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Green supply chain planning considering consumer's transportation process

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ABSTRACT

This article addresses a product delivery and store network layout strategy problem considering not only firms' but also consumers' cost. The study presents several mathematical programming models to minimize the cost or maximize the profit. Then, we design a two-step solution method for exact solutions and present an implementation. The results show that a carbon cap will do more good than harm for the environment. Trying to minimize the cost from both sides will not only improve the efficiency of social resource use but also enable stores to attract more consumers. Limiting emissions for firms will result in significant emissions reduction without an excessive cost increase.

1. Introduction

In the 21st century, many countries have begun to pay more attention to environmental issues and have developed their national development strategies based on a low-carbon economy. In 2003, the UK government put forward the low-carbon economy for the first time with the purpose of developing an economy with low energy consumption, low pollution and low emissions as basic features (Britain, 2003). Many countries have enacted laws or adopted measures, such as carbon taxes, carbon caps and trading mechanisms, to reduce carbon emissions from production and transportation. For firms, increased consumer awareness of the environment makes it imperative to develop strategies to reduce carbon emissions from production operations. Particularly in China, because of its complex road conditions, great market demand and frequent manufacturer replenishment, the logistics industry consumes much energy and produces substantial carbon emissions. Therefore, it is necessary to reduce the carbon emissions from the logistics process and improve the efficiency of energy use (Xiao et al., 2015).

Currently, the urban environment in many countries is deteriorating, and people are facing challenges of unsustainable development (Gracht and Darkow, 2016). Most of the current emission reduction measures affect the carbon emissions from production processes. Even if these policies are very effective, we cannot ignore the emissions from the supply chain. Some firm decisions, such as facility location and transportation mode selection, can significantly influence their carbon footprint. Therefore, it is important to consider emission reduction issues in supply chains (SC) and logistics systems (Choudhary et al., 2015). In addition, increasing numbers of consumers are concerned about the emissions associated with the products they buy. These include emissions from the production process, supply chain and logistics. The environmental aspect is important for consumers when considering stores, as consumers can gain psychological benefits and become willing to pay for the products if they are produced in an environmentally friendly way (Sheu, 2014). Logistics network design models typically focus on minimizing fixed and variable costs in SC. Practice and research in green supply chain management (GSCM) is becoming a hot topic (Baud-Lavigne et al., 2014, Brandenburg, 2015, Fahimnia et al., 2015a,b,c). Most of the research seeks to build an effective system that allows companies to take the initiative to

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reduce their own carbon footprint. However, more than 65% of the carbon emissions generated during transport are derived from the consumption of gasoline in private cars (EPA, 2012). Hence, when we study low-carbon logistics management, the emissions from consumers are non-ignorable.

Generally, when consumers consider a purchase, they pay attention to the quality, price and convenience of getting the product. This article considers logistics. Therefore, we assume the quality of the product is intrinsic. We focus on the product price and buying convenience. Consumers view convenience as the time they spend and the cost they must bear to go shopping. Therefore, we use consumers' transportation cost to represent convenience. However, increasing consumer awareness of the environment makes the emissions associated with the product an attractive point. These kinds of emissions are generated from the production process and supply chain process. While we do not study the production process, the latter processes are important to us. For firms, factors of a supply chain network that influence emissions include not only fuel efficiency and facility location but also the distance traveled and the weight carried. As the density of stores increases, a denser network is created in the market area, and the average distance between consumers and stores decreases, such that they need not travel far to shop (Glaeser, 2011, Owen, 2010). In contrast, the firm must travel farther to replenish its stores. Under normal circumstances, firms' decision makers aim to minimize the total supply chain cost to gain more profits, and government usually imposes a carbon threshold policy on enterprises. However, if managers want to attract more consumers by tactical supply chain decision making such as delivery schemes and store density, they should enhance the store's appeal to consumers in market areas. Making the purchasing process more convenient can attract more consumers because the consumers' transportation cost is reduced. Controlling firms' logistic emissions can also gain the goodwill of environmentalists and encourage them to buy from the concerned stores. This research proposes four models to consider whether the firm takes account of consumers' transportation cost and whether the carbon cap is necessary. Then, we compare the results obtained using CPLEX software and draw some conclusions. We also propose another model to study firms' profit maximizing decision.

The remainder of the paper is composed of the following sections. Section 2 systematically reviews the related literature and previous models to build a foundation for the presented research and clarifies the paper's position and relative contribution to the literature. In Section 3, we present a series of mathematical programming models. Section 4 presents real case data and designs a solution method based on the reality of the problem for the computational experiments. Then, it provides a discussion of the results from the above four models and we come up with a profit maximizing model including some omitted details. Section 5 discusses the managerial implications of the paper. Section 6 concludes this research with a note for future research directions.

2. Foundational literature background

GSCM has been the subject of much recent study (Brandenburg et al., 2014, Sarkar et al., 2016, Yu et al., 2014). GSCM is the integration of environmental thinking into supply chain management; it covers everything from production to recycling and requires a high level of research and detailed planning (Beamon, 1999, Hafezalkotob, 2017, Sheu and Talley, 2011, Chin et al., 2015). Zhu (2004) assessed the relationship between GSCM practices and environmental and economic performance.

Detailed overviews of GSCM and low carbon logistics with their solution techniques are presented in Fahimnia et al. (2015a,b,c), Malviya and Kant (2015), Varsei (2016) and Singh et al. (2016). Dekker et al. (2012) reviewed operational management issues that consider carbon emissions and other environmental factors. They outlined present and future developments, particularly in planning, design and control for inventory, transportation and facility decisions in a supply chain.

For inventory optimization and decisions, Chen and Monahan (2010) analyzed the impacts of different environment policies on firms' decisions of production basing on a stochastic model. They proposed an additional planned stock level called an "environmental safety stock" that firms could reserve as a voluntary control approach. Cheng et al. (2017) solved a green inventory routing problem involving a heterogeneous fleet and constructed a mixed-integer program. They found that a high carbon price does not necessarily imply benefit to the environment, which can provide reference to governments when implementing carbon policies. Rahimi et al. (2017) presented a multi-objective mathematical framework that considers the environmental footprint to address uncertainty by introducing fuzzy distributions. They showed that there are some negative economic impacts when service level objects are exogenous.

For transportation decisions, Hoen et al. (2014) examined the trade-offs between transportation costs and lead times under the influence of carbon policies when selecting a transport mode. They found that even though great emission reductions can be achieved by switching to an optimal mode, the firm's decision depends on non-monetary and regulatory considerations. Xiao and Konak (2016) proposed a model that allows vehicles to stop on arcs and could reduce emissions up to an additional 8% on simulated data. They also designed a hybrid algorithm to solve the mixed integer linear programming problem. Chen and Wang (2016) studied transportation mode selection and retailers' ordering problems with stochastic customer demand and investigated the optimal transport mode selection and ordering decisions under different emission reduction policies. Their analytical results verified that there are thresholds for transport mode shifts under different emissions reduction policies. Wang et al. (2017) investigated an optimization of the vehicle routing problem considering time windows for cold-chain logistics with a carbon tax in China. The authors designed a cycle evolutionary genetic algorithm to solve the problem, and the results provided implications that are relevant not only for the government in considering carbon tax policy but also for companies in controlling emissions from distribution. Sheu and Kundu (2017) addressed the dynamic and stochastic challenges with a multi-methodological approach that is the basis of international logistic network reconfiguration. Although their method did not consider a green supply chain, it is still useful for the study of a low-carbon logistics network. Song et al. (2017) built a two-stage stochastic model to study the capacity expansion problem under cap-and-trade and carbon tax policies in logistics. They argued that the carbon tax has different impacts on optimal capacity expansion decisions, and the volatility of capacity investment cost can strongly affect optimal capacity expansion.

Table 1
Details about the presented papers.

Articles	Model type	Economic objective	Ecological objective	Decision variable				Carbon tax	Carbon cap
				Transportation/ location	Inventory/ production	Facilities open or not	Store density		
Baud-Lavigne et al. (2014)	Mixed-integer nonlinear programming	√	√	√	√	√			
Harris et al. (2014)	Mixed-integer linear programming	√	√			√			
Mohammadi et al. (2014)	Mixed-integer linear programming	√				√		√	
Choudhary et al. (2015)	Mixed-integer linear programming	√		√		√			√
Brandenburg (2015)	Mixed-integer linear programming	√	√	√	√	√			
Fahimnia et al. (2015a,b,c)	Mixed-integer nonlinear programming	√	√	√	√	√			√
Xiao and Konak (2016)	Mixed-integer linear programming		√	√					
Cheng et al. (2017)	Mixed-integer linear programming	√		√	√			√	
Rahimi et al. (2017)	Mixed-integer linear programming	√	√	√	√				
Wang et al. (2017)	Mixed-integer linear programming	√		√		√		√	
Song et al.(2017)	Linear programming	√		√	√			√	
Toro et al. (2017)	Mixed-integer linear programming	√	√	√		√			
Current paper	Mixed-integer nonlinear programming	√		√	√	√	√		√

For facility decisions, Harris et al. (2014) proposed a multi-objective optimization approach to solve the capacitated facility location–allocation problem by simultaneously including financial costs and CO_2 emissions. They extended their exploration by considering a range of trade-offs for customer allocation. Mohammadi et al. (2014) studied a novel sustainable hub location problem incorporating two environmentally based cost functions for air and noise pollution of vehicles. They used simulated annealing and an imperialist competitive algorithm to solve real-sized instances and compared the performances with a proposed lower bound. Toro et al. (2017) introduced a bi-objective vehicle routing problem that integrates the open location routing problem and solved it by using the epsilon constraint technique. The problem considered the minimization of environmental effects and operational costs. The authors found that the proposed model can generate a set of trade-off solutions and lead to interesting conclusions about the relationship between environmental impact and operational costs.

Table 1 describes the previous papers in the field of green supply chain optimization. As shown, the research in this area is mainly focused on transportation, inventory, facility location and production decisions and studies enterprise operation processes. The low-carbon logistics study of store density involving the customer purchase process is an area that has not been developed. Thus, this paper studies the delivery and store network layout strategy problem considering carbon emissions not only of firms but also of consumers. The paper explores the impact of store density on a firm's delivery strategies and carbon emissions.

The end-user market area is often seen as a "black box" and only shows the demand attributes. Previous papers tend to ignore details of the end market area. However, many attributes within these market areas affect the supply chain and logistics decisions of enterprises, which in turn affect the achievement of carbon emission targets. Therefore, to fill this important research gap, this paper opens the "black box" of the market area to study the impact of the density problem of retail stores on the whole supply chain cost and carbon emission and provides the basis for the supply chain assignment and the shop establishment decisions. At the same time, considering that the distribution density of the stores in the market area will affect the firm's attractiveness to consumers, this paper adds the transportation cost from consumer shopping into the following models to optimize the supply chain structure and reduce environmental impact.

3. Problem formulation and mathematical model

In this section, we discuss the problem formulation and present our mathematical models to illustrate how retail store density can affect the carbon emissions in the supply chain, accounting for consumers' emissions and transportation cost. Our models provide decision makers, such as firm managers, with support for decisions on how to design the delivery scheme and how many retail stores should be built in a market area. The models under consideration treat a multi-period, single-product integrated forward logistics network with or without strict carbon caps for a single firm and transportation costs for consumers. By making small changes in the model, a firm can incorporate flexibility in carbon emissions, and it can also consider both its own and consumers' transportation costs with flexibility.

A common problem for the firm is how much to purchase or order under a distribution plan in a specific planning period. This may lead to important variations of carbon emissions across the whole supply chain. Without regard to emissions considerations, firms make decisions to minimize the sum of the fixed and variable costs to maximize their profit. However, if firms take carbon emissions into account, they must minimize the cost while limiting emissions. The cost associated with limiting emissions is generally higher than the cost when ignoring emissions.

For the market, the retailer's transportation cost can be modeled by the traveling salesman problem (TSP). The consumer's transportation problem is like the continuous version of the well-known k-median problem (Cachon, 2014). Fisher and Hochbaum (1980) considered the k-median problem, in which n store locations must be selected from a set of random sites to minimize the total distance that consumers must travel to the closest of the n stores. They found that the optimal cost grows proportionally to $\sqrt{\frac{1}{n}}$. For the TSP, Beardwood et al. (1959) found that the shortest distance through n random points in a unit area is asymptotically proportional to $\sqrt{n}$. Given a set of n store locations, the consumers over area a can be divided into n sub-regions that represent the stores' service areas. Because the specific areas' shapes are unknown, the problem under this condition is too complex to solve. As a result, Cachon (2014) use a tiling with equilateral triangles as shown in Figs. 1 and 2.

He found that within a store's service area, consumers' average round trip distance could be computed as follows:

$$d_c = \phi_c n^{-\frac{1}{2}} \tag{1}$$

ϕ_c is a constant that depends on the number of sides of a regular polygon s and the overall size of the region a, which can be represented by the area of the region in Fig. 1:

$$\phi_c = \frac{2}{3}\sqrt{\frac{a}{s\tan\theta}}\left(\sqrt{1+\tan^2\theta} + \ln(\tan\theta + \sqrt{1+\tan^2\theta})\tan^{-1}\theta\right) \tag{2}$$

In this paper, the regular polygon of the sub-region is a triangle, Therefore, the number of sides s is 3.

The retailer's distance to deliver to all the stores is

$$d_t = \phi_t n^{\frac{1}{2}} \tag{3}$$

ϕ_t only depends on the number of sides s and the area of the region a:

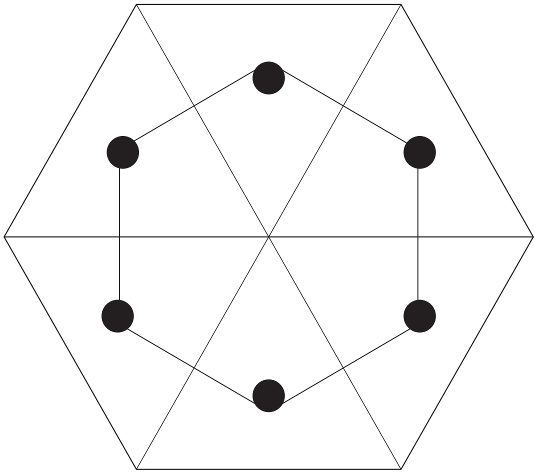

Fig. 1. Triangle tessellation of stores.

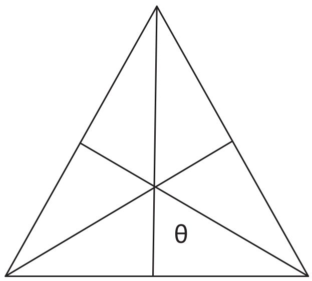

Fig. 2. Sub-regions within a store's single service area given a triangle tessellation.

$$\phi_t = 2\sqrt{\frac{a}{s\tan\theta}} \quad (4)$$

3.1. Assumptions

The schematic view of the SC under study is shown in Fig. 3.

The objective of this model is to determine the tactical planning decisions for the SC, including purchasing and distribution allocation strategies, and the optimal retail store density in each market area to minimize the whole SC cost and reduce the negative environmental impacts.

The following key assumptions are considered for mathematical modeling:

- Number, location and capacity of suppliers (a) and distribution centers (i) are known.
- Number and location of market areas (j) are known.
- Demand is deterministic and available. The average demand is assumed to be known.
- The firm produces only one kind of product.
- The demand for the product has to be satisfied. A penalty cost is incurred if the demand at one period is backordered. Then, it must be satisfied in the subsequent periods before the end of the planning horizon.
- The firm transports the product by truck, and consumers go to buy it by car.
- Transportation costs and emission rates are available and intrinsic for trucks and cars.
- Carbon emission and inventory cost rates are available for distribution centers and stores.
- Market areas can be divided into a few equilateral triangles, and each store is assumed to be the same and can only serve one equilateral triangle market area.

3.2. Parameters and decision variables

The sets and indices used in this research include the following:

A a set of suppliers, indexed by a

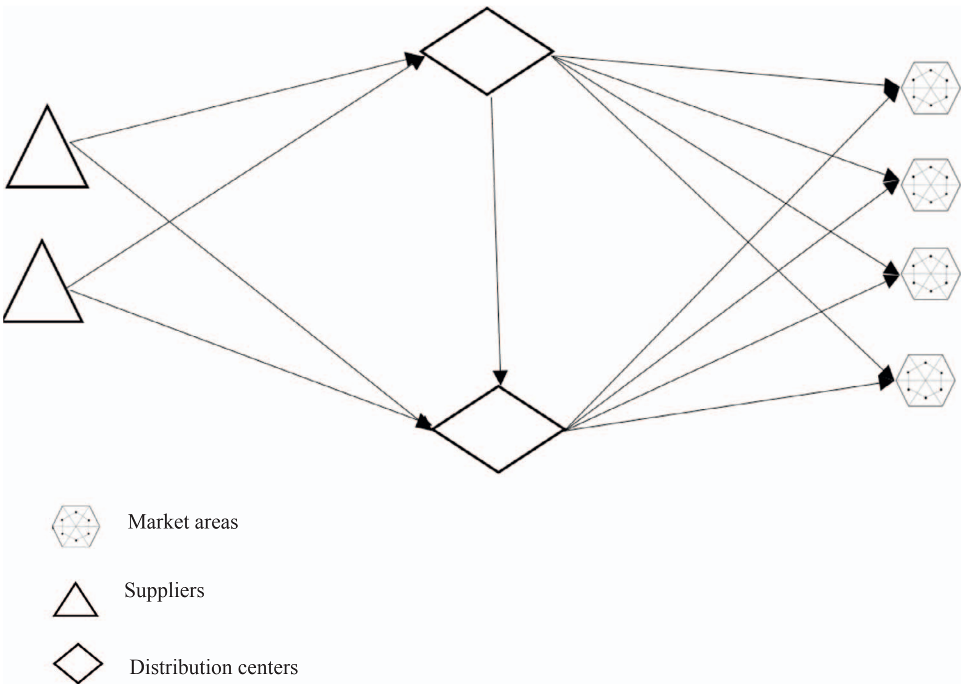

Fig. 3. Structure of logistics network.

I a set of distribution centers, indexed by i
J a set of market areas, indexed by j
T a set of time periods, indexed by t

The SC has a network structure. Let W be the set of transportation arcs, thus $W = \{(h,k)|h \in A,I;k \in I,J\}$. The input parameters are given in Table 2.

Continuous decision variables include the following:

Table 2
Input parameters.

Symbol	Description	Unit
M_a	Supplying capacity of a	Box
R_i	Holding capacity of i	Box
S_j	Maximum selling capacity of each retailer store in market area j	Box per week
s_j	Minimum selling capacity of each retailer store in market area j	Box per week
CO_2CAP	Maximum amount of carbon that can be emitted in SC	Kilogram
λ_{jt}	Aggregate demand in market area j at t	Box
λ_j	Average demand over the periods considered in market area j	Box
d_{hk}	Distance between suppliers, distribution centers and market areas $(h,k) \in W$	Kilometer
d_j	The shortest distance through all stores in market area j for firm replenishing	Kilometer
d_j'	Average distance for consumers in market area j to the nearest store.	Kilometer
C_{hkt}	Transportation cost multiplier for shipment from h to k at t, $(h,k) \in W$	¥ per km per box
C_{jt}^{rr}	Transportation cost multiplier for shipment between retailer stores in the market area j at t	¥ per km per box
C_{jt}^{rc}	Transportation cost multiplier for shipment from retailer stores to consumers' houses in the market area j at t	¥ per km per box
C_{it}	Cost coefficient for holding inventory in distribution centers i at t	¥ per day per box
C_{jt}	Cost coefficient for holding inventory in retailer stores in market area j at t	¥ per day per box
C_{jt}^{s}	Unit shortage cost in market area j at t	¥ per box
E_{hkt}	Carbon emission multiplier for shipment from h to k at t, $(h,k) \in W$	kg per km per box
E_{it}	Carbon emission coefficient for holding inventory in distribution centers i at t	kg per week per box
E_{jt}^{rr}	Carbon emission coefficient for shipment between retailer stores in market area j at t	kg per km per box
E_{jt}	Carbon emission coefficient holding inventory in retailer stores in market area j at t	kg per week per box
E_{jt}^{rc}	Carbon emission multiplier for shipment from retailer stores to consumers' houses in market area j at t	kg per km per box

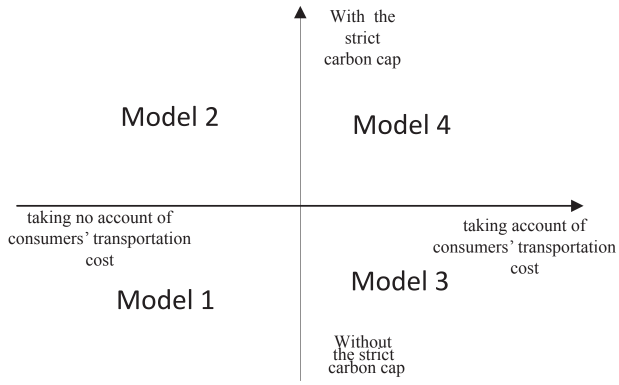

Fig. 4. The relationship between models.

Q_{hkt} quantity of the product shipped from h to k at t, $(h,k) \in W$
Y_{it} inventory amount of the product in i at the end of t
Y_{jt} inventory amount of the product in each of the stores in j at the end of t
S_{jt} quantity of the product backordered in j at the end of t

Binary decision variables include the following:

$$O_{\text{it}} = \begin{cases} 1, & \text{if } i \text{ is open to the product in } t \\ 0, & \text{otherwise} \end{cases}$$

Integral decision variables include the following:

n_j number of firm's stores in the region of market area j

With the above assumptions and parameters, we propose four models. They differ in whether the firm considers the consumers' transportation cost and whether it joins the strict carbon emission cap. The relationships among the models are shown in Fig. 4.

3.3. Model 1: A single firm taking no account of consumers' transportation cost without strict carbon cap

3.3.1. Objective function

Using parameters and decision variables defined in Section 3.2, the objective function can be formulated as follows:
Minimize

$$\sum_{t\in T}\sum_{a\in A}\sum_{i\in I} d_{ai}C_{ait}Q_{ait} + \sum_{t\in T}\sum_{i\in I}\sum_{j\in J}(d_{ij}C_{ijt}Q_{ijt} + d_{ii'}C_{ii't}Q_{ii't}) + \sum_{t\in T}\sum_{j\in J}\frac{1}{2}\left(\sum_{i\in I}Q_{ijt}\right)d_jC_{jt}^{rr} + \sum_{t\in T}\left[\sum_{i\in I}C_{it}Y_{it} + \sum_{j\in J}n_jC_{jt}Y_{jt}\right] + \sum_{t\in T}\sum_{j\in J}C_{jt}^{s}S_{jt} \quad (5)$$

This is a mixed-integer nonlinear programming (MINLP) model. The first term is the cost for the shipment from suppliers to distribution centers. The second term is the cost for the shipment between distribution centers and from them to market areas. The third term considers the cost for the shipment between retail stores in market areas (d_j can be calculated from $d_j = \phi_j n_j^{\frac{1}{2}}$ and $\phi_j = 2\sqrt{\frac{a_j}{s_j\tan\theta_j}}$). The fourth term minimizes the inventory cost from distribution centers and retail stores. The last is the penalty costs for being out of stock. The following constraints must be satisfied simultaneously for the model above.

3.3.2. Model constraints

1. Capacity constraints:
   Restrictions on the product supply:

$$\sum_{i\in I} Q_{ait} \leqslant M_a, \forall\, a \in A, t \in T \quad (6)$$

Distribution center holding capacity restriction:

$$Y_{it} \leqslant R_i, \forall\ i \in I, t \in T \tag{7}$$

2. Balance constraints:
   Inventory balance at distribution centers:

$$Y_{it} - Y_{it-1} = \sum_{a \in A} Q_{ait} + Q_{i'it} - \sum_{j \in J} Q_{ijt} - Q_{ii't}, \forall\ i \in I, t \in T \tag{8}$$

   Inventory balance at retailer stores:

$$\sum_{i \in I} Q_{ijt} + n_j(Y_{jt-1} - Y_{jt}) + S_{jt} - S_{jt-1} = \lambda_{jt}, \forall\ j \in J, t \in T \tag{9}$$

   Demand satisfaction constraint:

$$\sum_{a \in A} \sum_{i \in I} \sum_{t \in T} Q_{ait} = \sum_{j \in J} \sum_{t \in T} \lambda_{jt} + \sum_{i \in I} Y_{i\bar{t}} + \sum_{j \in J} n_j(Y_{j\bar{t}} - S_{j\bar{t}}) \tag{10}$$

3. Other constraints:
   At the end of the planning horizon:

$$t = \bar{t}, t \in T \tag{11}$$

   Distribution center restriction for opening or not:

$$\sum_{a \in A} Q_{ait} \leqslant \Omega O_{it}, i \in I; t \in T \tag{12}$$

$$\sum_{j \in J} Q_{ijt} \leqslant \Omega O_{it}, i \in I; t \in T \tag{13}$$

$$Q_{ii't} \leqslant W O_{it} O_{i't}, i, i' \in I; t \in T \tag{14}$$

It is

$$Q_{ii't} \leqslant W(O_{it} + O_{i't} - 1), i, i' \in I; t \in T \tag{15}$$

   Restrictions on decision variables:

$$O_{\mathrm{it}} = \{0,1\}\ \mathrm{i} \in \mathrm{I}, \mathrm{t} \in \mathrm{T} \tag{16}$$

$$Q_{hkt} \geqslant 0, (h,k) \in W, t \in T \tag{17}$$

$$Q_{iit} = 0, i \in I, t \in T \tag{18}$$

$$Y_{it} \geqslant 0, i \in I, t \in T \tag{19}$$

$$Y_{jt} \geqslant 0, j \in J, t \in T \tag{20}$$

It is important to note that the proposed model does not consider the stochastic environment. However, the fuel price and traffic condition for a particular scenario is so changeable that transportation cost cannot be considered as a constant. In addition, firms have to consider uncertain consumer demands. Sometimes, the retailer stores aim to grab market share and defeat competitors. Their goal is thus not to minimize the cost. Our model could be extended to incorporate these uncertainties and scenarios.

In the abovementioned formulation, we consider a firm that has several distribution centers and many retail stores in a few market areas. The managers need to determine the optimal number of stores in each area and then design the delivery scheme to minimize the total cost. However, they do not have to consider the carbon emissions or consumers' transportation costs to increase their stores' attractiveness. Next, we discuss another logistics network model for a single firm in which the managers must make decisions under a strict carbon cap.

3.4. Model 2: A single firm taking no account of consumers' transportation cost with strict carbon cap

Using parameters and decision variables defined in Section 3.2, the objective function can be formulated as follows:
Minimize

$$\sum_{t\in T}\sum_{a\in A}\sum_{i\in I} d_{ai}C_{ait}Q_{ait} + \sum_{t\in T}\sum_{i\in I}\sum_{j\in J}(d_{ij}C_{ijt}Q_{ijt} + d_{ii'}C_{ii't}Q_{ii't}) + \sum_{t\in T}\sum_{j\in J}\frac{1}{2}\left(\sum_{i\in I} Q_{ijt}\right)d_jC_{jt}^{rr} + \sum_{t\in T}\left[\sum_{i\in I} C_{it}Y_{it} + \sum_{j\in J} n_jC_{jt}Y_{jt}\right] + \sum_{t\in T}\sum_{j\in J} C_{jt}^{s}S_{jt} \tag{21}$$

subject to the constraints mentioned in Eqs. (6)–(20). Then, we need to calculate the carbon emission from SC:

$$\sum_{t\in T}\sum_{a\in A}\sum_{i\in I} d_{ai}E_{ait}Q_{ait} + \sum_{t\in T}\sum_{i\in I}\sum_{j\in J}(d_{ij}E_{ijt}Q_{ijt} + d_{ii'}E_{ii't}Q_{ii't}) + \sum_{t\in T}\sum_{j\in J}\frac{1}{2}\left(\sum_{i\in I} Q_{ijt}\right)d_jE_{jt}^{rr} + \sum_{t\in T}\left[\sum_{i\in I} E_{it}Y_{it} + \sum_{j\in J} n_jE_{jt}Y_{jt}\right] \tag{22}$$

The first term is the carbon emissions for the shipment from suppliers to distribution centers. The second term is for the shipment between distribution centers and from them to market areas. The third term is the emissions for the shipment between retail stores in market areas. The last term treats the inventory carbon emissions from distribution centers and retail stores (The inventory emissions are from four primary sources: cooling and operating office equipment, electricity for lighting and natural gas for heating). In addition, we can also get the carbon emissions from consumer transportation $\left(\sum_{t\in T}\sum_{j\in J}\frac{1}{2}[n_j(Y_{jt-1}-Y_{jt}) + \sum_{i\in I} Q_{ijt}]d_j{}'E_{jt}^{rc}\right)$.

Therefore, the model should be optimized under the following restriction:

$$\sum_{t\in T}\sum_{a\in A}\sum_{i\in I} d_{ai}E_{ait}Q_{ait} + \sum_{t\in T}\sum_{i\in I}\sum_{j\in J}(d_{ij}E_{ijt}Q_{ijt} + d_{ii'}E_{ii't}Q_{ii't}) + \sum_{t\in T}\sum_{j\in J}\frac{1}{2}\left(\sum_{i\in I} Q_{ijt}\right)d_jE_{jt}^{rr} + \sum_{t\in T}\left[\sum_{i\in I} E_{it}Y_{it} + \sum_{j\in J} n_jE_{jt}Y_{jt}\right] \leqslant CO_2CAP \tag{23}$$

Eq. (23) restricts the carbon emissions to less than or equal to the carbon cap specified for the logistic networks. Here, we have considered a carbon emission cap over all planning periods, but it is possible to model the system in which the cap affects smaller subsets of periods or each small period. The cap can also be associated with each unit transported or ordered; for example, firms may wish to sell products whose carbon emissions per unit do not exceed a certain threshold. We assume that emission is linearly increased with the decision variables while defining carbon emission parameters. However, it can be shown that increasing emissions can be defined with non-linear functions by making a few changes in the model. We also assume that the carbon emission coefficients are available, which is not always the case in reality. It is a huge task for any firm to achieve quantitative measurement of carbon emissions.

Next, we will discuss the logistics network model introducing the attractiveness of the store to customers. The model aims to minimize the total cost of the firm and consumers.

3.5. Model 3: A single firm taking account of consumers' transportation cost without strict carbon cap

Now we assume that the firm needs to consider the buying convenience for consumers, namely, consumers' transportation cost when they make purchases. Therefore, the managers need to minimize not only their own cost but also consumers' cost. In this way, the firm can control its supply chain cost and attract more consumers by making purchases more convenient.

Using parameters and decision variables defined in Section 3.2, the objective function can be formulated as follows:

Minimize

$$\sum_{t\in T}\sum_{a\in A}\sum_{i\in I} d_{ai}C_{ait}Q_{ait} + \sum_{t\in T}\sum_{i\in I}\sum_{j\in J}(d_{ij}C_{ijt}Q_{ijt} + d_{ii'}C_{ii't}Q_{ii't}) + \sum_{t\in T}\sum_{j\in J}\frac{1}{2}\left(\sum_{i\in I} Q_{ijt}\right)d_jC_{jt}^{rr} + \sum_{t\in T}\left[\sum_{i\in I} C_{it}Y_{it} + \sum_{j\in J} n_jC_{jt}Y_{jt}\right] + \sum_{t\in T}\sum_{j\in J}\frac{1}{2}\left[n_j(Y_{jt-1}-Y_{jt}) + \sum_{i\in I} Q_{ijt}\right]d_j{}'C_{jt}^{rc} + \sum_{t\in T}\sum_{j\in J} C_{jt}^{s}S_{jt} \tag{24}$$

Consumers' transportation cost represents the penultimate cost before the last part of the cost, penalty costs for being out of stock ($d_j{}'$ can be calculated from $d_j{}' = \phi_j{}'n_j^{-\frac{1}{2}}$ and $\phi_j{}' = \frac{2}{3}\sqrt{\frac{a_j}{s_j\tan\theta_j}}(\sqrt{1+\tan^2\theta_j} + \ln(\tan\theta_j + \sqrt{1+\tan^2\theta_j})\tan^{-1}\theta_j))$.

Subject to the constraints mentioned in Eqs. (6)–(20).

Firm managers aim to minimize the total cost of not only the firm but also consumers so that the stores can attract more consumers. As the number of stores increases, the network will become dense. Consumers find themselves closer to some stores, Therefore, they do not have to travel far to go shopping. However, the firm must travel farther to replenish its stores. Next, we extend our proposed model to incorporate the carbon cap and consumers' transportation cost in city planning.

3.6. Model 4: A single firm taking account of consumers' transportation cost with strict carbon cap

Using parameters and decision variables defined in Section 3.2, the objective function can be formulated as follows:

Minimize

$$\sum_{t\in T}\sum_{a\in A}\sum_{i\in I} d_{ai}C_{ait}Q_{ait} + \sum_{t\in T}\sum_{i\in I}\sum_{j\in J}(d_{ij}C_{ijt}Q_{ijt} + d_{ii'}C_{ii't}Q_{ii't}) + \sum_{t\in T}\sum_{j\in J}\frac{1}{2}\left(\sum_{i\in I}Q_{ijt}\right)d_jC_{jt}^{rr} + \sum_{t\in T}\left[\sum_{i\in I}C_{it}Y_{it} + \sum_{j\in J}n_jC_{jt}Y_{jt}\right] + \sum_{t\in T}\sum_{j\in J}\frac{1}{2}\left[n_j(Y_{jt-1}-Y_{jt}) + \sum_{i\in I}Q_{ijt}\right]d_j'C_{jt}^{rc} + \sum_{t\in T}\sum_{j\in J}C_{jt}^{s}S_{jt} \tag{25}$$

This is the same as the object in model 3 and is subject to the constraints mentioned in Eqs. (6)–(20). However, the firm must make decisions under a carbon cap:

$$\sum_{t\in T}\sum_{a\in A}\sum_{i\in I} d_{ai}E_{ait}Q_{ait} + \sum_{t\in T}\sum_{i\in I}\sum_{j\in J}(d_{ij}E_{ijt}Q_{ijt} + d_{ii'}E_{ii't}Q_{ii't}) + \sum_{t\in T}\sum_{j\in J}\frac{1}{2}\left(\sum_{i\in I}Q_{ijt}\right)d_jE_{jt}^{rr} + \sum_{t\in T}\left[\sum_{i\in I}E_{it}Y_{it} + \sum_{j\in J}n_jE_{jt}Y_{jt}\right] \leqslant CO_2CAP \tag{26}$$

Currently, increasing consumer awareness of the environment also makes the emissions from firm's processes important to increase stores' attractiveness. Therefore, from the perspective of a firm manager, the total carbon emissions from the firm's activities should be considered while optimizing the SC. Its aim is to make the urban logistics more efficient and more environmentally friendly. In this way, the stores can attract more environmentalist consumers to make purchases. In addition, all consumers prefer to go to the nearest store. Therefore, the key element associated with consumers' emissions is the density of retail stores in market area j. The next section discusses an example and presents a numerical analysis to solve the model proposed in Section 3.

4. Model implementation

4.1. The case company parameters

First, we apply the above models to a logistics case study in China to determine optimal store density and delivery strategies for a firm with consideration of carbon emissions and inventory cost. This company, DELTA, is the world's leading manufacturer of switching power supplies and fans and is a world-class leader in a number of product areas. It was named among the "Top 100 Low Carbon Businesses" by CNBC European Business in 2008. The study period is 1 month measured in units of weeks (T = 4). The firm has two suppliers in Jiangsu and Wuhu and two distribution centers in Huqiu District of Suzhou and Luyang District of Hefei. At the beginning of each period, the DCs will transport products to the firm's stores located in Foshan, Shenzhen, Guangzhou and Dongguan. First, the managers need to decide how many stores should be opened in these cities to minimize the total cost. The firm uses three types of vehicles. One type is used to transport products from suppliers to DCs. Another is used to transport products between DCs and market areas. The last type is used to replenish products for stores in market areas. Consumers go shopping by car.

Table 3 shows the distance between suppliers and DCs.

Table 4 shows the distance between DCs and market areas. The distance between DCs is 404.1 km.

Table 5 shows the details about market areas.

Tables 6and 7 present various transportation carbon emission parameters between suppliers and DCs and DCs and market areas. The carbon emission parameter between DCs is 0.01 kg per km per box.

Table 8 shows the transportation costs and inventory costs. The transportation cost between DCs is 0.038 ¥ per km per box.

Table 9 presents the demand in the market areas in each period.

Table 10 shows the supplying capacity of suppliers and holding capacity of DCs in each period.

The carbon emission coefficient for holding inventory is 1.455 kg per week per box.

With the above parameter values, we will discuss the models using actual store figures.

4.2. Base case for given store numbers

Before we study the effect of the store density, we apply the four models when the actual number of stores is given considering costs and emissions. We set this as the base case in which n_j equal 214, 404, 413 and 423 for the four models.

When the integral decision variables n_j are given, the above models will follow integer linear programming, which makes the models easily solved. Details about the solutions are as follows.

Firstly, the total emissions consist of both firm's and consumers' emissions. From the above Table 11 and Figs. 5 and 6, we can see that when the store numbers are given, strict carbon caps in model 2 can control the emissions but can also create more cost.

Table 3
Distance (in kilometers) matrix for supplier to distribution center.

DC	1	2
Supplier		
1	29.5	393.9
2	257.16	141.3

Table 4
Distance (in kilometers) matrix for distribution center to market area.

DC	Market area			
	1	2	3	4
1	1464.9	1462.9	1440.3	1452.2
2	1049.6	1047.8	1061.3	1047.9

Table 5
Details about market area.

Market area	Parameter						
	Inventory cost (¥ per day per box)	Shortage cost (¥ per box)	Maximum selling capacity of each store (box per week)	Minimum selling capacity of each store (box per week)	The area of the market (km^2)	Carbon emission parameter for replenishing (kg per km per box)	Carbon emission parameter for consumers (kg per km per box)
1	0.69	3000	6	2.18	3875	0.0106	0.0455
2	1.08	3400	11	3.68	1996.85	0.0211	0.0782
3	0.91	2800	13	4.8	7434	0.0265	0.0864
4	0.78	1400	8	2.9	2512	0.0175	0.0653

Table 6
Carbon emission parameters (in kg per km per box) between suppliers and DCs.

Supplier	DC	
	1	2
1	0.0191	0.0111
2	0.0168	0.0145

Table 7
Carbon emission parameters (in kg per km per box) between DCs and market areas.

DC	Market area			
	1	2	3	4
1	0.0083	0.0083	0.0083	0.0083
2	0.0094	0.0094	0.0094	0.0094

Table 8
Transportation costs (in ¥ per km per box) and inventory costs (in ¥ per day per box).

Various costs	Values
Transportation cost between suppliers and DCs	0.04
Transportation cost between DCs and market areas	0.038
Transportation cost in market areas for replenishing	0.087
Transportation cost in market areas for consumers	25
Inventory cost in DC 1	0.48
Inventory cost in DC 2	0.282

However, considering consumers' increasing environmental consciousness, firms are willing to control their own carbon emissions. Particularly when we minimize the total costs of both firm and consumers in model 3, not only does the total cost decrease, but the emissions also achieve a slight reduction compared to model 1. This may be because both carbon emissions and total cost are somewhat related to transport distances, even if they do not just include the transport process. In model 4, if we set a strict cap for the emissions and minimize both the firm's and consumers' costs, we can reduce the supply chain emissions significantly without bearing too much cost.

This is the result of the base case. In this paper, we want to illustrate how retail store density can affect the carbon emissions in the supply chain. Therefore, the next section will discuss the above problem with decision variable n_j. However, when the store numbers are not given, the models are MINLP and are difficult to solve directly. Thus, we will later explain how to solve the above MINLP models.

Table 9
Demand (in box) in the market areas in each period.

Market area	Period			
	1	2	3	4
1	1741.3	1702.5	1684.6	1711.3
2	2981.4	2946.7	2907.7	2820.7
3	3751.5	3748.1	3714.6	3771.7
4	2273.3	2261.4	2226.5	2231.7

Table 10
Supplying capacity (in box) of suppliers and holding capacity of DCs in each period.

Suppliers or DCs	Capacity
Supplier 1	7000
Supplier 2	6000
DC 1	8400
DC 2	5600

Table 11
Details about the solutions.

	Details				
Model	n_j	Firm's cost (¥)	Total cost (¥)	Firm's emission (kg)	Total emission (kg)
1	$n_1 = 214$ $n_2 = 404$ $n_3 = 293$ $n_4 = 198$	5,067,581	10,317,852	1,260,756	1,277,095
2	$n_1 = 214$ $n_2 = 404$ $n_3 = 293$ $n_4 = 198$	5,068,057	10,318,367	1,250,000	1,269,154
3	$n_1 = 214$ $n_2 = 404$ $n_3 = 293$ $n_4 = 198$	5,068,274	10,316,299	1,260,499	1,276,832
4	$n_1 = 214$ $n_2 = 404$ $n_3 = 293$ $n_4 = 198$	5,068,944	10,317,654	1,250,000	1,267,975

4.3. Two-step solution methodology

As shown above, when the models consider consumers' transportation cost or a strict carbon cap, they follow mixed-integer nonlinear programming. To solve the models quickly and accurately, we design a two-step solution method based on the reality of the problem. The retailer stores have maximum selling capacity and minimum selling capacity, as they cannot be so small that there are too many stores in a market area.

We can obtain the range of n_j using the following (n_j are natural number):

$$s_j \leqslant \frac{\lambda_j}{n_j} \leqslant S_j ,\forall\ j \in J \tag{27}$$

That is

$$\frac{\lambda_j}{S_j} \leqslant n_j \leqslant \frac{\lambda_j}{s_j} ,\forall\ j \in J \tag{28}$$

Thus we can solve for the range of the number of stores. In this way, the MINLP problems can be transformed into integer linear programming. The steps of the algorithm are as follows:

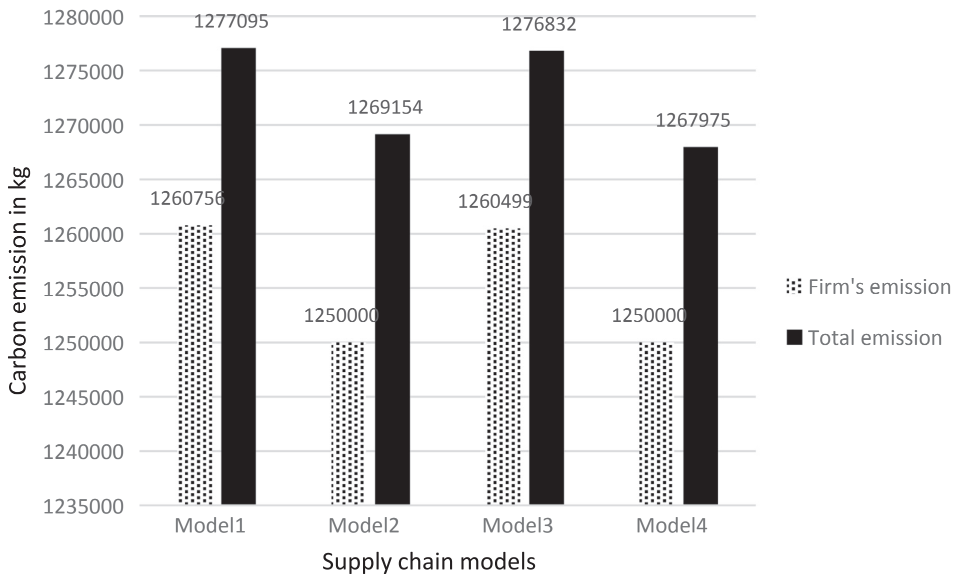

Fig. 5. Comparison of carbon emissions with given store numbers under four models for market area 1.

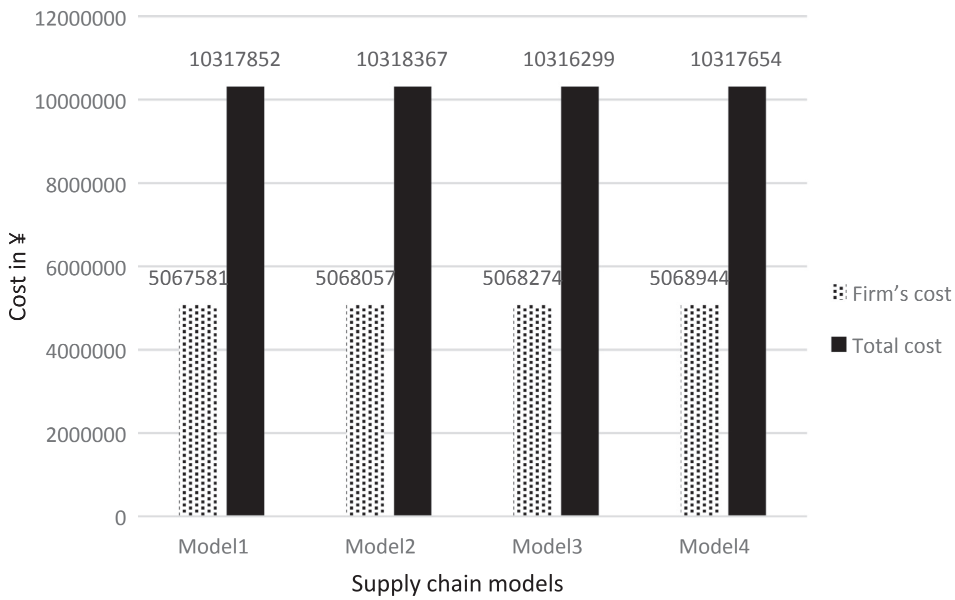

Fig. 6. Comparison of supply chain cost with given store numbers under four models for market area 1.

Step 1: Use the actual parameters and Eq. (28) to obtain the range of the number of stores.
Step 2: Solve the models and obtain the exact solutions with CPLEX for each integer n_j, which is the number of stores in market area j. Then, compare the results and draw conclusions.

According to Eq. (28), we can obtain the range of the number of stores in each market area, as shown in Table 12.
Next, we are going to use this methodology to solve the MINLP models and analyze the results.

4.4. Results and discussion

With the above methodology, we can obtain the results of the models. In the traditional operation pattern of a supply chain, the firm's process is the same as that in model 1. In this situation, managers focus on minimizing the firm's costs under the traditional material balance constraints at each node in the supply chain. This process will change observably if we consider both logistics costs and CO_2 emissions in supply chain optimization. The government usually sets a strict carbon cap for firms, such as that in model 2.

Table 12
Range of number of stores in each market area.

Market area	Minimum value	Maximum value
1	159	437
2	148	442
3	161	436
4	157	433

Therefore, the computational result for market area 1 with a minimum number of stores in other market areas (Fig. 7) shows that when the firm has to make decisions under a strict carbon cap, its costs will always be higher than the costs in the scenario of model 1. We know that there is a contradiction between economic efficiency and environmental benefit. In normal conditions, we need to bear higher cost to achieve a green supply chain. In addition, we can also find that regardless of whether the firm considers carbon emissions, the firm's cost will increase with the number of stores. This is because when the number increases, the distance the firm travels to replenish its stores will also increase owing to the TSP problem. The carbon cap can shrink the solution domain to make the range of number of stores smaller. Therefore, we can see that when there are more than 236 stores, there is no solution for model 2. According to this phenomenon, the trend line for model 2 is obviously shorter than it is for model 1.

As we can see, for models 2, the cost will rise sharply when the number of stores reaches a certain level. This is because all stores face a strict carbon cap, which changes the feasibility of the models. When the number of stores exceeds a certain threshold, this logistics network must bear a particularly high cost to make emissions meet the constraint.

If we see the design of supply chain as a means of attracting consumers, we should consider not only firms' but also consumers' transportation cost. In this way, the operation process is like model 3. With the increase in consumer awareness of the environment, to attract more consumers and realize low carbon logistics, the carbon emissions from the firm's activities should also be considered while optimizing the SC. Firm managers can generate an operation strategy under the carbon cap and get the optimal solution to minimize both firms' and consumers' cost. The operation process is the same as that in model 4. From the computational result for market area 1 (Fig. 8), we can find that no matter which model we use, the total cost will first decrease when the number of stores is growing, and then it will increase after reaching an inflection point. At this point, we can achieve the lowest total cost. Therefore, a firm's manager will decide that the number of stores should be equal to the inflection point. However, considering the carbon cap, the total cost in model 4 is always higher than the total cost in model 3, and when the number of stores exceeds 236, there is no solution for model 4. The total cost will decrease at first because when there are few stores, the average round-trip distance consumers travel to a store is long, as seen in the well-known k-median problem and Eq. (1). As the stores become more numerous, the distance consumers travel becomes shorter than before, and thus they will bear a smaller transportation cost. Nevertheless, the firm needs to replenish its stores, and the length of the truck's route will increase with the number of stores in the market area from the TSP problem and Eq. (3). As a result, there is an inflection point at which the total cost is the lowest.

To sum up, because the carbon cap in model 4 restricts the firm's emissions whiling optimizing both the firm's and consumers' cost, it is more comprehensive and environmentally friendly than the model in model 2. For models 1 and 2, the firm's number of stores must be equal to the lower limit because at this point, the firm's cost is smallest. However, for models 3 and 4, the firm's store number is equal to the inflection point to achieve low total cost. Table 13 shows the details about the optimal solutions, and Figs. 9 and 10 compare the optimal solutions in different models.

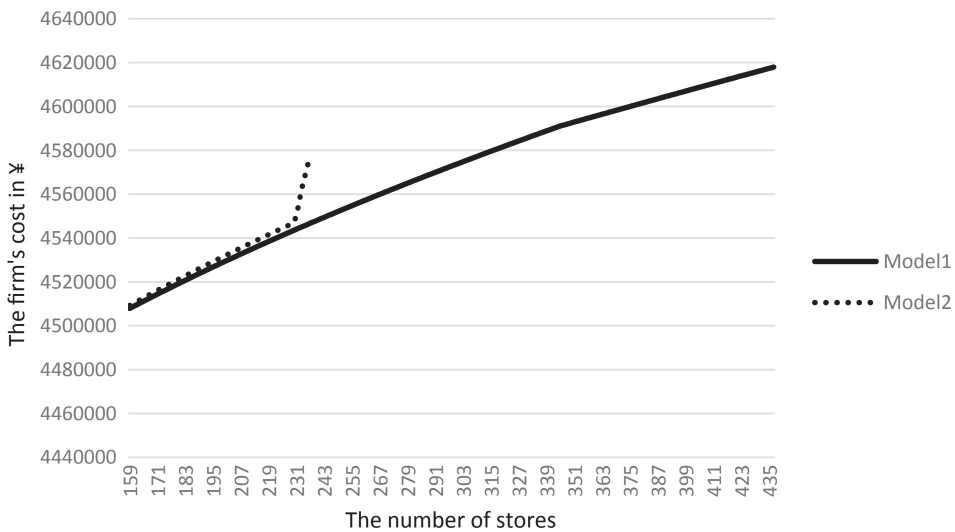

Fig. 7. Comparison of the firm's cost with the number of stores for market area 1 between model 1 and 2.

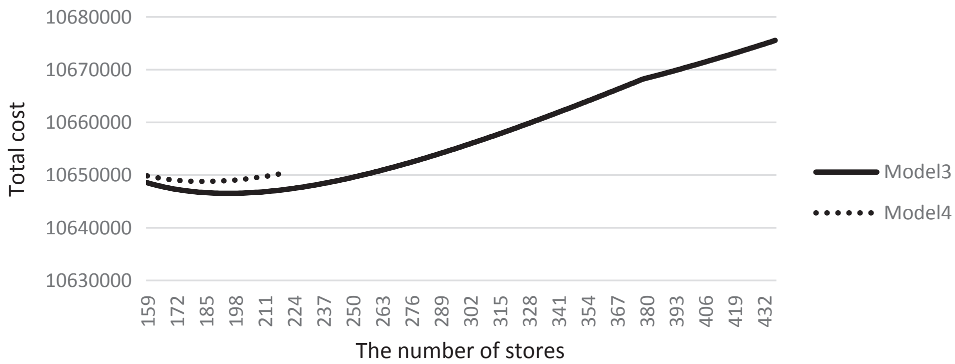

Fig. 8. Comparison of total cost with the number of stores for market area 1 between model 3 and 4.

We can see that in models 1 and 2, the firm will set the number of retail stores in market area 1 as 159, which is the minimum value in Table 12. This is because the firm does not need to consider consumers' cost. Thus, the firm's cost will always increase with the number of stores. The decision makers will open as few stores as possible as a matter of course. Because there is a carbon cap for the firm and therefore a contradiction between economy and the environment in model 2, the emissions is lower and the cost is higher than that in Model 1.

For models 3 and 4, the optimal number of stores is not the minimum value because there are inflection points, as shown in Fig. 8. As expected, the total cost in model 3 is lowest because the objective is to minimize the costs of both the firm and consumers. Of course, the level of emissions is higher than in the other models. Therefore, we add a carbon cap for the emissions of the firm. In this way, the supply chain becomes more environmentally friendly, and the total emission is lowest without an excessive cost increase.

Table 13 and Figs. 9 and 10 show that in a traditional supply chain, the firm will open stores as long as the number is equal to the lower limit. However, at this point, the firm's emissions are so high that this pattern cannot meet the public's environmental requirement. Because there are few stores, consumers need to travel far to buy products, and the store's attractiveness to consumers is affected. Consumers favor the convenience of a nearby store over a more distant store. Nevertheless, if government sets a carbon cap for the firm, the firm might be more willing to accept it if it has few stores. This is because even though the cap will cause the firm's cost to increase, the firm need not open new stores because the optimal number of stores does not change. In this way, the firm does not have to bear extra fixed and variable costs to open stores and redesign the delivery scheme. This part of the cost is often very large. In addition, if the firm optimizes its supply chain under a carbon cap to minimize its own cost, consumers' transportation cost will not change because this process does not influence the store density. Therefore, the carbon cap only for the firm will not reduce its attractiveness to consumers. Setting a carbon cap is necessary and does more good than harm for the environment and society. In addition, firms' managers should try to improve the utilization efficiency of social resources and attract more consumers. To achieve their goals, it is indispensable to minimize the total cost, including the firm's and the consumers' costs. Of course, if we need to make the logistics more environmentally friendly, we should also consider controlling the firm's emissions in the above situation. This measure can also increase the firm's attractiveness to consumers with stronger environmental awareness. From models 3 and 4 and their optimal solutions, we know that there are inflection points and an optimal numbers of stores. They may be not equal and between floor and ceiling. From the firms' view, this result is acceptable; although the supply chain cost is slightly higher than before, the optimal store density is greater, and there will be more consumers making purchases. In addition, the total emissions can achieve significant reductions, making the supply chain more environmental friendly. The above results of other market areas are similar.

4.5. *Profit maximization with truck capacity and order frequency*

In the above four models and experiments, we suppose that the firm managers aim to minimize the total cost no matter whether consumers' transportation cost is considered. We also omit some details such as transport capacity and order frequency. However, more dense retail stores would lead to higher sales and it can influence the firm's profit. Besides, the firm's transportation cost is affected by the capacity, which is in turn affected by the order frequency of the stores. To consider this case, we reformulate our

Table 13
Details about the optimal solutions.

Model	Details				
	Optimal n_1	Firm's cost (¥)	Total cost (¥)	Firm's emission (kg)	Total emission (kg)
1	159	4,507,878	10,648,551	1,124,715	1,143,718
2	159	4,509,194	10,649,866	1,122,000	1,141,003
3	191	4,524,777	10,646,555	1,126,761	1,145,739
4	182	4,522,217	10,648,795	1,122,000	1,140,243

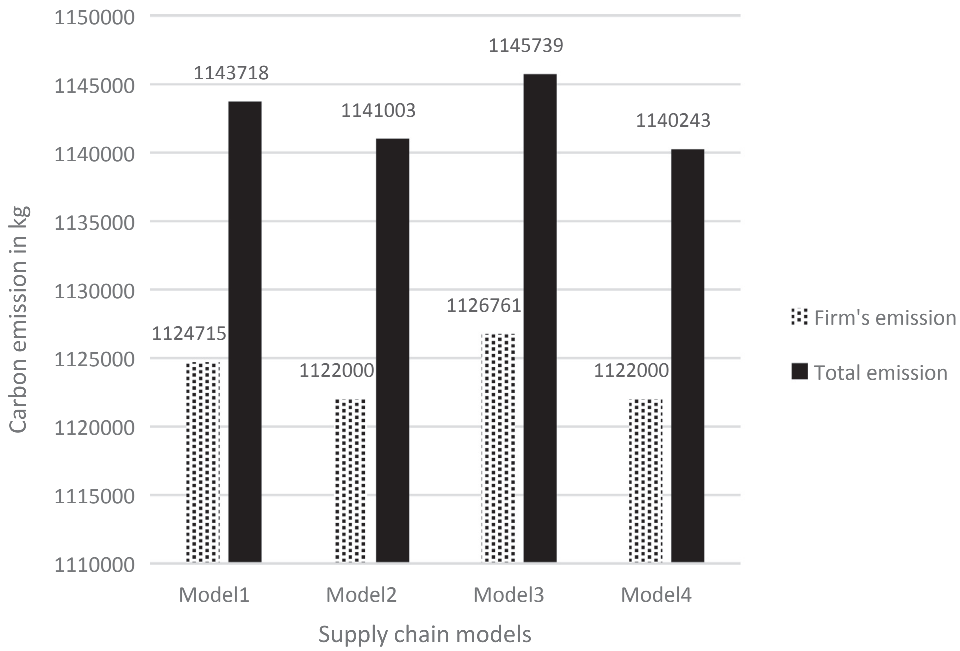

Fig. 9. Comparison of carbon emissions for the optimal solutions under four models.

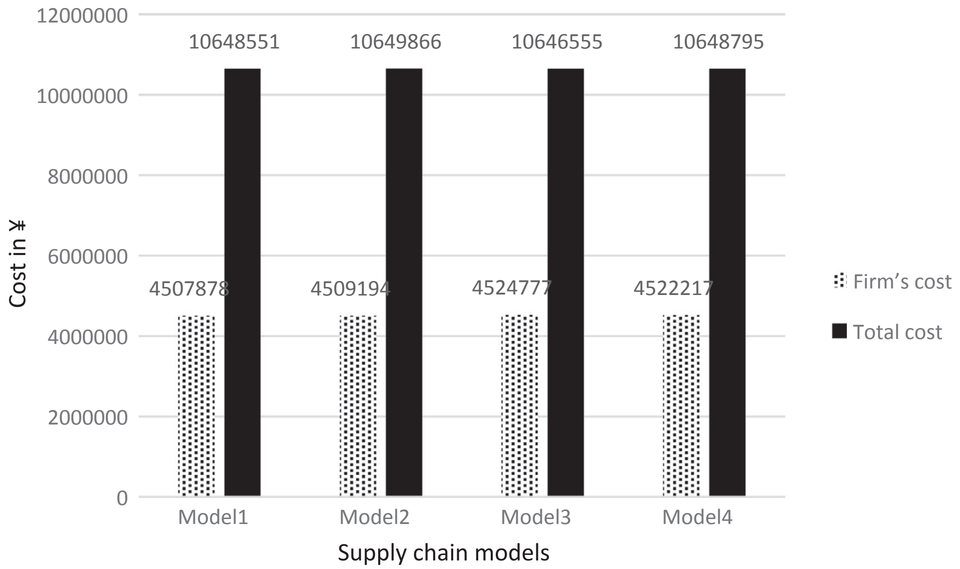

Fig. 10. Comparison of supply chain cost for the optimal solutions under four models.

models to a profit maximized problem.

For this, we need to define some equations in the scenario of model 4.

As we know, the absolute value of price-demand elasticity is calculated with the following formula:

$$E = \frac{|\%\ change\ in\ demand|}{|\%\ change\ in\ price|} \tag{29}$$

We assume λ as demand and p as product price. According to Williams (2013), we can get $E = -\frac{d\lambda}{dp}\cdot\frac{p}{\lambda}$. Then we know $\int E\frac{dp}{p} = -\int\frac{d\lambda}{\lambda}$. It leads to $E\cdot\ln p = -\ln\lambda + C$, C is a constant. Then we can get $\ln p^E = \ln\frac{1}{\lambda} + \ln e^C$. So it shows $p^E = \frac{e^C}{\lambda}$ and $p = \left(\frac{e^C}{\lambda}\right)^{\frac{1}{E}}$. We let $h = e^{\frac{C}{E}}$, so it is obvious that h is the product price which corresponds to demand of one unit. Thus it leads to the following function and P_{jt} is the values of product price in different market areas and planning periods:

$$P_{jt} = h_j \lambda_{jt}^{-1/E}, j \in J, t \in T \tag{30}$$

h_j is the product price in different market areas that corresponds to demand of one unit. The values of h_j are calculated from the demand, price, and elasticity data of previous periods. In addition, in order to use the elasticity data of previous periods, it should be assumed that the value of price elasticity remains stable during its lifetime. This assumption is valid for most commodity products (Kaplan and Türkay, 2011).

When the store number increases, it is more convenient to buy the product from nearby stores. Thus there will be more product demand. However, the basic market demand must be a constant (Giri and Roy, 2016, Li et al., 2016). So no matter how many stores there are, the demand cannot exceed but only be infinitely close to it. We find that inverse proportional function also shows this kind of character. Although the exact mathematical expression requires future empirical research, here we can make an estimate and assume that the value of aggregate demand in each market area can be calculated with the following function:

$$\lambda_{jt} = kn_j^{-1} + \lambda'_{jt}, j \in J, t \in T \tag{31}$$

λ'_{jt} is the basic market demand. k is a coefficient for this inverse proportional function and we assume $k < 0$ to ensure λ_{jt} will approach λ'_{jt} when n_j increases. n_j is the number of stores in the region of market area j. Because n_j must be in the range in Table 12, it is impossible that the value of n_j can make $\lambda_{jt} < 0$ in reality.

In this model, we also consider that the order frequency can influence the firm's transportation cost. The quantity of the product needed to be transported for each order in each period can be expressed as $\frac{\lambda_{jt}}{f_{jt}}$. f_{jt} is the order times in period t in market area j. Ω is the maximum load of each truck. Thus, $\frac{\lambda_{jt}}{\Omega f_{jt}}$ is the number of trucks needed for each order. To get the realistic number of trucks, it is necessary to use ceiling function. In this way, the truck number needed for each order in each period can be calculated with the following function:

$$\text{Truck number} = \left\lceil \frac{\lambda_{jt}}{\Omega f_{jt}} \right\rceil, j \in J, t \in T \tag{32}$$

Using parameters and decision variables defined above and in Section 3.2, the objective function can be formulated as follows: Maximize

$$\sum_{t \in T} \sum_{j \in J} h_j (kn_j^{-1} + \lambda'_{jt})^{1-1/E} - \Big(\sum_{t \in T} \sum_{a \in A} \sum_{i \in I} d_{ai} C_{ait} Q_{ait} + \sum_{t \in T} \sum_{i \in I} \sum_{j \in J} (d_{ij} C_{ijt} Q_{ijt} + d_{ii'} C_{ii't} Q_{ii't}) + \sum_{t \in T} \sum_{j \in J} \left\lceil \frac{\lambda_{jt}}{\Omega f_{jt}} \right\rceil f_{jt} d_j C_{jt}^{rrt}$$
$$+ \sum_{t \in T} \left[\sum_{i \in I} C_{it} Y_{it} + \sum_{j \in J} n_j C_{jt} Y_{jt} \right] + \sum_{t \in T} \sum_{j \in J} \frac{1}{2} \left[n_j (Y_{jt-1} - Y_{jt}) + \sum_{i \in I} Q_{ijt} \right] d_j' C_{jt}^{rc} + \sum_{t \in T} \sum_{j \in J} C_{jt}^{s} S_{jt} \Big) \tag{33}$$

C_{jt}^{rrt} is the transportation cost per kilometer per truck for shipment between retailer stores in the market area j at t. The model is subject to the constraints mentioned in Eqs. (6)–(20) and the firm must make decisions under a carbon cap:

$$\sum_{t \in T} \sum_{a \in A} \sum_{i \in I} d_{ai} E_{ait} Q_{ait} + \sum_{t \in T} \sum_{i \in I} \sum_{j \in J} (d_{ij} E_{ijt} Q_{ijt} + d_{ii'} E_{ii't} Q_{ii't}) + \sum_{t \in T} \sum_{j \in J} \left\lceil \frac{\lambda_{jt}}{\Omega f_{jt}} \right\rceil f_{jt} d_j E_{jt}^{rrt} + \sum_{t \in T} \left[\sum_{i \in I} E_{it} Y_{it} + \sum_{j \in J} n_j E_{jt} Y_{jt} \right] \leqslant$$
$$CO_2CAP \tag{34}$$

E_{jt}^{rrt} is the carbon emission per kilometer per truck for shipment between retailer stores in market area j at t. In this situation, firm managers aim to maximize the total profit and the cost term also includes consumers' transportation cost so that the stores can attract more consumers.

Then we apply this model in the case of Section 4.1. The values of some other parameters are shown in Tables 14–16.

From the demand, price, and elasticity data of previous periods, we calculated that $h_1 = 1096, h_2 = 1825, h_3 = 1577, h_4 = 1452, E = 4$. After interviewing the firm's managers, we assume that $\lambda'_{1t} = 1800, \lambda'_{2t} = 3000, \lambda'_{3t} = 3800, \lambda'_{4t} = 2400$ and $k = -30000$. In addition, Ω is 64. C_{jt}^{rrt} and E_{jt}^{rrt} is 5.568 ¥ per km per truck and 0.6784 kg per km per truck respectively.

With the methodology in Section 4.3, we can obtain the results of this model. When the government sets a strict carbon cap for firms, the computational result for market area 1 with a minimum number of stores in other market areas (Fig. 11) shows that the

Table 14
Order times matrix.

j	t			
	1	2	3	4
1	3	4	2	5
2	2	1	3	2
3	4	3	3	1
4	2	2	3	4

Table 15
Product price (¥ per box) in the market areas in previous period.

Previous period	Market area			
	1	2	3	4
1	172	250	202	211
2	170	248	203	213

Table 16
Demand (in box) in the market areas in previous period.

Previous period	Market area			
	1	2	3	4
1	1647.6	2838.8	3713.7	2241.5
2	1725.6	2930.5	3640.0	2157.5

firm's profit will first increase when the number of stores is growing, and then it will decrease after reaching an inflection point. At this point, we can achieve the highest total profit. We have explained the reason in Section 4.4.

Table 17 shows the details about the optimal solutions and we can see that the optimal store number is slightly larger than which in model 4. The reason is that we consider the scenario that more dense retail stores would lead to higher sales and order frequency could affect the firm's transportation cost. However, in this model, although the optimal n_1 is larger, the firm can achieve the highest profit and the total emission would not be too much with a strict carbon cap for the firm. Thus, this measure could also increase the firm's attractiveness to consumers with environmental awareness. The above results of other market areas are similar.

We can see from this part that the results are similar to the above cost minimized models when we consider the firm's profit and order frequency. However, although Eq. (31) seems reasonable, we cannot conclude that it is precise in reality. The exact formula needs to be explore for future research.

The next section discusses some managerial implications for designing low-carbon logistics.

5. Managerial implications

In the above sections, this paper presents several MINLP models that explore the impact of carbon emission caps on a firm's strategy for product delivery and store network layout. It also studies whether the object function should consider consumer cost. Now, we discuss the managerial implications of this paper and the related findings in theory and practice.

First, we fill the important research gap on the "black box" of the market area and study the impact of the density problem of retail stores on the whole supply chain cost and carbon emissions, providing the basis for supply chain assignment and store establishment decisions. This allows the firm to adjust its costs or profit and carbon emissions and ultimately set the optimal number of stores.

Second, introducing carbon caps and optimizing the total cost for not only firms but also consumers extends the traditional GSCM model into a comprehensive management model. Our study shows that the total cost and emissions from both sides can be reduced, and more consumers can be attracted. The firm also need not bear too much supply chain cost, such that both economic and

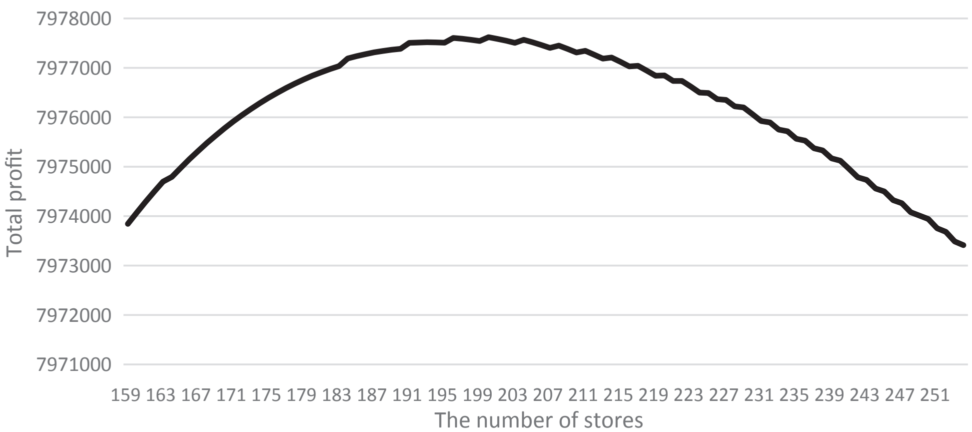

Fig. 11. The total profit with the number of stores for market area 1.

Table 17
Details about the optimal solutions.

Optimal n_1	Firm's profit (¥)	Consumers' cost (¥)	Firm's emission (kg)	Total emission (kg)
200	7,977,622	6,119,027	1,122,000	1,141,171

environmental goals can be achieved.

Third, we find that there is an inflection point of the cost or profit when we consider consumers' transportation costs. Only when the store number equals the inflection point can the object function be optimized. This implies that the firm should carefully consider the range of stores that can be accommodated in each market area and try to find the optimal number of stores.

Fourth, our approach is a good starting point for a standardized methodology to calculate the environmental impact with respect to the density of retail stores in a region. For the MINLP models, we also provide a methodology to calculate the exact optimal solution according to the reality of the firm and the market areas.

Fifth, we try to express the relationship between demand and store numbers in a market area and consider the effect that order frequency has on firms' transportation cost, proving that the profit maximized model can also show the similar results to the cost minimized models. It can help firm managers who aim to maximize profit design their green supply chain network.

Finally, this study provides guidance for environmentally friendly behaviors of firms to improve the attractiveness of their stores to consumers and a reference for the government in designing carbon emission policy.

6. Conclusions and scope of future research

With the emergence of more carbon emissions laws and regulations, it is imperative that companies manage carbon footprints in their business activities. This paper presented five multidimensional MINLP models for a low-carbon logistics system at a tactical planning level. The models can be used to explore the optimal store density in final market areas and help firm managers to design delivery schemes. From actual company data, we found how to provide guidance for tactical decisions in the supply chain.

This article also provides a reference for managers to improve the attractiveness of their stores to consumers and for the government to design carbon policy. In the models, we showed how to determine the distribution of a city's stores to meet the goal of minimizing the total cost born by firms and consumers or maximizing the profit. From the above models, we observe that it is possible to reduce carbon emissions and attract more consumers without significantly increasing the total cost.

The current paper inevitably has some limitations, and we now present some guidelines for future research. In our models, we have considered the carbon cap policy. However, to reduce emissions, the government can also implement a carbon tax policy or a carbon trading policy. These measures should also be considered and compared in making operational decisions. Moreover, for an optimal store distribution predicted by our model, one can apply a sensitivity analysis to explore the extent to which the parameters in these models vary with the optimal solution remaining unchanged. This will show the robustness of the predicted store density. In this paper, we have considered a single product. For future research, one may also introduce multiple products. Furthermore, increasing numbers of companies have established transnational supply chains. Some supply chain settings, such as carbon footprint policies and transportation and inventory costs, vary from one country to another. Therefore, it is interesting for multinational companies to consider how these supply chain decisions are made to minimize costs and make efficient use of enterprise resources.

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Appendix A. Supplementary material

Supplementary data associated with this article can be found, in the online version, at http://dx.doi.org/10.1016/j.tre.2017.12.001.

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