5849.76	5849.76
Emission [kgCO_2e]	7635.91	7635.91	7635.91	7635.91	7635.91	7635.91	7635.91	7635.91	7635.91	7635.91	7635.91	7635.91	7635.91
Total cost [€]	8943.36	8946.03	8948.71	8951.38	8954.05	8956.72	8959.40	8962.07	8964.74	8967.41	8970.09	8972.76	8975.43
Credit bought [kgCO_2e]	0.00	0.00	0.00	381.80	763.59	1145.39	1527.18	1908.98	2290.77	2672.57	3054.36	3436.16	3817.95
Credit sold [kgCO_2e]	763.59	381.80	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Emission cost [€]	0.00	0.00	0.00	2.67	5.35	8.02	10.69	13.36	16.04	18.71	21.38	24.05	26.73
Emission revenue [€]	5.35	2.67	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Operational cost [€]	8948.71	8948.71	8948.71	8948.71	8948.71	8948.71	8948.71	8948.71	8948.71	8948.71	8948.71	8948.71	8948.71
Emission reduction [%]	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
Operational cost incr. [%]	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
Average saturation [%]	86.21%	86.21%	86.21%	86.21%	86.21%	86.21%	86.21%	86.21%	86.21%	86.21%	86.21%	86.21%	86.21%
Number of vehicles	10	10	10	10	10	10	10	10	10	10	10	10	10
LDV	4	4	4	4	4	4	4	4	4	4	4	4	4
MDV	6	6	6	6	6	6	6	6	6	6	6	6	6
HDV	0	0	0	0	0	0	0	0	0	0	0	0	0

Table 28 - Cap-and-trade policy with heterogeneous fleet. Sensitivity analysis on cap value with fixed emissions allowance price equal to 7€/tonCO_2e.

Cap value [%]	110%	105%	100%	95%	90%	85%	80%	75%	70%	65%	60%	55%	50%
Computer time [s]	3422	1582	4072	4589	4021	3489	3654	3583	2546	1589	1673	1654	2072
Driving time [h]	81.20	81.20	81.20	81.20	81.20	81.20	81.20	81.20	81.20	81.20	81.20	81.20	81.20
Inventory cost [€]	3270.39	3270.39	3270.39	3270.39	3270.39	3270.39	3270.39	3270.39	3270.39	3270.39	3270.39	3270.39	3270.39
Driver cost [€]	876.97	876.97	876.97	876.97	876.97	876.97	876.97	876.97	876.97	876.97	876.97	876.97	876.97
Fuel cost [€]	5012.03	5012.03	5012.03	5012.03	5012.03	5012.03	5012.03	5012.03	5012.03	5012.03	5012.03	5012.03	5012.03
Routing cost [€]	5889.00	5889.00	5889.00	5889.00	5889.00	5889.00	5889.00	5889.00	5889.00	5889.00	5889.00	5889.00	5889.00
Emission [$kgCO_2e$]	7753.90	7753.90	7753.90	7753.90	7753.90	7753.90	7753.90	7753.90	7753.90	7753.90	7753.90	7753.90	7753.90
Total cost [€]	9153.96	9156.67	9159.39	9162.10	9164.82	9167.53	9170.24	9172.96	9175.67	9178.39	9181.10	9183.81	9186.11
Credit bought [$kgCO_2e$]	0.00	0.00	0.00	387.70	775.39	1163.09	1550.78	1938.48	2326.17	2713.87	3101.56	3489.26	3876.95
Credit sold [$kgCO_2e$]	775.39	387.70	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Emission cost [€]	0.00	0.00	0.00	2.71	5.43	8.14	10.86	13.57	16.28	19.00	21.71	24.42	26.73
Emission revenue [€]	5.43	2.71	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Operational cost [€]	9159.39	9159.39	9159.39	9159.39	9159.39	9159.39	9159.39	9159.39	9159.39	9159.39	9159.39	9159.39	9159.39
Emission reduction [%]	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
Operational cost incr. [%]	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
Average saturation [%]	62.06%	62.06%	62.06%	62.06%	62.06%	62.06%	62.06%	62.06%	62.06%	62.06%	62.06%	62.06%	62.06%
Number of vehicles	10	10	10	10	10	10	10	10	10	10	10	10	10

Table 29 - Cap-and-trade policy with homogeneous fleet. Sensitivity analysis on cap value with fixed emissions allowance price equal to 7€/tonCO_2e.

Cap value [%]	110%	105%	100%	95%	90%	85%	80%	75%	70%	65%	60%	55%	50%
Computer time [s]	438	486	364	3549	459	416	325	254	541	589	741	256	492
Driving time [h]	70.74	70.74	70.74	70.74	70.74	70.74	70.74	70.74	70.74	70.74	70.74	70.74	70.74
Inventory cost [€]	3952.93	3952.93	3952.93	3952.93	3952.93	3952.93	3952.93	3952.93	3952.93	3952.93	3952.93	3952.93	3952.93
Driver cost [€]	763.99	763.99	763.99	763.99	763.99	763.99	763.99	763.99	763.99	763.99	763.99	763.99	763.99
Fuel cost [€]	4290.58	4290.58	4290.58	4290.58	4290.58	4290.58	4290.58	4290.58	4290.58	4290.58	4290.58	4290.58	4290.58
Routing cost [€]	5054.56	5054.56	5054.56	5054.56	5054.56	5054.56	5054.56	5054.56	5054.56	5054.56	5054.56	5054.56	5054.56
Emission [kgCO_2e]	6637.78	6637.78	6637.78	6637.78	6637.78	6637.78	6637.78	6637.78	6637.78	6637.78	6637.78	6637.78	6637.78
Total cost [€]	8766.14	8818.44	8870.75	8923.06	8975.36	9027.67	9079.97	9132.28	9184.59	9236.89	9289.20	9341.50	9393.81
Credit bought [kgCO_2e]	0.00	0.00	0.00	0.00	0.00	147.25	529.05	910.84	1292.64	1674.43	2056.23	2438.03	2819.82
Credit sold [kgCO_2e]	1761.72	1379.93	998.13	616.34	234.54	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Emission cost [€]	0.00	0.00	0.00	0.00	0.00	20.17	72.48	124.79	177.09	229.40	281.70	334.01	386.32
Emission revenue [€]	241.36	189.05	136.74	84.44	32.13	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Operational cost [€]	9007.49	9007.49	9007.49	9007.49	9007.49	9007.49	9007.49	9007.49	9007.49	9007.49	9007.49	9007.49	9007.49
Emission reduction [%]	13.07%	13.07%	13.07%	13.07%	13.07%	13.07%	13.07%	13.07%	13.07%	13.07%	13.07%	13.07%	13.07%
Operational cost incr. [%]	0.66%	0.66%	0.66%	0.66%	0.66%	0.66%	0.66%	0.66%	0.66%	0.66%	0.66%	0.66%	0.66%
Average saturation [%]	85.34%	85.34%	85.34%	85.34%	85.34%	85.34%	85.34%	85.34%	85.34%	85.34%	85.34%	85.34%	85.34%
Number of vehicles	9	9	9	9	9	9	9	9	9	9	9	9	9
LDV	3	3	3	3	3	3	3	3	3	3	3	3	3
MDV	5	5	5	5	5	5	5	5	5	5	5	5	5
HDV	1	1	1	1	1	1	1	1	1	1	1	1	1

Table 30 - Cap-and-trade policy with heterogeneous fleet. Sensitivity analysis on cap value with fixed emissions allowance price equal to 137€/tonCO_2e.

Cap value [%]	110%	105%	100%	95%	90%	85%	80%	75%	70%	65%	60%	55%	50%
Computer time [s]	1900	2546	4258	3652	1254	4786	3574	1593	4583	2586	2896	2586	3534
Driving time [h]	74.78	74.78	74.78	74.78	74.78	74.78	74.78	74.78	74.78	74.78	74.78	74.78	74.78
Inventory cost [€]	3734.67	3734.67	3734.67	3734.67	3734.67	3734.67	3734.67	3734.67	3734.67	3734.67	3734.67	3734.67	3734.67
Driver cost [€]	807.64	807.64	807.64	807.64	807.64	807.64	807.64	807.64	807.64	807.64	807.64	807.64	807.64
Fuel cost [€]	4659.39	4659.39	4659.39	4659.39	4659.39	4659.39	4659.39	4659.39	4659.39	4659.39	4659.39	4659.39	4659.39
Routing cost [€]	5467.02	5467.02	5467.02	5467.02	5467.02	5467.02	5467.02	5467.02	5467.02	5467.02	5467.02	5467.02	5467.02
Emission [kgCO_2e]	7208.35	7208.35	7208.35	7208.35	7208.35	7208.35	7208.35	7208.35	7208.35	7208.35	7208.35	7208.35	7208.35
Total cost [€]	9020.73	9073.84	9126.95	9180.07	9233.18	9286.30	9339.41	9392.52	9445.64	9498.75	9551.87	9604.98	9658.10
Credit bought [kgCO_2e]	0.00	0.00	0.00	0.00	229.83	617.53	1005.22	1392.92	1780.61	2168.31	2556.00	2943.70	3331.39
Credit sold [kgCO_2e]	1320.95	933.25	545.56	157.86	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Emission cost [€]	0.00	0.00	0.00	0.00	31.49	84.60	137.72	190.83	243.94	297.06	350.17	403.29	456.40
Emission revenue [€]	180.97	127.86	74.74	21.63	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Operational cost [€]	9201.69	9201.69	9201.69	9201.69	9201.69	9201.69	9201.69	9201.69	9201.69	9201.69	9201.69	9201.69	9201.69
Emission reduction [%]	7.04%	7.04%	7.04%	7.04%	7.04%	7.04%	7.04%	7.04%	7.04%	7.04%	7.04%	7.04%	7.04%
Operational cost incr. [%]	0.46%	0.46%	0.46%	0.46%	0.46%	0.46%	0.46%	0.46%	0.46%	0.46%	0.46%	0.46%	0.46%
Average saturation [%]	68.69%	68.69%	68.69%	68.69%	68.69%	68.69%	68.69%	68.69%	68.69%	68.69%	68.69%	68.69%	68.69%
Number of vehicles	9	9	9	9	9	9	9	9	9	9	9	9	9

Table 31 - Cap-and-trade policy with homogeneous fleet. Sensitivity analysis on cap value with fixed emissions allowance price equal to 137€/tonCO_2e.

Carbon price [€/tonCO_2e]	0	50	100	150	200	250	300	350	400	450	500
Computer time [s]	315	324	376	354	232	241	238	454	329	500	372
Driving time [h]	84.63	84.63	70.74	70.74	70.74	70.74	71.30	71.30	71.30	71.30	71.30
Inventory cost [€]	3098.95	3098.95	3952.93	3952.93	3952.93	3952.93	4220.19	4220.19	4220.19	4220.19	4220.19
Driver cost [€]	914.00	914.00	763.99	763.99	763.99	763.99	770.00	770.00	770.00	770.00	770.00
Fuel cost [€]	4935.76	4935.76	4290.58	4290.58	4290.58	4290.58	4098.16	4098.16	4098.16	4098.16	4098.16
Routing cost [€]	5849.76	5849.76	5054.56	5054.56	5054.56	5054.56	4868.16	4868.16	4868.16	4868.16	4868.16
Emission [kgCO_2e]	7635.91	7635.91	6637.78	6637.78	6637.78	6637.78	6340.10	6340.10	6340.10	6340.10	6340.10
Total cost [€]	8948.71	8948.71	8907.68	8857.77	8807.87	8757.96	8699.61	8634.82	8570.03	8505.24	8440.45
Credit bought [kgCO_2e]	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Credit sold [kgCO_2e]	0.00	0.00	998.13	998.13	998.13	998.13	1295.81	1295.81	1295.81	1295.81	1295.81
Emission cost [€]	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Emission revenue [€]	0.00	0.00	99.81	149.72	199.63	249.53	388.74	453.53	518.32	583.11	647.90
Operational cost [€]	8948.71	8948.71	9007.49	9007.49	9007.49	9007.49	9088.35	9088.35	9088.35	9088.35	9088.35
Emission reduction [%]	0.00%	0.00%	13.07%	13.07%	13.07%	13.07%	16.97%	16.97%	16.97%	16.97%	16.97%
Operational cost incr. [%]	0.00%	0.00%	0.66%	0.66%	0.66%	0.66%	1.56%	1.56%	1.56%	1.56%	1.56%
Average saturation [%]	86.21%	86.21%	85.34%	85.34%	85.34%	85.34%	90.17%	90.17%	90.17%	90.17%	90.17%
Number of vehicles	10	10	9	9	9	9	10	10	10	10	10
LDV	4	4	3	3	3	3	5	5	5	5	5
MDV	6	6	5	5	5	5	4	4	4	4	4
HDV	0	0	1	1	1	1	1	1	1	1	1

Table 32 - Cap-and-trade policy with heterogeneous fleet. Sensitivity analysis on emissions allowance price with fixed cap value equal to 100%.

Carbon price [€/tonCO_2e]	0	50	100	150	200	250	300	350	400	450	500
Computer time [s]	1275	3663	7156	4333	1859	2567	1904	808	704	951	300
Driving time [h]	81.20	81.20	74.78	74.78	62.56	62.56	59.09	59.09	59.09	59.09	59.09
Inventory cost [€]	3270.39	3270.39	3734.67	3734.67	4753.91	4753.91	5121.33	5121.33	5121.33	5121.33	5121.33
Driver cost [€]	876.97	876.97	807.64	807.64	675.65	675.65	638.22	638.22	638.22	638.22	638.22
Fuel cost [€]	5012.03	5012.03	4659.39	4659.39	3961.21	3961.21	3732.45	3732.45	3732.45	3732.45	3732.45
Routing cost [€]	5889.00	5889.00	5467.02	5467.02	4636.85	4636.85	4370.67	4370.67	4370.67	4370.67	4370.67
Emission [kgCO_2e]	7753.90	7753.90	7208.35	7208.35	6128.22	6128.22	5774.32	5774.32	5774.32	5774.32	5774.32
Total cost [€]	9159.39	9159.39	9147.14	9119.32	9065.63	8984.35	8898.12	8799.14	8700.16	8601.19	8502.21
Credit bought [kgCO_2e]	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Credit sold [kgCO_2e]	0.00	0.00	545.55	545.55	1625.68	1625.68	1979.58	1979.58	1979.58	1979.58	1979.58
Emission cost [€]	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Emission revenue [€]	0.00	0.00	54.56	82.38	325.14	406.42	593.87	692.85	791.83	890.81	989.79
Operational cost [€]	9159.39	9159.39	9201.69	9201.69	9390.77	9390.77	9492.00	9492.00	9492.00	9492.00	9492.00
Emission reduction [%]	0.00%	0.00%	7.04%	7.04%	20.97%	20.97%	25.53%	25.53%	25.53%	25.53%	25.53%
Operational cost incr. [%]	0.00%	0.00%	0.46%	0.46%	2.53%	2.53%	3.63%	3.63%	3.63%	3.63%	3.63%
Average saturation [%]	62.06%	62.06%	68.96%	68.96%	77.58%	77.58%	77.58%	77.58%	77.58%	77.58%	77.58%
Number of vehicles	10	10	9	9	8	8	8	8	8	8	8

Table 33 - Cap-and-trade policy with homogeneous fleet. Sensitivity analysis on emissions allowance price with fixed cap value equal to 100%.

Carbon price [€/tonCO_2e]	0	50	100	150	200	250	300	350	400	450	500
Computer time [s]	478	505	724	599	456	312	428	388	372	306	278
Driving time [h]	84,63	84,63	70,74	70,74	70,74	70,74	71,30	71,30	71,30	71,30	71,30
Inventory cost [€]	3098,95	3098,95	3952,93	3952,93	3952,93	3952,93	4220,19	4220,19	4220,19	4220,19	4220,19
Driver cost [€]	914,00	914,00	763,99	763,99	763,99	763,99	770,00	770,00	770,00	770,00	770,00
Fuel cost [€]	4935,76	4935,76	4290,58	4290,58	4290,58	4290,58	4098,16	4098,16	4098,16	4098,16	4098,16
Routing cost [€]	5849,76	5849,76	5054,56	5054,56	5054,56	5054,56	4868,16	4868,16	4868,16	4868,16	4868,16
Emission [kgCO_2e]	7635,91	7635,91	6637,78	6637,78	6637,78	6637,78	6340,10	6340,10	6340,10	6340,10	6340,10
Total cost [€]	8948,71	9139,60	9289,48	9430,47	9571,46	9712,45	9845,00	9971,10	10097,21	10223,32	10349,42
Credit bought [kgCO_2e]	3818,00	3817,95	2819,82	2819,82	2819,82	2819,82	2522,15	2522,15	2522,15	2522,15	2522,15
Credit sold [kgCO_2e]	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
Emission cost [€]	0,00	190,90	281,98	422,97	563,96	704,96	756,64	882,75	1008,86	1134,97	1261,07
Emission revenue [€]	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
Operational cost [€]	8948,71	8948,71	9007,49	9007,49	9007,49	9007,49	9088,35	9088,35	9088,35	9088,35	9088,35
Emission reduction [%]	0,00%	0,00%	13,07%	13,07%	13,07%	13,07%	16,97%	16,97%	16,97%	16,97%	16,97%
Operational cost incr. [%]	0,00%	0,00%	0,66%	0,66%	0,66%	0,66%	1,56%	1,56%	1,56%	1,56%	1,56%
Average saturation [%]	86,21%	86,21%	85,34%	85,34%	85,34%	85,34%	90,17%	90,17%	90,17%	90,17%	90,17%
Number of vehicles	10	10	9	9	9	9	10	10	10	10	10
LDV	4	4	3	3	3	3	5	5	5	5	5
MDV	6	6	5	5	5	5	4	4	4	4	4
HDV	0	0	1	1	1	1	1	1	1	1	1

Table 34 - Cap-and-trade policy with heterogeneous fleet. Sensitivity analysis on emissions allowance price with fixed cap value equal to 50%.

Carbon price [€/tonCO_2e]	0	50	100	150	200	250	300	350	400	450	500
Computer time [s]	1936	5370	5572	5575	3840	1953	1850	723	599	857	459
Driving time [h]	81.20	81.20	74.78	74.78	62.56	62.56	59.09	59.09	59.09	59.09	59.09
Inventory cost [€]	3270.39	3270.39	3734.67	3734.67	4753.91	4753.91	5121.33	5121.33	5121.33	5121.33	5121.33
Driver cost [€]	876.97	876.97	807.64	807.64	675.65	675.65	638.22	638.22	638.22	638.22	638.22
Fuel cost [€]	5012.03	5012.03	4659.39	4659.39	3961.21	3961.21	3732.45	3732.45	3732.45	3732.45	3732.45
Routing cost [€]	5889.00	5889.00	5467.02	5467.02	4636.85	4636.85	4370.67	4370.67	4370.67	4370.67	4370.67
Emission [kgCO_2e]	7753.90	7753.90	7208.35	7208.35	6128.22	6128.22	5774.32	5774.32	5774.32	5774.32	5774.32
Total cost [€]	9159.39	9353.24	9534.83	9703.07	9841.02	9953.58	10061.21	10156.08	10250.94	10345.81	10440.68
Credit bought [kgCO_2e]	3876.95	3876.95	3331.40	3331.40	2251.27	2251.27	1897.37	1897.37	1897.37	1897.37	1897.37
Credit sold [kgCO_2e]	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Emission cost [€]	0.00	193.85	333.14	501.38	450.25	562.82	569.21	664.08	758.95	853.82	948.68
Emission revenue [€]	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Operational cost [€]	9159.39	9159.39	9201.69	9201.69	9390.77	9390.77	9492.00	9492.00	9492.00	9492.00	9492.00
Emission reduction [%]	0.00%	0.00%	7.04%	7.04%	20.97%	20.97%	25.53%	25.53%	25.53%	25.53%	25.53%
Operational cost incr. [%]	0.00%	0.00%	0.46%	0.46%	2.53%	2.53%	3.63%	3.63%	3.63%	3.63%	3.63%
Average saturation [%]	62.06%	62.06%	68.96%	68.96%	77.58%	77.58%	77.58%	77.58%	77.58%	77.58%	77.58%
Number of vehicles	10	10	9	9	8	8	8	8	8	8	8

Table 35 - Cap-and-trade policy with homogeneous fleet. Sensitivity analysis on emissions allowance price with fixed cap value equal to 50%.

Cap value	110%	105%	100%	95%	90%	85%	80%	75%	70%	65%	60%	55%	50%
Computer time [s]	533	458	475	352	476	298	387	364	486	682	349	371	457
Driving time [h]	84.63	84.63	84.63	84.63	84.63	84.63	84.63	84.63	84.63	84.63	84.63	84.63	84.63
Inventory cost [€]	3098.95	3098.95	3098.95	3098.95	3098.95	3098.95	3098.95	3098.95	3098.95	3098.95	3098.95	3098.95	3098.95
Driver cost [€]	914.00	914.00	914.00	914.00	914.00	914.00	914.00	914.00	914.00	914.00	914.00	914.00	914.00
Fuel cost [€]	4935.76	4935.76	4935.76	4935.76	4935.76	4935.76	4935.76	4935.76	4935.76	4935.76	4935.76	4935.76	4935.76
Routing cost [€]	5849.76	5849.76	5849.76	5849.76	5849.76	5849.76	5849.76	5849.76	5849.76	5849.76	5849.76	5849.76	5849.76
Emission [kgCO_2e]	7635.91	7635.91	7635.91	7635.91	7635.91	7635.91	7635.91	7635.91	7635.91	7635.91	7635.91	7635.91	7635.91
Total cost [€]	8948.71	8948.71	8948.71	8951.48	8954.26	8957.03	8959.81	8962.58	8965.36	8968.14	8970.91	8973.69	8976.46
Credit bought [kgCO_2e]	0.00	0.00	0.00	381.80	763.59	1145.39	1527.18	1908.98	2290.77	2672.57	3054.36	3436.16	3817.95
Emission cost [€]	0.00	0.00	0.00	2.78	5.55	8.33	11.10	13.88	16.65	19.43	22.21	24.98	27.76
Operational cost [€]	8948.71	8948.71	8948.71	8948.71	8948.71	8948.71	8948.71	8948.71	8948.71	8948.71	8948.71	8948.71	8948.71
Emission reduction [%]	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
Operational cost incr. [%]	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
Average saturation [%]	86.21%	86.21%	86.21%	86.21%	86.21%	86.21%	86.21%	86.21%	86.21%	86.21%	86.21%	86.21%	86.21%
Number of vehicles	10	10	10	10	10	10	10	10	10	10	10	10	10
LDV	4	4	4	4	4	4	4	4	4	4	4	4	4
MDV	6	6	6	6	6	6	6	6	6	6	6	6	6
HDV	0	0	0	0	0	0	0	0	0	0	0	0	0

Table 36 - Cap-and-offset policy with heterogeneous fleet. Sensitivity analysis on cap value with fixed emissions credit price equal to 7.27€/tonCO_2e.

Cap value	110%	105%	100%	95%	90%	85%	80%	75%	70%	65%	60%	55%	50%
Computer time [s]	3697	3794	3458	3156	2458	2548	3698	3167	3486	4758	3524	3974	3966
Driving time [h]	81,20	81,20	81,20	81,20	81,20	81,20	81,20	81,20	81,20	81,20	81,20	81,20	81,20
Inventory cost [€]	3270,39	3270,39	3270,39	3270,39	3270,39	3270,39	3270,39	3270,39	3270,39	3270,39	3270,39	3270,39	3270,39
Driver cost [€]	876,97	876,97	876,97	876,97	876,97	876,97	876,97	876,97	876,97	876,97	876,97	876,97	876,97
Fuel cost [€]	5012,03	5012,03	5012,03	5012,03	5012,03	5012,03	5012,03	5012,03	5012,03	5012,03	5012,03	5012,03	5012,03
Routing cost [€]	5889,00	5889,00	5889,00	5889,00	5889,00	5889,00	5889,00	5889,00	5889,00	5889,00	5889,00	5889,00	5889,00
Emission [kgCO_2e]	7753,90	7753,90	7753,90	7753,90	7753,90	7753,90	7753,90	7753,90	7753,90	7753,90	7753,90	7753,90	7753,90
Total cost [€]	9159,39	9159,39	9159,39	9162,21	9165,03	9167,84	9170,66	9173,48	9176,30	9179,12	9181,94	9184,76	9187,57
Credit bought [kgCO_2e]	0,00	0,00	0,00	387,70	775,39	1163,09	1550,78	1938,48	2326,17	2713,87	3101,56	3489,26	3876,95
Emission cost [€]	0,00	0,00	0,00	2,82	5,64	8,46	11,27	14,09	16,91	19,73	22,55	25,37	28,19
Operational cost [€]	9159,39	9159,39	9159,39	9159,39	9159,39	9159,39	9159,39	9159,39	9159,39	9159,39	9159,39	9159,39	9159,39
Emission reduction [%]	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%
Operational cost incr. [%]	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%
Average saturation [%]	62,06%	62,06%	62,06%	62,06%	62,06%	62,06%	62,06%	62,06%	62,06%	62,06%	62,06%	62,06%	62,06%
Number of vehicles	10	10	10	10	10	10	10	10	10	10	10	10	10

Table 37 - Cap-and-offset policy with homogeneous fleet. Sensitivity analysis on cap value with fixed emissions credit price equal to 7.27€/tonCO_2e.