Int. J. Production Economics 173 (2016) 80–98

Contents lists available at ScienceDirect

Int. J. Production Economics

journal homepage: www.elsevier.com/locate/ijpe

Design of forward supply chains: Impact of a carbon emissions-sensitive demand

Imen Nouira [a], Ramzi Hammami [a,*], Yannick Frein [b], Cecilia Temponi [c]

[a] ESC Rennes School of Business School, 2 rue Robert d'Arbrissel CS 76522, 35065 Rennes, France
[b] Laboratoire G-SCOP, Grenoble INP, UJF, CNRS, 46 Avenue Felix Viallet, 38031 Grenoble, France
[c] McCoy College of Business, Texas State University, San Marcos, TX 78666, USA

ARTICLE INFO

Article history:
Received 13 February 2015
Accepted 4 November 2015
Available online 14 December 2015

Keywords:
Supply chain design
Carbon emissions-sensitive demand
Emissions in production and transportation
Environmental insights

ABSTRACT

We explore the impacts of a carbon emissions-sensitive demand on decisions relative to the design of forward supply chains (facility location, supplier selection, production technology selection and transportation mode selection). We investigate the design of a forward SC where a set of input items (components) are purchased from a network of external suppliers and used to manufacture a finished product in one or multiple production facilities to fulfill the demand of one or multiple customers. The demand for the final product is an endogenous variable sensitive to carbon emissions per unit and it is also assumed to increase with a decrease in the per unit carbon emissions of the product. We consider the case of a single customer and extend the model to multiple customers. Based on numerical experiments conducted on a case study from the textile industry, we use the models to provide a series of insights that might be instrumental to firms and policy makers. For instance, results indicate that customers' environmental awareness may encourage companies to bring the area of production close to the area of consumption and to select local suppliers. It might even be optimal to dedicate a production facility to each customer in spite of the incurred additional costs. However, if the customers are very demanding (in terms of reducing carbon emissions) then the best strategy can be to design a supply chain with relatively high emissions level because satisfying customer requirements may be very expensive in this case. Furthermore, if the customers are willing to pay a higher price for the product then this can lead to reducing per unit emissions. Our results augment the research to the fields of design of forward and greener supply chains by modeling and experimenting an endogenous demand sensitive to carbon emissions.

1. Introduction

External pressures such as government regulations, non-government organization requirements, and other external circumstances have made sustainability an important component for todays' corporations. In addition, an increasing number of consumers are becoming interested in the environmental impact of products (Altmann, 2015; Young et al., 2010; Mahenc, 2008; Rao, 2002; Chen, 2001). In particular, customers are increasingly concerned by the carbon footprint, identified by many researchers as one of the most important ways to evaluate the environmental impact of a product (Hammami et al., 2015; Benjaafar et al., 2013; Bjorklund et al., 2012; Dekker et al., 2012). According to the European Commission surveys (2008,2009), 83% of Europeans are very much attuned to environmental impacts, mainly the carbon footprint, when buying products. Today, there is a broad consensus that demand for many products is becoming sensitive to their carbon emissions level, as highlighted by Krass et al. (2013), Tang and Zhou (2012), Letmathe and Balakrishnan (2005), and Letmathe and Balakrishnan (2005).

Responding to the environmental concerns raised by the firms' customers, firms worldwide are taking initiatives to reduce the carbon emissions associated with their products and are using this criterion as a marketing tool to retain and increase their customer base. For instance, various firms are starting to attach carbon footprint labels to their products and to position these products as greener alternatives (Benjaafar et al., 2013). Two leading retailers in Europe, Tesco in the UK and Casino in France, have already embarked on aggressive labeling efforts (Benjaafar et al., 2013).

The amount of carbon emissions associated with a product depends on many decisions, some of which are not related to the design of the product itself but rather to the design of the product's supply chain (SC). For instance, the location of production facilities and the selection of raw materials suppliers impact the total distance traveled by a final product and its components and,

* Corresponding author. Tel.: +33 2 99 54 63 63.
E-mail address: hammami.ramzi@gmail.com (R. Hammami).

http://dx.doi.org/10.1016/j.ijpe.2015.11.002
0925-5273/

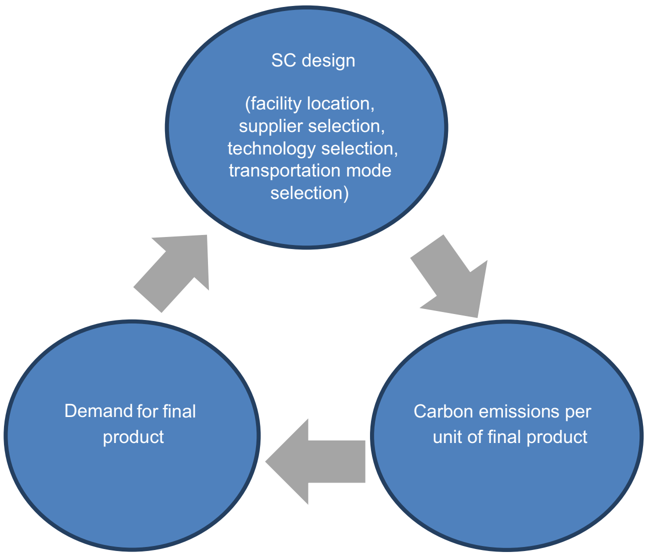

Fig. 1. Supply chain design with integration of carbon emissions-sensitive demand.

consequently, affect the carbon emissions generated during transportation. The selection of transportation modes and production technologies are other examples of SC decisions affecting carbon emissions. The level of carbon emissions is then impacted by SC design decisions. Thus, the demand of a product depends on its associated carbon emissions level, which depends on SC decisions.

We suggest that SC design models (in particular, optimization-based models) should evolve to capture customers' environmental preferences. The approach ought to consider the relation between SC design decisions, carbon emissions, and customer demand as presented in Fig. 1. Thus, demand should no longer be considered as an exogenous input parameter, as in most published SC design models, but rather be modeled as an endogenous decision variable sensitive to carbon emissions and, consequently, to SC design decisions.

In spite of the growing body of literature on green supply chain management (GSCM), recent research lacks quantitative models on forward SC design integrating environmental considerations (Tang and Zhou, 2012; Dekker et al., 2012). In addition, the quantitative models of GSCM focus mostly on the impacts of regulations, while largely ignoring market forces (Tang and Zhou, 2012). In particular, there is a lack of models capturing consumers' response to, and interest in, the environmental impact of products. This observation is in line with the conclusions drawn by Altmann (2015), Nouira et al. (2014), Krass et al. (2013) and Hassini et al. (2012). The main objective of our work is to develop SC design models that include carbon emissions-sensitive demand. Our research provides two main contributions to the field of GSCM:

- First, we address the environmental issues in SC literature from a new perspective as we incorporate carbon emissions-sensitive demand in SC design optimization models. The demand is assumed to be a piecewise linear function of the per unit emissions of the final product, which depend on SC decisions pertaining to facility location, supplier selection, production technology selection, and transportation mode selection. Two different models are developed, one model presents the case of a single customer supplied by a single production facility. The second model includes multiple customers, each supplied by a single production facility. Extensions of the model such as the case of a customer supplied by different production facilities and the use of other demand functions are also discussed.
- Second, our models provide insights for firms and policy-makers alike in their strategic decision making. Customers' sensitivity to carbon emissions raises different research questions that have not been explored yet in the literature. Some of these research questions include: what is the impact of customers' sensitivity on SC decisions and firm's performance? Could the environmental awareness of customers act as a driver for a greener SC without the existence of environmental legislation? In the case of multiple customers, should firms supply each customer from a dedicated local facility (in order to decrease emissions and increase demand) or should they open a unique facility to supply all customer zones? Our models are instrumental to assist on most of these issues.

A literature review on the integration of environmental issues in SC optimization models is presented in Section 2. We address the main features and assumptions of our models in Section 3. Section 4 focuses on the formulation of our mathematical models. In Section 5, computational experiments are presented and insights from results are discussed. Conclusions and suggestions for future research directions are drawn in Section 6.

2. Literature review

Environmental issues have been considered in quantitative SC models from different perspectives. There is a large body of literature on the design and management of reverse logistics networks. However, there are relatively few works dedicated to the consideration of environmental issues in the design of a forward SC as highlighted by many authors (Comas Martí et al., 2015; Diabat and Al-Salem, 2015; Dekker et al., 2012; Tang and Zhou, 2012). In this section, we provide an overview of environmental concerns in forward SC design models. A wider scope is then considered by reviewing research that focus on decisions pertaining to manufacturing management and technology selection, transportation mode selection, and supplier selection. We also investigate the relation between environmental considerations and demand. The section is concluded with overall comments as they pertain to our proposed models.

2.1. Supply chain design and facility location

The location of production and distribution facilities determines the total distance covered by components, semi-finished products, and finished products as they travel between the different sites of a company and onward to customers. It also has an impact on the emission of pollutants and on the energy consumption in the different arcs of the SC. The following models are amongst the most current on SC design and facility location integrating environmental considerations.

Hugo and Pistikopoulos (2005) proposed a multi-objective optimization model for SC design and planning. They maximized the net present value and minimized the environmental impact. Their evaluation was based on the LCA method and took into account the stages of procurement, manufacturing and transportation in the SC. In the model, the main SC decisions impacting the environment were the location of manufacturing plants and the allocation of products to plants. Technology selection and its environmental impact were implicitly considered due to the association of plants and manufacturing technology.

Diabat and Simchi-Levi (2010) develop a MIP model for the design of a SC with three echelons (plants–warehouses–retailers). The main decision in the model was to determine which plants and distribution centers to open so that logistics costs were minimized and total carbon emissions did not overstep the predetermined emissions cap. The carbon emissions were generated by plants, warehouses, and the different transport links in the network.

Wang et al. (2011) proposed a multi-objective optimization model for the design of a SC with three echelons (suppliers–facilities–customers) integrating environmental concerns. The impact of facility location and supplier selection on the environment considered the carbon emissions on the different arcs of the SC. An integer variable representing the level of environmental protection in each facility and possibly reflecting the technology selection decision was introduced in their model. The objectives in Wang et al.'s model were to minimize the total cost as well as the total carbon emissions in the nodes and arcs of the SC.

Cachon (2011) combined the traveling salesmen problem and the *k*-median problem to locate a retailer and to determine the best route a truck should take to deliver supplies from a single warehouse. The retailer's objective function includes the carbon cost during transportation for the retailer's and the consumers'.

Chaabane et al. (2011) considered the design of a forward SC while incorporating the cap-and-trade system and environmental regulation requirements. The two objective functions were minimizing the total logistics cost and minimizing the total emissions. Included in the model were the emissions generated by transportation and by production activities. The amount of emissions were a function of logistics decisions including: production facility location, supplier selection, transportation mode, and technology selected.

Chaabane et al. (2012) extended the work of Ramudhin and Chaabane (2010) by developing a comprehensive multi-objective optimization model for the design of a SC integrating an emissions trading scheme. The model considered a closed loop SC with suppliers, production facilities, distribution centers, customers, and recycling centers and the aggregate environmental impacts in terms of input consumptions and output emissions. The model minimized the total amount of these emissions as well as the total cost. It was assumed that carbon emissions credits may be purchased and sold as long as the company complies with the carbon emissions limit.

Motivated by a real-world case of a German company, Altmann (2015) proposed a large-size SC design model considering environmentally sensitive customers. The environmental impact is considered on all three levels: suppliers, production and distribution. The model integrates many logistics and financial decisions such as opening/closing facilities, use of resources, selection of suppliers, and determination of free cash flow and capital expenditures.

Diabat and Al-Salem (2015) developed a nonlinear MIP model that minimizes the cost of a stochastic two-echelon SC. The model incorporated the environmental aspect to a joint location inventory model. The uncertainty of demand is addressed using a Genetic Algorithm. The model uses stochastic demand and environmental consideration extensions (emissions minimization).

Comas Martí et al. (2015) proposed a SC network design model that simultaneously considers the emissions and costs related to both facility location and transport mode decisions, while taking into account the innovative or functional nature of products through the explicit consideration of demand uncertainty and inventory costs. The model explicitly addressed differences across facility locations in terms of costs/emissions of raw materials or components, manufacturing technologies and labor. Their model emphasized carbon footprint and SC responsiveness trade-offs, and their implications on the SC network design.

2.2. Manufacturing management and technology selection

Many industrial sectors select to produce within a traditional technology or a green one. The green technologies offer lower gas emissions and energy consumption levels but are known to be in general more expensive. In this section, we review optimization models focusing on manufacturing management and technology selection integrating environmental considerations.

Letmathe and Balakrishnan (2005) integrated environmental concerns into a production planning model with technology selection decisions. Different technologies with different emissions and types of resources consumption may be used to manufacture a product. The objective of the model was to maximize the total profit (revenue–costs). The revenue was generated by selling products and trading emissions. Costs generated from the use of resources in manufacturing operations, the price of purchasing traded emissions, and emissions penalties. The demand for products was assumed to decrease with an increase in emissions levels. Environmental legislation was considered in this model.

Radulescu et al. (2009) considered the problem of production planning by integrating uncertainty and environmental requirements linked to several pollution emissions. Two types of environmental constraints were considered: safety-first and mean-type. The model determined the amount of money to be invested in order to manufacture each of the considered products. Each product was associated with a manufacturing technology generating the emission of pollution. These authors formulated two stochastic programming problems. One of the problems was the maximum expected return and the other one was the minimum pollution risk.

Drake et al. (2012) addressed a firm's technology selection and capacity investment decisions. Their research integrated the cap-and-trade system and emissions-related tax regulations for a firm wishing to maximize its profits. The main decision was choosing between single and multiple technologies when clean and high gas emissions technologies were considered.

Krass et al. (2013) studied the problem of a profit-maximizing monopolistic firm facing price-dependent demand. In the case studied, the firm had to choose between green and high gas emissions technologies, with different levels of emissions, and to set production quantity and price in response to the environmental tax, subsidy, and rebate levels set by the regulator. The environmental tax was defined by unit of pollutant emitted. The authors also analyzed the situation when the regulator sets tax, subsidy and rebate levels with the objective of maximizing social welfare (i.e., firm's profit + consumer surplus – environmental impact).

Nouira et al. (2014) developed two optimization models that included the selection of production processes and raw materials. In the first model, a single product was offered by the firm and the demand for this product depended on its greenness. In the second model, the market was segmented between ordinary and green customers and the firm offered a different variety of the final product to each segment. In this case, both, demand and price depend on product greenness.

Zanoni et al. (2014) proposed an integrated production-inventory-marketing model for a two- echelon (vendor–buyer) SC where an investment is needed to elevate the environmental burdens of a production process. The demand is sensitive to the product's price and its environmental performance. The sum of the profit functions of the vendor and the buyer is the profit function for the integrated SC model. The function was jointly optimized to determine the production and shipping policies, and ordering and pricing policies.

Bozorgi et al. (2014) introduced a new inventory model that is a variation of the EOQ model with holding and transportation unit capacities considering objectives of minimizing both costs and emissions functions. The non-linear, non-continuous cost and emissions functions were studied to find the optimal order quantity based on minimization of such functions. Due to the structure of the two functions, they found that the emissions function is more sensitive to deviation from optimality than the cost function.

2.3. Transportation modes/channels

Transportation issues have been included in different types of optimization models dealing with environmental issues such as facility location models, and lot sizing models. Our review focuses on the selection of transportation modes/channels.

Pan et al. (2011) proposed an optimization model to explore the environmental impact of a pooling SC in the case of a three-echelon network. The model assigned the upstream and downstream hubs for the transportation of a set of commodities from origin to destination nodes while minimizing the carbon emissions generated by the three transportation sections.

Paksoy et al. (2011) considered a closed-loop SC with multiple echelons in both forward and reverse networks. They minimized an objective function with the cost of emissions in each arc. The emissions depended on the selection of transportation modes and the size of product flows on each arc.

Erdogan and Miller-Hooks (2012) observed that some companies were converting their fleet of trucks to include alternative fuel vehicles, either to reduce their environmental impact voluntarily or to meet new environmental regulations. The authors revisited the classical vehicle routing problem while considering the difficulty of limited refueling infrastructures restricting the use of alternative fuel vehicles. The model incorporated stops at alternative fuel stations to eliminate the risk of running out of fuel while maintaining low cost routes.

Hoen et al. (2014) considered a company that had outsourced its transportation activities and wanted to select a single transportation mode for the procurement of a single product. The demand was continuously distributed. The optimization model's objective was to minimize the expected total cost. The model considered backorders penalty cost, holding cost, and transportation cost accounting for emissions cost. Load and distance were the principal factors in the model.

Palak et al. (2014) studied the impacts of potential carbon regulatory policies, such as carbon cap, tax, cap-and-trade and offset on supplier and transportation mode selection decisions by using an economic lot-sizing model with multiple replenishment modes. The model accounted for supplier and transportation mode selection decisions for replenishing inventories. The suppliers and transportation modes were based on costs and emissions levels.

Arikan et al. (2014) studied a serial inventory system consisting of a shipper, i.e. a manufacturer or a retailer, who works with overseas suppliers and has to decide on replenishments in the presence of uncertain customer demands as well as uncertain lead times associated to ocean freights. A simulation model based on a standard multi-period inventory control policy in a dual transportation mode setting (air bound and sea bound) investigated the effect of lead time variability reduction on carbon emissions and SC performance.

2.4. Supplier selection and order allocation

The selection of suppliers impacts the environment in many ways. For instance, the location of the supplier (close to or far from the buyer's site) affects the level of emissions and energy consumption during transportation. In SC optimization literature, the supplier selection decision and the allocation of orders between suppliers are generally undertaken simultaneously as they are highly correlated. For instance, Mafakheri et al. (2011) proposed a two-stage supplier selection approach where the Analytical Hierarchical Process (AHP) method was used in the first stage to evaluate suppliers according to several criteria; one of these criteria was environmental performance. Orders were allocated to suppliers using a bi-objective optimization model; the weights of suppliers obtained in the first stage of the model were maximized.

Shaw et al. (2012) developed a multi-objective optimization model for supplier selection and order allocation. Among the objectives, the authors included minimizing the total greenhouse gas emissions of the purchased product, i.e. the sum of emissions from each supplier. They also included carbon footprint restrictions for sourcing.

Kannan et al. (2013) proposed a supplier selection approach that is quite similar to the model developed by Mafakheri et al. (2011). The difference between Kannan et al's model and Mafakheri et al's model is in the first stage. The former uses TOPSIS to rank potential suppliers in the first stage, and the latter uses AHP in the same first stage.

2.5. Environmental considerations and demand

The inclusion of the influence of demand and its sensitivity to environmentally conscious customers merits some comments before moving to the model section. There has been a broad consensus that demand for many products is becoming sensitive to their carbon emissions level, as discussed earlier. The willingness of customers to pay more for environmentally conscious products has been analyzed in the literature (Jayaraman et al., 2012; Tate et al., 2010; Sarkis, 2003). Sensitive transportation and manufacturing practices were investigated. Some researchers found positive correlations between the consumers' behavior and sustainable manufacturing practices.

Chen (2001) suggested two categories of customers: ordinary customers who are not interested in product emissions and green customers who are sensitive to the carbon emissions of products. He also indicated that these two categories of customers might determine the demand for products. His view was shared in part by Zhu et al. (2005), who proposed that one of the major drivers for the adoption of green supplies were customers' requirements and the firm's needs for competitive advantage. Hovelaque and Bironneau (2015) revisited the classic EOQ lot sizing model by considering a linear price- and carbon emissions-sensitive demand. The objective was to determine the optimal order quantity that maximizes firm's profit. Considered are cases of an exogenous price and also for price as an endogenous variable. Zhang et al. (2015) analyzed the impact of consumer environmental awareness on order quantities and channel coordination within a one-manufacturer and one-retailer SC. The manufacturer produces two types of products (the environmental and the traditional products) that differ in their price and environmental quality. Product demand is assumed to linearly increase with environmental quality and decrease with price.

The increasing number of consumers interested in the environmental impact of goods is a reality. Additionally, the increased regulation and pressures from government and environmental agencies to have a decreased of the carbon footprint support the idea of viewing demand decreasing with an increase in carbon emissions. Industry as well as academia cannot disregard any longer the correlation between the demand and the environmental performance (in particular, carbon emissions) and, consequently, the SC decisions. We believe that SC design models (in particular, optimization-based models) should evolve to consider the relation between SC design decisions, carbon emissions, and customer demand. Demand should no longer be considered as an exogenous input parameter, as in most published SC design models. The demand needs to be modeled as an endogenous decision variable sensitive to carbon emissions and, consequently, to SC design decisions, which is a major component in our proposed models.

2.6. Overall comments

The researched SC design models including environmental concerns generally consider demand as an exogenous parameter and, consequently, ignore the relation between demand and environmental performance resulting from SC decisions. The paper of Altmann (2015) is one of the rare exceptions. While there is clearly value in such a research, the author does not model the demand as a function of per unit carbon emissions but rather as a function of total carbon emissions per time period. However, consumers are more likely to be concerned by the emissions per unit when they purchase a product as highlighted by the European Commission surveys (2008,2009) and by many researchers (Benjaafar et al., 2013; Krass et al., 2013). Modeling the per unit emissions in SC design models, where the configuration of the SC and the flows of products are not known in advance, is a challenging task as we will explain in the next sections. In addition, an important contribution of our paper compared to Altmann's paper is that we use our model to conduct extensive experiments and to derive managerial insights that are less likely to be obtained with other models of the literature.

As per models addressing traditional and green technologies, most models favored approaches that generated higher profits and compromise aspects of environmental issues as a means to strike a balance (Letmathe and Balakrishnan, 2005; Radulescu et al., 2009). For instance, Bozorgi et al. (2014) found that the emissions function is more sensitive to deviation from optimality than the cost function.

The concerns of transportation modes and channels have been considered for instance by Pan et al. (2011), Paksoy et al. (2011), Hoen et al. (2014) and Palak et al. (2014). Most of their concerns gravitated on suppliers and transportation modes that were based on costs and emissions levels. Results showed that carbon regulatory mechanisms have an impact on supplier and transportation mode selection decisions. Moreover, the selection of suppliers impacts the environment in many ways. Models addressing suppliers' environmental performance, carbon footprint restrictions for sourcing, and supply chain networks redesign favoring low greenhouse emissions have been developed by Mafakheri et al. (2011), Shaw et al. (2012) and Kannan et al. (2013).

Most models available in the archive literature present specific aspects of low carbon footprints with diverse aspect of production technology selection, or suppliers selection, or transportation modes, and so forth. Most researchers focus on technology selection in a production system and do not address an integrated SC design. However, the integration of low carbon footprint with facility location, suppliers and transportation modes, plus technology selection, and aspects related to the impact of low carbon footprint on the demand, as an endogenous variable for decision-making has not been fully addressed.

The relation between demand and carbon emissions is ignored by most of the SC design models discussed in our literature review. Our work tries to bridge this gap. Including carbon emissions-sensitive demand is a challenging task in our context since the configuration of the SC is not known in advance and many decisions are undertaken simultaneously. In addition, the integration of carbon emissions-sensitive demand in SC design models provides several opportunities for insights at a strategic level.

3. Problem statement

Our paper proposes the design of a forward SC where a set of input items (components) are purchased from a network of external suppliers and used to manufacture a final product in one or multiple production facilities in order to fulfill the demand of one or multiple customers. Customer demand is assumed to increase with a decrease in the per unit carbon emissions of the final product.

3.1. Main decisions

The main SC decisions included in our models are as follows:

- Location of production facilities. Different potential facilities are available; each is characterized by its (fixed and variable) costs and its location (which affects the amount of emissions generated during upstream and downstream transportation). The model selects the production facilities to be opened.
- Selection of production technologies. In each facility, we have various potential production processes (technologies) with different (fixed and variable) costs and carbon emissions. If a production facility is opened then we must select the technology used in this facility (only one technology per facility).
- Selection of suppliers. The model selects the suppliers of each component required to make the final product. The purchasing cost of a component and the emissions generated in transportation between the supplier and the production facility depend on the supplier selected.
- Selection of transportation modes on the different arcs of the SC. On each upstream or downstream arc of the SC (from suppliers to facilities or from facilities to customers), various transportation modes are available with different emissions and costs. The model selects only one transportation mode on each arc.

3.2. Underlying assumptions

3.2.1. Emissions-sensitive demand

In the proposed models, we assume Chen's (2001) categories. The categories are ordinary customers who are not interested in product emissions and green customers who are sensitive to the carbon emissions of products. Thus, in addition to the base demand $D^{\min}$ of ordinary customers, the firm can attract green customers by decreasing the per unit carbon emissions of the final product (i.e., by improving the environmental performance). Green customers will not be interested in the product if its per unit emissions exceed a given threshold value $E^{\max}$. Indeed, in this case, the product is considered dirty and its total demand is equal to the base demand $D^{\min}$ (i.e., only ordinary customers will purchase the product). If the per unit emissions drop below a minimum level $E^{\min}$ then the green customers' demand will be at its maximum. In this case, total demand reaches the maximum level $D^{\max}$. It should be noted that $(D^{\max} - D^{\min})$ represents the total size of the green segment and not necessarily the number of green customers that will be attracted to the firm. The threshold values $E^{\min}$ and $E^{\max}$ can be determined according to environmental legislation and standards, and/or by benchmarking with similar products. For instance, $E^{\min}$ refers to the per unit emissions of the cleanest comparable product on the market while $E^{\max}$ reflects the per unit emissions of the dirtiest.

Over the interval $[E^{\min}, E^{\max}]$, the total demand for the final product (denoted by δ) is assumed to be a decreasing function of its per unit carbon emissions (denoted by ω). Indeed, while the demand of ordinary customers is constant (equal to $D^{\min}$), we can logically assume that the greater the per unit emissions the smaller the number of green customers interested in the product. The nature of this decreasing demand function is addressed next.

3.2.2. The piecewise linear function

Customer behavior with regard to environmental issues is still a new research area. To our knowledge, researchers have not yet clearly established how demand might be impacted by customers' environmental awareness, in particular, in relation to carbon emissions. Clearly, this is a challenging research topic since the result would depend on the type of product, the market sector, the country into consideration, etc.

We assume that demand linearly decreases from D^{max} to D^{min} with an increase in per unit emissions over interval $[E^{min}, E^{max}]$. The linear assumption is widely used in operations management literature (for different problems than the one addressed in this paper) in order to model demand sensitivity in relation to different criteria such as price (Krass et al., 2013). With the emergence of environmental issues, some authors have used the same linear assumption to model the demand sensitivity to environmental criteria (e.g., Letmathe and Balakrishnan, 2005; Glock et al., 2012; Nouira et al., 2014). As usual in operations management literature dealing with price-sensitive demand, exponential demand can also be considered. However, there is no evidence that an exponential assumption is better than a linear assumption when it comes to modeling emissions-dependent demand. Additionally, emergent complexities would not be possible to solve it to optimality with exact methods, hence depriving us of the opportunity to conduct experiments and derive insights. Thus, our demand is represented by the piecewise linear function given in Fig. 2. Equation (1) represents the mathematical formulation of total demand δ as a function of per unit emissions ω:

$$\delta(\omega)=\begin{cases} D^{max} & \text{if } \omega \le E^{min} \\ \dfrac{1}{E^{max}-E^{min}}\left[\left(E^{max}D^{max}-E^{min}D^{min}\right)-\left(D^{max}-D^{min}\right)\omega\right] & \text{if } E^{min} \le \omega \le E^{max} \\ D^{min} & \text{if } \omega \ge E^{max} \end{cases} \tag{1}$$

3.2.3. Measurement of per unit emissions ω

Total demand depends on the amount of emissions per unit of final product, ω. In order to calculate ω, we consider the following carbon emissions generated in the different nodes and arcs of the SC:

- Emissions in upstream and downstream arcs. These are carbon emissions generated by the transportation of components (from suppliers to facilities) and the transportation of the final product (from facilities to customers). They depend on two factors: (1) the distance between the origin and the destination node, which is correlated to supplier selection and/or facility location decisions, and (2) the choice of transportation mode.

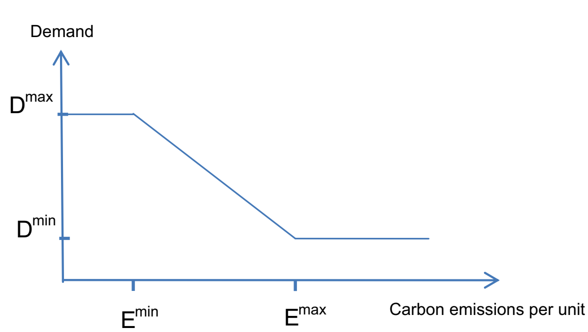

Fig. 2. Total demand as a function of per unit emissions.

- Emissions in production facilities. These are the carbon emissions generated by the manufacturing of the final product. Clearly, this type of emission depends on the selected production technology.

As underlined in previous research, the calculation of ω is a challenging task that requires a number of assumptions to be considered. For instance, if different transportation modes are used to ship a given product between two nodes (suppliers-facilities or facilities-customers) then we may have different emissions levels associated with the same product on the same arc. This raises the following question: what is the amount of emissions per unit of the product transported on this arc? Taking the mean value or maximum value into account is questionable. To overcome this problem, we assume that only one transportation mode is selected for each product in each arc of the SC. This is a fairly realistic assumption as it is the approach adopted in many real-world situations.

For the same reasons, we assume that only one production technology is selected in each production facility. We also assume that each production facility selects only one supplier for each given component (clearly, different components can have different suppliers). The SC literature makes wide use of such assumptions. Companies also put them into practice for various reasons, such as reducing costs and quality problems or simplifying management tasks.

3.3. Objective of the models

The objective of our models is to maximize the firm's profit, taken to be the difference between revenue and costs. Revenue is generated by selling the final product to customers. We assume that the final product is sold at a fixed price. Regarding costs, both fixed and variable costs are taken into account. Fixed costs are the expenses entailed when opening facilities and implementing a production technology in a given facility. Variable costs are generated by the purchasing of components (including the supplier-to-facility transportation costs), the manufacturing of the final product in production facilities, and the transportation of the final product from production facilities to customers.

Thus, on the one hand, reducing the per unit emissions leads to an increase in demand (and, consequently, revenue). However, it can also lead to higher costs since it generally requires selecting expensive nearshore suppliers and facilities (versus low-cost offshore suppliers and facilities) as well as using expensive production technologies and transportation modes. On the other hand, reducing costs can lead to an increase in emissions and loss of sales. The proposed models can be used to obtain the optimal trade-off.

4. Mathematical models

In this section we explain the mathematical formulation developed for our models. We first present the base model ($M1$) where we consider a single production facility and only one customer. We then turn to the model ($M2$) with multiple production facilities and multiple customers. We close with a discussion of the extensions of our model.

4.1. Base model (M1): one customer supplied by a single production facility

We consider the following notation:
Index sets:

- P: set of input products (components).
- J: set of potential production facilities.

- H: set of potential production technologies.
- S: set of potential suppliers.
- M: set of potential transportation modes.

Demand parameters:

- $D^{\min}$: minimum demand (corresponds to the cases where the per unit emissions are greater than $E^{\max}$).
- $D^{\max}$: maximum demand (corresponds to cases where the per unit emissions are smaller than $E^{\min}$).
- $E^{\max}$: amount of per unit emissions associated with minimum demand $D^{\min}$.
- $E^{\min}$ amount of per unit emissions associated with maximum demand $D^{\max}$.

Carbon emissions parameters:

- Ω_{mj}: amount of carbon emissions generated by the shipment of one unit of the final product from facility j to the customer with transportation mode m.
- Ω_{pmsj}: amount of carbon emissions generated by the shipment of one unit of component p from supplier s to facility j with transportation mode m.
- Ω_{hj}: amount of carbon emissions per unit of final product manufactured in facility j with production technology h.

Price and cost factors:

- A: unit selling price of final product.
- OC_j: fixed cost of opening/operating facility j.
- HC_{hj}: fixed cost of implementing production technology h in facility j.
- PC_{pmsj}: unit purchasing cost (including transportation cost) of component p by facility j from supplier s using transportation mode m.
- MC_{hj}: unit production cost of the final product with technology h in facility j.
- TC_{mj}: unit cost of transporting the final product from site j to the customer with transportation mode m.

Note: For fixed costs (OC_j and HC_{hj}), depreciation is taken into account according to the length of the planning horizon. In this paper, we implicitly assume that the transportation is carried out by a fleet owned by the company. Otherwise, the transportation cost and emissions should be adjusted accordingly.

Bill of materials:

- N_p: quantity of component p required per unit of final product

Main decision variables:

- δ: demand for final product.
- ω: amount of carbon emissions associated with one unit of the final product.
- y_j: (binary) equals 1 if facility j is open, 0 otherwise.
- y_{hj}: (binary) equals 1 if production technology h is used in facility j, 0 otherwise.
- y_{pmsj}: (binary) equals 1 if component p is shipped from supplier s to facility j with transportation mode m, 0 otherwise.
- y_{mj}: (binary) equals 1 if the final product is shipped from facility j to the customer with transportation mode m, 0 otherwise.
- q_{pmsj}: quantity of component p shipped from supplier s to facility j with transportation mode m.
- x_{hj}: quantity of final product manufactured in facility j with production technology h.
- z_{mj}: quantity of final product shipped from site j to the customer with transportation mode m.

Objective function: The objective function maximizes the total profit, i.e. the difference between revenue and costs as given in Eq. (2). The revenue is generated by selling the quantity $(\sum_{j\in J}\sum_{m\in M} z_{mj})$ of final product to the customer at unit price A. The costs cover the facility fixed cost, the fixed cost of implementing production technologies, the purchasing costs, the production costs, and the cost of transportation from facilities to the customer:

$$\begin{aligned}\text{Max } \Pi = {} & A\left(\sum_{j\in J}\sum_{m\in M} z_{mj}\right) - \sum_{j\in J} OC_j y_j - \sum_{j\in J}\sum_{h\in H} HC_{hj} y_{hj} \\ & - \sum_{j\in J}\sum_{p\in P}\sum_{m\in M}\sum_{s\in S} PC_{pmsj} q_{pmsj} - \sum_{j\in J}\sum_{h\in H} MC_{hj} x_{hj} \\ & - \sum_{j\in J}\sum_{m\in M} TC_{mj} z_{mj} \end{aligned} \tag{2}$$

Calculation of demand: As shown in Eq. (1), the demand function $\delta(\omega)$ is not linear over its domain $[0, +\infty[$. Since we aim to solve our models to optimality with exact methods, we linearize the demand function before we integrate it into the model. We thus introduce the following binary variables:

- a: (binary) equals 1 if $\omega \le E^{\min}$, 0 otherwise.
- b: (binary) equals 1 if $E^{\min} < \omega < E^{\max}$, 0 otherwise.
- c: (binary) equals 1 if $\omega \ge E^{\max}$, 0 otherwise.

Firstly, we add the following linear constraints in order to define variables a, b, and c (Ψ being a sufficiently large positive number). Indeed, constraint (3) guarantees that $a=1$ *if* $\omega \le E^{\min}$. Constraint (4) guarantees that $c=1$ if $\omega \ge E^{\max}$. The combination of constraints (3)–(5) guarantees that $b=1$ *if* $E^{\min} < \omega < E^{\max}$:

$$\Psi(a-1) \le E^{\min} - \omega < \Psi a \tag{3}$$

$$\Psi(c-1) \le \omega - E^{\max} < \Psi c \tag{4}$$

$$a + b + c = 1 \tag{5}$$

Thus, demand function $\delta(\omega)$ is given by Eq. (6):

$$\begin{aligned}\delta = D^{\max} a + & \left(\frac{1}{E^{\max} - E^{\min}}\left[\left(E^{\max} D^{\max} - E^{\min} D^{\min}\right)\right.\right. \\ & \left.\left. - \left(D^{\max} - D^{\min}\right)\omega\right]\right) b + D^{\min} c \end{aligned} \tag{6}$$

Clearly, this equation is still non-linear (due to the multiplication of continuous variable ω by binary variable b). However, this type of non-linearity is common in the literature and can be easily linearized. Indeed, Eq. (6) is equivalent to linear Eq. (7) when we add linear constraints (8)–(10) to the model. In these constraints, we use a new continuous non-negative variable, e. Note that $e = \omega b$:

$$\delta = D^{\max} a + \left(\frac{E^{\max} D^{\max} - E^{\min} D^{\min}}{E^{\max} - E^{\min}} b - \frac{D^{\max} - D^{\min}}{E^{\max} - E^{\min}} e\right) + D^{\min} c \tag{7}$$

$$e \le \Psi b \tag{8}$$

$$e \ge \Psi(b-1) + \omega \tag{9}$$

$$e \le \omega \tag{10}$$

- *Measurement of per unit emissions*:

The per unit emissions ω are determined by Eq. (11). This value covers the emissions generated by transportation of the components from the suppliers to the production facility, the emissions generated by the production technology, and the emissions given off during transportation from the production facility to the customer:

$$\omega = \sum_{j \in J}\sum_{p \in P}\sum_{m \in M}\sum_{s \in S} N_p \Omega_{pmsj} y_{pmsj} + \sum_{j \in J}\sum_{h \in H} \Omega_{hj} y_{hj} + \sum_{j \in J}\sum_{m \in M} \Omega_{mj} y_{mj} \tag{11}$$

- *Flow conservation conditions*:

Constraint (12) guarantees that the total quantity of final product shipped to the customer cannot exceed the demand. According to constraint (13), the outbound quantity of final product in facility j ($\sum_{m \in M} z_{mj}$) must be equal to the quantity manufactured in this facility ($\sum_{h \in H} x_{hj}$). Constraint (14) guarantees that the required quantity of component p in facility j ($N_p \sum_{h \in H} x_{hj}$) is equal to the quantity of p purchased from the suppliers $\left(\sum_{m \in M}\sum_{s \in S} q_{pmsj}\right)$:

$$\sum_{j \in J}\sum_{m \in M} z_{mj} \le \delta \tag{12}$$

$$\sum_{m \in M} z_{mj} = \sum_{h \in H} x_{hj} \quad j \in J \tag{13}$$

$$\sum_{m \in M}\sum_{s \in S} q_{pmsj} = N_p \sum_{h \in H} x_{hj} \quad p \in P,\ j \in J \tag{14}$$

- *Supply chain configuration constraints*:

As explained earlier, we assume that at most only one supplier can be used to provide a given facility with a given component. In addition, only one transportation mode is used in this case. These assumptions are guaranteed by constraint (15):

$$\sum_{m \in M}\sum_{s \in S} y_{pmsj} \le 1 \quad p \in P,\ j \in J \tag{15}$$

Constraint (16) imposes that at most only one transportation mode can be selected to ship the final product from a given facility to the customer:

$$\sum_{m \in M} y_{mj} \le 1 \quad j \in J \tag{16}$$

Model ($M1$) deals with the case of a single production facility. In addition, the selected production facility cannot use more than one production technology. We add constraint (17) to take both of these assumptions into account:

$$\sum_{j \in J}\sum_{h \in H} y_{hj} \le 1 \tag{17}$$

- *Logical constraints on the relation between continuous and binary variables*:

Finally, we add the following logical constraints. Indeed, according to constraint (18), process h is used in facility j (i.e., $y_{hj} = 1$) if and only if facility j generates output using process h (i.e., $x_{hj} > 0$). Constraint (19) guarantees that facility j is opened (i.e., $y_j = 1$) if and only if it generates a certain level of output (i.e., $\sum_{h \in H} x_{hj} > 0$). In constraint (20), we impose that transportation mode m is selected to ship the final product from facility j to the customer (i.e., $y_{mj} = 1$) if and only if the quantity transported from j to the customer using mode m is strictly positive (i.e., $z_{mj} > 0$). Similarly, constraint (21) ensures that $y_{pmsj} = 1$ if and only if $q_{pmsj} > 0$:

$$\frac{1}{\Psi} y_{hj} \le x_{hj} \le \Psi y_{hj} \quad h \in H,\ j \in J \tag{18}$$

$$\frac{1}{\Psi} y_j \le \sum_{h \in H} x_{hj} \le \Psi y_j \quad h \in H,\ j \in J \tag{19}$$

$$\frac{1}{\Psi} y_{mj} \le z_{mj} \le \Psi y_{mj} \quad m \in M,\ j \in J \tag{20}$$

$$\frac{1}{\Psi} y_{pmsj} \le q_{pmsj} \le \Psi y_{pmsj} \quad p \in P,\ m \in M,\ s \in S,\ j \in J \tag{21}$$

4.2. Model (M2): Multiple customers, each supplied by a single production facility

We extend the base model by considering multiple production facilities and multiple customers. Thus, the product purchased by a given customer k may now have a different per unit emissions compared to the same product purchased by another customer k' (whether the same facility j supplies both customers or not). We recall that the per unit emissions value ω includes the transportation emissions on the arc between facilities and customers, which depend on both production facility location and customer location. Hence, unlike the case of ($M1$), the per unit emissions value, ω, must here be indexed by j and k. We let ω_{jk} denote the amount of carbon emissions per unit of final product delivered to customer k by facility j. Consequently, since demand is sensitive to carbon emissions then the demand of each customer k must also be indexed by j (in addition to k). We denote by δ_{jk} the total demand of customer k when this customer is supplied by facility j.

In order to simplify the calculation of per unit emissions ω_{jk}, we impose that a given customer cannot be supplied by more than one facility. This assumption is valid in many real-world situations and is often introduced by firms in an effort to reduce quality and logistics incidents. We experienced several French automotive companies (e.g., Valeo and Faurecia) that have adopted this purchasing strategy for some strategic components. Clearly, the system is not constrained to select a specific facility for each customer since a facility can supply different customers.

In order to develop model ($M2$), we need to edit a number of notations. Note that the notation introduced previously is still applicable unless modified here.

Index sets, parameters and cost factors:

- K: set of customers.
- $D_k^{\min}$: minimum demand of customer k.
- $D_k^{\max}$: maximum demand of customer k.
- $E_k^{\max}$: amount of per unit emissions associated with $D_k^{\min}$.
- $E_k^{\min}$: amount of per unit emissions associated with $D_k^{\max}$.
- Ω_{mjk}: amount of carbon emissions generated by the shipment of one unit of final product from facility j to customer k with transportation mode m.
- A_k: unit selling price of final product to customer k.
- TC_{mjk}: unit transportation cost of final product from facility j to customer k with transportation mode m.

Decision variables:

- δ_{jk}: total demand of customer k if it is supplied by facility j.
- ω_{jk}: amount of carbon emissions per unit of final product delivered to customer k by facility j.
- y_{mjk}: (binary) equals 1 if the final product is shipped from facility j to customer k with transportation mode m, 0 otherwise.
- z_{mjk}: quantity of final product shipped from facility j to customer k with transportation mode m.
- a_{jk}: (binary) equals 1 if $\omega_{jk} \le E_k^{\min}$, 0 otherwise.
- b_{jk}: (binary) equals 1 if $E_k^{\min} < \omega_{jk} < E_k^{\max}$, 0 otherwise.
- c_{jk}: (binary) equals 1 if $\omega_{jk} \ge E_k^{\max}$, 0 otherwise.

We present hereafter the objective function and constraints of model ($M2$) while focusing on the differences between ($M1$) and ($M2$).

Objective function: Like the base model, the objective function of model ($M2$) is to maximize the total profit (revenue–costs). Here, the revenue and costs are determined by considering multiple customers:

$$\text{Max } \Pi = \sum_{k \in K} A_k \left(\sum_{j \in J} \sum_{m \in M} z_{mjk} \right) - \sum_{j \in J} OC_j y_j - \sum_{j \in J} \sum_{h \in H} HC_{hj} y_{hj} - \sum_{j \in J} \sum_{p \in P} \sum_{m \in M} \sum_{s \in S} PC_{pmsj} q_{pmsj} - \sum_{j \in J} \sum_{h \in H} MC_{hj} x_{hj} - \sum_{k \in K} \sum_{j \in J} \sum_{m \in M} TC_{mjk} z_{mjk} \quad (22)$$

Calculation of demand: The demand of customer k supplied by facility j is determined by Eq. (23):

$$\delta_{jk} = D_k^{\max} a_{jk} + \left(\frac{1}{E_k^{\max} - E_k^{\min}} \left[\left(E_k^{\max} D_k^{\max} - E_k^{\min} D_k^{\min} \right) - \left(D_k^{\max} - D_k^{\min} \right) \omega_{jk} \right] \right) b_{jk} + D_k^{\min} c_{jk} \quad j \in J, \ k \in K \quad (23)$$

Clearly, we need to add the constraints relative to the definition of a_{jk}, b_{jk} and c_{jk} as well as those required for the linearization of Eq. (23). These constraints are similar to those used in model ($M1$) except that the different variables are here indexed by j and k. To simplify the presentation of the model, we shall not provide these constraints again.

Measurement of per unit emissions: The per unit emissions value ω_{jk} is given by Eq. (24):

$$\omega_{jk} = \sum_{p \in P} \sum_{m \in M} \sum_{s \in S} N_p \Omega_{pmsj} y_{pmsj} + \sum_{h \in H} \Omega_{hj} y_{hj} + \sum_{m \in M} \Omega_{mjk} y_{mjk} \quad j \in J, \ k \in K \quad (24)$$

Flow conservation conditions: Constraint (25) imposes that the quantities delivered to the customers must not be greater than their demand:

$$\sum_{m \in M} z_{mjk} \le \delta_{jk} \quad j \in J, \ k \in K \quad (25)$$

The constraints on the inbound quantities of products in production facilities are not provided here since they are similar to constraint (14) in model ($M1$). The flow conservation conditions for the final product are given by constraint (26):

$$\sum_{k \in K} \sum_{m \in M} z_{mjk} = \sum_{h \in H} x_{hj} \quad j \in J \quad (26)$$

Supply chain configuration constraints: Constraint (27) guarantees that, on the one hand, at most only one facility can be selected to supply a given customer and, on the other hand, only one transportation mode can be used between a production facility and a customer:

$$\sum_{j \in J} \sum_{m \in M} y_{mjk} \le 1 \quad k \in K \quad (27)$$

We add constraint (28) in order to ensure that a production facility cannot use more than one production process. Unlike model ($M1$), we do not impose here that at most only one facility can be selected:

$$\sum_{h \in H} y_{hj} \le 1 \quad j \in J \quad (28)$$

Note that we must also include the constraints pertaining to the selection of suppliers and transportation modes in the upstream stages of the SC, which are similar to constraint (15) in model ($M1$).

Logical constraints on the relation between continuous and binary variables: Finally, we add the constraints on the relation between continuous and binary variables as in model ($M1$). The only difference is that we replace constraint (20) by constraint (29) in order to consider multiple customers:

$$\frac{1}{\Psi} y_{mjk} \le z_{mjk} \le \Psi y_{mjk} \quad m \in M, \ j \in J, \ k \in K \quad (29)$$

4.3. Modeling extensions

Model ($M2$) can also be extended in many ways. The following extensions are of particular relevance in theory and practice.

4.3.1. Customer supplied by multiple production facilities

In model ($M2$), we assumed that a customer cannot be supplied by more than one facility. If we consider that a customer can now be supplied by several production facilities then this customer can receive different varieties of the final product (in terms of carbon emissions). Indeed, the per unit emissions can differ according to the origin of the product (i.e., according to the facility where it is manufactured). Basically, this leads to two alternatives:

- The customer agrees to have different varieties of the same product in terms of carbon emissions. Clearly, the demand for each variety depends on its emissions performance. In this case, we need to edit constraint (27) in order to allow model ($M2$) to select different production facilities for a given customer. Constraint (27) must be rewritten as follows:

$$\sum_{m \in M} y_{mjk} \le 1 \quad k \in K, \ j \in J \quad (30)$$

- The customer does not agree to different varieties. Only one per unit emissions level should be communicated to the customer. In this case, a judicious approach would be to communicate the worst per unit emissions of the different varieties of the final product. Clearly, the demand will depend on this worst emissions level. In terms of modeling, we need to introduce variables ω_k and δ_k, which respectively denote the quoted per unit emissions of product delivered to customer k and the total demand of customer k (from all production facilities).
Thus, for customer k, the quoted per unit emissions value ω_k is equal to the maximum per unit emissions of the different varieties of product received by this customer. Therefore, we add constraint (31) to the model in order to define ω_k. Furthermore, constraints (23) and (25) must be replaced by constraints (32) and (33), respectively. Indeed, constraint (32) determines the demand of each customer k as a function of ω_k while constraint (33) guarantees that the quantities supplied by the different facilities to a given customer cannot exceed the customer's demand. Also, similarly to the first case, constraint (27) must be replaced by constraint (30):

$$\omega_k = \max\{\omega_{jk}, \quad j \in J\} \ k \in K \quad (31)$$

$$\delta_k = D_k^{\max} a_k + \left(\frac{1}{E_k^{\max} - E_k^{\min}} \left[\left(E_k^{\max} D_k^{\max} - E_k^{\min} D_k^{\min} \right) - \left(D_k^{\max} - D_k^{\min} \right) \omega_k \right] \right) b_k + D_k^{\min} c_k \quad k \in K \quad (32)$$

$$\sum_{j \in J} \sum_{m \in M} z_{mjk} \le \delta_k \quad k \in K \quad (33)$$

In constraint (32), note that a_k, b_k, and c_k are defined as follows:

- $a_k = 1$ if $\omega_k \le E_k^{\min}$, 0 otherwise.
- $b_k = 1$ if $E_k^{\min} < \omega_k < E_k^{\max}$, 0 otherwise.
- $c_k = 1$ if $\omega_k \ge E_k^{\max}$, 0 otherwise.

4.3.2. Integration of lead times

Incorporating lead times is expected to impact SC design decisions that take into account environmental considerations. For instance, if the time factor is not considered in the model then air transportation will never be used since it is not only expensive but also environmentally unfriendly. Lead time issues have been addressed in many papers dealing with production-inventory management. However, except very few works (such as Hammami and Frein, 2013), the optimization-based SC design models often ignore lead times due to the difficulty of combining strategic decisions with tactical aspects. Hammami and Frein (2013) developed a SC design model where, for each customer order over the planning horizon, the delivery lead time quoted to the customer must be smaller than the lead time required by this customer. This led to a very complex model, for which it is not possible to integrate a carbon emissions-sensitive demand as we do in this paper. While the issue of lead times is beyond the scope of this research, we nevertheless show in what follows how the impact of lead times can be captured in our models for a specific and relatively simple situation.

For instance, we let $\Delta_k^{\max}$ denote the time elapsing between the order being placed by customer k and the due date of that order. Therefore, the delivery lead time achieved by each facility supplying customer k must not exceed $\Delta_k^{\max}$. We assume that production facilities adopt a make-to-stock policy. In this case, the delivery lead time that can be guaranteed by facility j is equal to the transportation lead time from j to k (if we assume that there are no shortages). This situation can be modeled by adding constraint (34), where Δ_{mjk} denotes the transportation lead time of the final product from facility j to customer k using transportation mode m (which is assumed to be independent of the transported quantity).

$$\sum_{m \in M} \Delta_{mjk}\, y_{mjk} \le \Delta_k^{\max} \quad j \in J,\ k \in K \tag{34}$$

4.3.3. Other demand functions

In this paper, we have modeled demand as a piecewise linear function of per unit emissions while considering three affine functions, two of which are constant. We can generalize our demand by including other pieces of affine functions as illustrated in Fig. 3. The piecewise linear function can also be used as an approximation for many other functions (such as the exponential function) by sampling the curve and interpolating linearly between the points. Piecewise approximations have become an attractive alternative for handling nonlinear functions, even though the size of the model increases in the continuous and integer domains (Jensen and Bard, 2003). Hence, if accurate data about demand and customer behavior are available then the piecewise linear function can be used to approximate the demand.

5. Experiments and insights

In order to derive a set of insights, we use model ($M2$). Indeed, on the one hand, ($M2$) is more comprehensive than ($M1$) and, on the other hand, it allows for studying some situations that cannot be considered by ($M1$) such as the selection of several production facilities to serve several customers. The insights, presented in the form of a series of observations, are based on the numerical results generated by solving the model for different instances while varying different parameters. We implemented the model and solved it to optimality using the optimization software Cplex. We designed the experiments based on a case study from the textile industry (described hereafter).

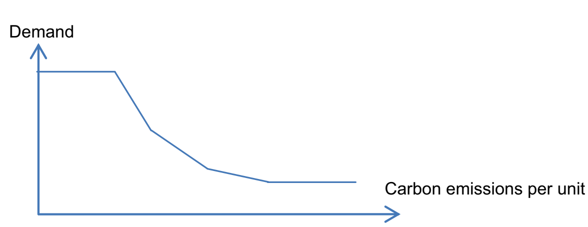

Fig. 3. Piecewise linear demand.

5.1. Case study

We consider the case of a multinational company in the textile sector referred to hereafter as company X. We consider only one final product: a medium-sized woman's jacket. At an aggregated level, there are 4 components: the fabric constituting the jacket, the lining, the fur for the jacket collar, and the cloth dye. These are denoted by $P1$, $P2$, $P3$, and $P4$ respectively. We assume that one unit of each component is required to make one unit of the final product (i.e., $N_p = 1\ \forall p$).

Company X manufactures the final product, which is delivered to two distribution centers located in Italy and Germany, respectively. The distribution centers play the role of customers (2 customers). We consider 4 potential locations for production facilities: China, Tunisia, Italy, and Poland. In each of these countries, there is one potential supplier for the different components. Thus, the total number of potential suppliers is 4. In each production facility, we can choose between two potential production technologies: a high gas emissions technology (with low cost and high carbon emissions), and a green technology (with high cost and low carbon emissions).

In order to ship the components and final product on the different arcs of the SC, we consider 4 potential transportation modes (some of which are not always available):

- *Mode* 1: by road. A truck is used for shipment.
- *Mode* 2: by rail. We consider a transit mode using an electric and/or diesel-powered train.
- *Mode* 3: by air. This refers to an airplane/truck combination.
- *Mode* 4: by water. This refers to a boat/truck combination.

Unless stated otherwise, the selling price $A_k = 100$ (€) for the two customers. In Table 1, we give the purchasing costs (including the transportation costs) and the carbon emissions for the shipment of component $P1$ from the different potential suppliers to the Chinese production facility via the different transportation modes. The data relative to the other components and production facilities are included in the Appendix. For the calculation of the carbon emissions we used the online calculator "www.ecotransit.org". In this calculator, the amount of emissions is based on the type of transportation mode, the traveled distance, and the weight of shipment. Roughly, we consider that one kilogram of item $P1$ is required to obtain one unit of the final product. The final product weighs around two kilograms.

In Table 2, we give the amount of carbon emissions and the cost of transporting the final product from the potential production facilities to the Italian customer using the different transportation modes. The data relative to the German customer are given in the Appendix.

The other parameters and costs are provided in Table 3.

5.2. Insights from the model

Observation 1: When the market is divided into ordinary and green customers, a firm that designs its supply chain without considering green customers' sensitivity to carbon emissions may

Table 1
Emissions Ω_{pmsj} (gCO_2) and purchasing cost PC_{pmsj} (€) of item $P1$ by Chinese facility.

	Chinese supplier		Tunisian supplier		Italian supplier		Polish supplier	
	Emission	Cost	Emission	Cost	Emission	Cost	Emission	Cost
Road	97	3.82	820	12.28	717	13.29	595	10.87
Rail	47	3.31	Impossible		216	9.56	182	7.87
Air	1577.1	5.3	6250	23.04	5834	23.4	5047	19.55
Water	24	3.24	150	7.86	97	9.8	172	9.38

Table 2
Emissions Ω_{mj} (gCO_2) and transp. cost TC_{mj} (€) per unit of final product from facilities to Italian customer.

	Chinese facility		Tunisian facility		Italian facility		Polish facility	
	Emission	Cost	Emission	Cost	Emission	Cost	Emission	Cost
Road	1394	12.2	533.9	4.75	54.7	0.49	219.2	1.96
Rail	406	4.8	Impossible		12.5	0.17	65.8	0.75
Air	11580	31	3163.9	4.36	1710.7	1.69	3556.8	5.12
Water	220	5.4	52.4	0.23	61.8	0.46	120.9	1.08

miss the opportunity of significantly increasing its profit. The larger the size of the green market, the greater the gain resulting from considering demand sensitivity to carbon emissions.

This observation is illustrated in Fig. 5 where, for increasing values of D_k^{max}, we give the percentage of possible gain achieved by a firm if it implements the solution put forward by our model ($M2$) instead of the solution obtained using a modified version of ($M2$) that ignores the correlation between demand and carbon emissions. In order to calculate this percentage of gain, we proceed as follows (this procedure is illustrated in Fig. 4):

- First, we solve our model ($M2$) for the different values of D_k^{max}. We let $\pi_2(D_k^{max})$ denote the optimal profit obtained in this case.
- Second, we solve a modified version of ($M2$) where we replace the emissions-sensitive demand by the maximum demand D_k^{max}. We denote this model by ($M0$). Indeed, ($M0$) is similar to ($M2$) except that the demand is assumed to be constant (insensitive to emissions). Hence, whatever the carbon emissions level, the demand of model ($M0$) is equal to D_k^{max}. We obtain the solution of ($M0$) for the different values of D_k^{max}.
- Third, for each D_k^{max} we calculate the profit given by model ($M2$) if we impose the solution obtained with ($M0$). We let $\pi_0(D_k^{max})$ denote the profit obtained in this case.
- Finally, for each D_k^{max}, we calculate the percentage of gain obtained by implementing the solution provided by our model ($M2$) instead of the solution given by ($M0$). This percentage of gain, denoted by G, is calculated as follows: $G(D_k^{max}) = 100*\pi_2(D_k^{max}) - \pi_0(D_k^{max})/\pi_0(D_k^{max})$.

Indeed, when the market is divided into ordinary customers (insensitive to carbon emissions) and green customers (sensitive to carbon emissions), decision-makers can capture green customers' sensitivity to carbon emissions using model ($M2$), which leads to optimal profit π_2. If the decision-makers ignored the emissions-sensitivity of demand then they would assume demand to be constant and would implement the optimal solution given by model ($M0$). However, since green customers really exist, then the optimal profit of the company is not the profit obtained with the optimal solution given by ($M0$) but rather π_0.

The variation in the percentage of gain G (resulting from implementing the solution of ($M2$) instead of ($M0$)) as a function of D_k^{max} is illustrated in Fig. 5. In these experiments, we set D_k^{min} to 100,000 and vary D_k^{max} from 100,000 to 300,000 for each customer k. The values of E_k^{min} and E_k^{max} are respectively set to 400 g CO_2 and 800 g CO_2. Fig. 5 shows that G can be very high hence demonstrating the advantage of our model. In addition, G increases with increasing values of D_k^{max}. Since ($D_k^{max} - D_k^{min}$) represents the size of the green market and D_k^{min} is constant then we can conclude that the percentage of gain G increases with an increase in the size of the green market.

Table 3
Data relative to production facilities.

	China ($j=1$)	Tunisia ($j=2$)	Italy ($j=3$)	Poland ($j=4$)
OC_j (€)	100,000	150,000	300,000	250,00
HC_{hj} (€)				
Green technology ($h=1$)	50,000	50,000	50,000	50,000
Dirty technology ($h=2$)	30,000	30,000	30,000	30,000
MC_{hj}(€)				
Green technology	15.4	17.6	27.5	20.9
Dirty technology	14	16	25	19
Ω_{hj} (gCO_2)				
Green technology	400	400	400	400
Dirty technology	600	600	600	600

Observation 2: If the demand is sensitive to carbon emissions then it can be optimal to bring the area of production close to the area of consumption and to select local suppliers. It can even be optimal to dedicate a production facility to each customer in spite of the incurred additional costs.

We solve model ($M2$) for different values of D_k^{max} with the same setting as Observation 1. As shown in Table 4, if the green market size is relatively small ($D_k^{max} \leq 120,000$) then the model serves both Italian and German customers from the low-cost Chinese facility. However, with an increase in D_k^{max}, the model opts for the Tunisian production facility to serve both customers. Indeed, Tunisia offers here a good trade-off between small production costs and customer proximity. If the green market size is relatively large ($D_k^{max} \geq 240,000$), then the model dedicates a production facility to each customer: the Italian customer is delivered by the Tunisian facility while the German customer is served from Poland. By doing this, the model minimizes the per unit emissions and increases the demand of each customer. The increase in cost (caused by opening two production facilities and operating the relatively expensive Polish facility) is offset by the increase in revenue.

In all these experiments, the model selects the local supplier. For cases where the Chinese facility is opened, selecting the Chinese supplier is obviously the optimal choice since it offers the lowest cost with the lowest transportation emissions in the upstream SC. However, in other cases, selecting the local supplier is more logical owing to the reduction in carbon emissions.

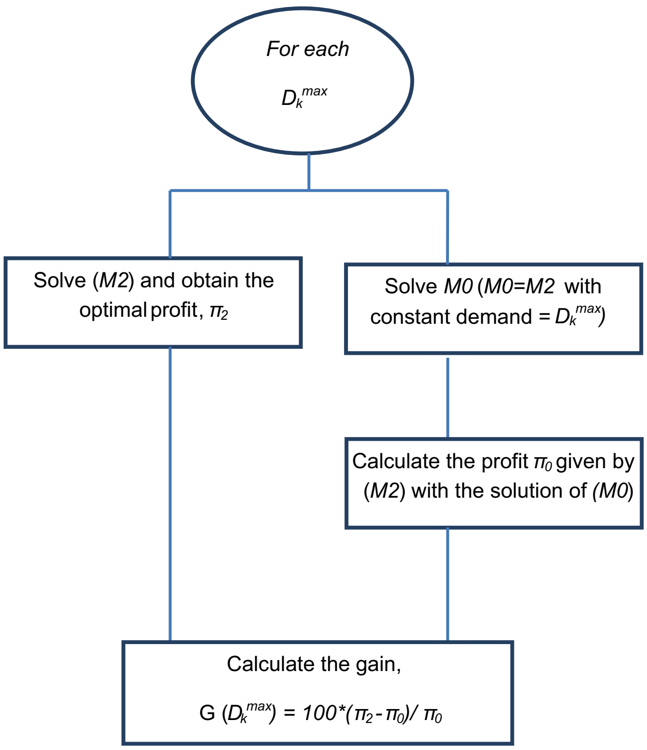

Fig. 4. Procedure for the calculation of gain $G(D_k^{max})$.

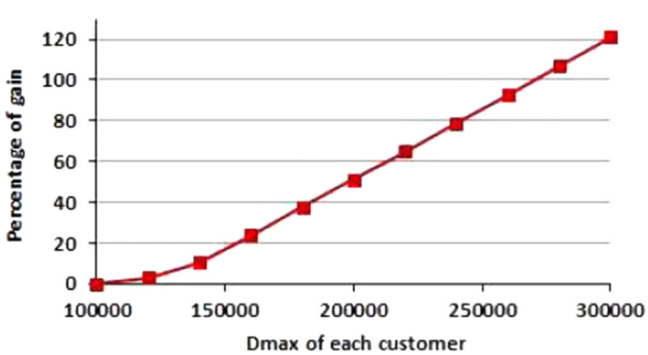

Fig. 5. Percentage of gain, G, resulting from the integration of emissions-sensitive demand.

It is important to highlight that our model does not take into account the risks associated with the selection of low-cost facilities and suppliers. According to Hammami et al. (2009), some low-cost suppliers have neither the technological potential nor the sufficient experience to supply big companies with the required quantity and quality of products. The authors highlighted that many multinational companies have experienced this kind of problem. Similarly, many firms that opened low-cost production facilities have experienced different technical, logistical, cultural, and organizational problems. Such issues are not dealt with in our model but should be taken into account by managers when undertaking the decisions in practice. For instance, it is common that managers proceed with two phases: in the first phase, they use a qualitative approach to select the potential candidates (facilities or suppliers) based on some criteria that cannot be embedded in mathematical models and, in the second phase, they use quantitative aid decision tools like the one developed in this paper while considering only the alternatives that have passed the first selection stage.

Observation 3: If demand is sensitive to carbon emissions then the selection of suppliers becomes a key factor with a significant impact on the location of production facilities in the supply chain and on the total profit of the company. In particular, the selection of a relatively expensive production facility that is close to an available supplier might be preferable to selecting a low-cost facility with no access to local suppliers.

Using the same setting as in the previous experiments, we consider two scenarios: (1) only the local and expensive Italian supplier is available, and (2) only the distant and low-cost Chinese supplier is available. In each of these cases and for increasing values of D_k^{max}, we calculate the percentage of loss compared with the base case where all suppliers are available. The results are presented in Fig. 6.

Selecting the Chinese supplier is the best option for small values of D_k^{max}, namely when minimizing cost is more important than reducing emissions and, consequently, when it is wiser to choose a Chinese production facility. However, with an increase in D_k^{max}, selecting the low-cost Chinese supplier leads to significant loss as it increases carbon emissions and, consequently, does not allow for capitalizing on the demand of green customers. Selecting the expensive Italian supplier is a poor decision for small values of D_k^{max} but proves to be a better option when the size of the green market increases (i.e., when D_k^{max} goes up). Indeed, with an increase in D_k^{max}, it becomes more profitable to select the Tunisian production facility as this enhances the role of the Italian supplier given the proximity between Italy and Tunisia. If we impose the Italian supplier for large values of D_k^{max} then the percentage of loss goes up slightly. Indeed, minimizing carbon emissions is crucial in this case, hence penalizing the Italian supplier who is located relatively far away from the German customer (compared with the Polish supplier). Overall, beyond a certain value of D_k^{max} (here, $D_k^{max} \geq 180,000$), the Italian supplier offers a greater advantage than the Chinese supplier in spite of its higher cost. This demonstrates that, unlike distant low-cost suppliers, local suppliers may benefit from customers' environmental awareness in spite of their high cost.

Table 4
Location of production facilities for increasing values of D_k^{max}.

D_k^{max} ($\forall k$)	100,000	120,000	140,000	160,000	180,000	200,000	220,000	240,000	260,000	280,000	300,000
Facility serving Italian customer	China	China	Tunisia	Tunisia	Tunisia	Tunisia	Tunisia	Tunisia	Tunisia	Tunisia	Tunisia
Facility serving German customer	China	China	Tunisia	Tunisia	Tunisia	Tunisia	Tunisia	Poland	Poland	Poland	Poland

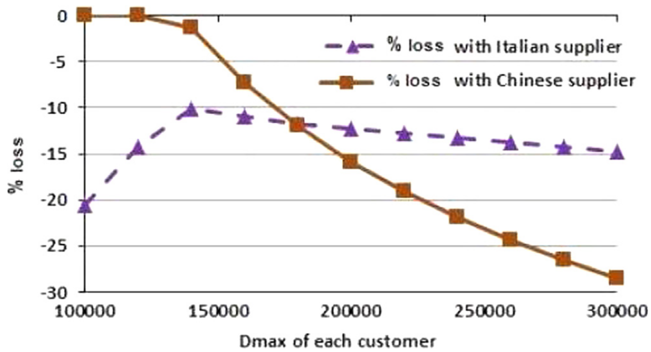

Fig. 6. Percentage of loss when only one supplier is available compared to the base case with all suppliers.

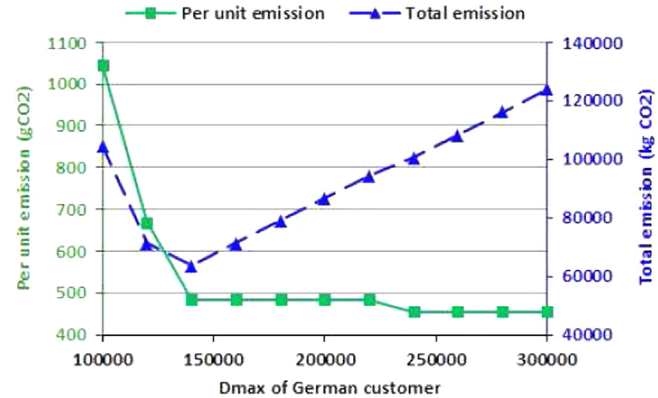

Fig. 8. Per unit and total emission associated with the German customer for increasing values of D_k^{max}.

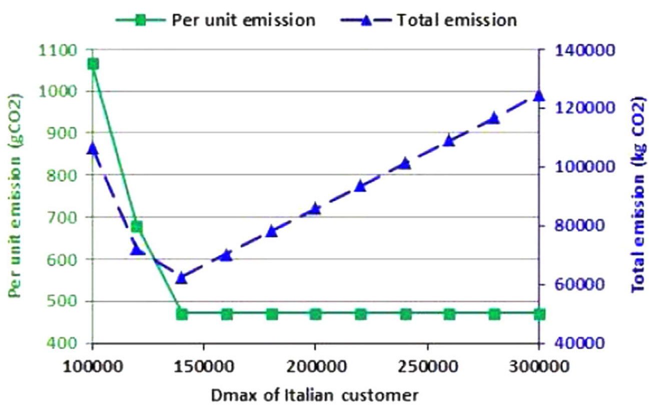

Fig. 7. Per unit and total emissions associated with the Italian customer for increasing values of D_k^{max}.

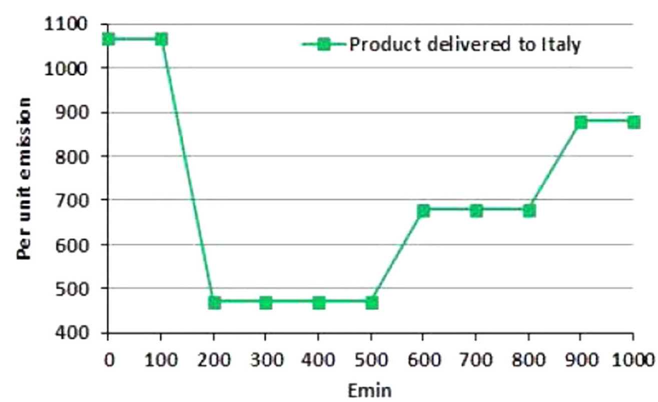

Fig. 9. Per unit emissions as a function of E_k^{min} when $(E_k^{max} - E_k^{min})$ is kept constant.

It is also important to highlight that, on markets where there are customers sensitive to carbon emissions, supplier selection and production facility location are highly correlated. The location of production facilities can even be constrained by the availability of local suppliers. Indeed, in the experiments illustrated in Fig. 6 and for all values of D_k^{max}, the model selected the Chinese facility when the Chinese supplier was imposed and the Tunisian facility selected when the Tunisian supplier was imposed. This is justified by the fact that emissions in the upstream SC play an important role in determining the per unit emissions, hence underlining the advantage of proximity between suppliers and production facilities.

Observation 4: The existence of a small green market can lead to a considerable reduction in both per unit emissions and total emissions. However, if the size of the green market increases, this does not necessarily lead to a significant reduction in per unit emissions. Total emissions may even go up with an increase in green market size.

This observation is illustrated in Figs. 7 and 8. Indeed, with the same previous setting, we solve model (*M*2) and observe the variation of per unit emissions and total emissions as a function of D_k^{max} for each customer (Fig. 7 pertains to the Italian customer while Fig. 8 represents the case of the German customer). Overall, the greater D_k^{max} (i.e., the larger the green market size) the smaller the per unit emissions. However, the most significant reduction in emissions occurs when we increase the green market size from 0 to 40,000 (recall that green market size $= D_k^{max} - D_k^{min}$ and $D_k^{min} = 100,000$). Beyond this value, the level of emissions reduction is insignificant even if the size of the green market grows considerably. Indeed, with an increase in D_k^{max} the model first selects greener technologies and transportation modes in order to reduce emissions and, consequently, increase revenue. Then, the size of the green market grows enough to justify the opening of relatively expensive production facilities since the increase in cost can be offset by the increase in revenue (due to the reduced emissions). If D_k^{max} continues to increase then this does not necessarily lead to significant changes in carbon emissions since the remaining options for reducing these may be non-profitable. For instance, in our example, the Italian production facility (close to the Italian customer) is never selected even for very large values of D_k^{max} as this would involve a cost increase that cannot be offset by greater revenue.

Regarding total emissions (generated by the total quantity of the final product), we observe that the value first goes down (when the per unit emissions significantly decrease) and then goes up substantially. Indeed, if D_k^{max} increases and the per unit emissions do not change (or slightly decrease) then the total demand can increase. In this case, when the increase in total demand is not offset by the decrease in per unit emissions then the total emissions increase.

Overall, the results of observation 4 imply that firms can react to the emergence of a green market by designing greener supply chains even in the absence of environmental legislation. This can lead to a decrease in both per unit emissions and total emissions. However, contrary to expectations, an increase in green market size does not necessarily favor the design of greener supply chains and a reduction in emissions.

Observation 5: A variation in per unit emissions can be non-monotonous with increasing values in E_k^{min}. In some cases, if the green customers are very demanding (in terms of reduced carbon

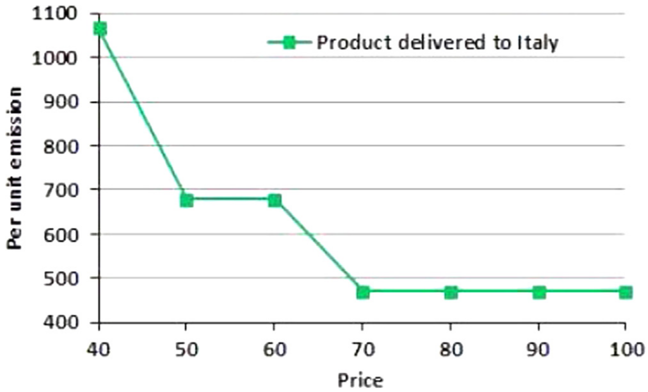

Fig. 10. Per unit emissions as a function of selling price.

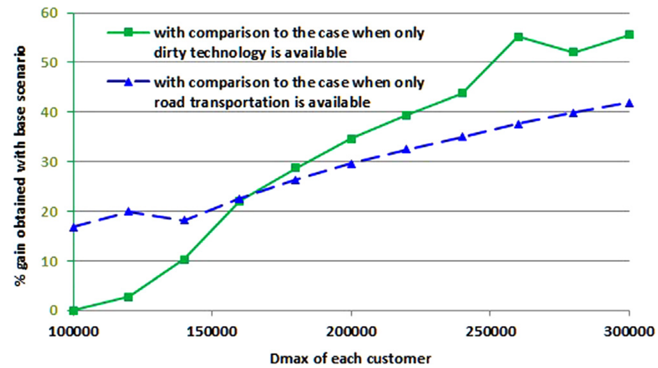

Fig. 11. % Gain obtained by considering green technology and transportation alternatives.

emissions) then, paradoxically, the best strategy can be to offer dirty products (i.e., products with high per unit emissions).

Fig. 9 shows the variation of per unit emissions when we increase $E_k^{\min}$ while keeping $D_k^{\min}$, $D_k^{\max}$ and $(E_k^{\max} - E_k^{\min})$ constant. In these experiments, $D_k^{\min} = 100,000$, $D_k^{\max} = 200,000$ and $(E_k^{\max} - E_k^{\min}) = 400$ gCO_2. We observe that if green customers are highly demanding in terms of carbon emissions (i.e., for small values of $E_k^{\min}$) then the optimal decision can be to offer a dirty product (with high per unit emissions). This is because satisfying customer requirements may be very expensive in this case. The per unit emissions decrease if the customers become less demanding. In fact, the firm can, in this case, capitalize on the sensitivity of demand to carbon emissions in order to increase revenue. However, as might be expected, if green customers continue to be less demanding (i.e., for large values of $E_k^{\min}$) then the per unit emissions increase.

We have shown that when green customers are very demanding then the best strategy can be to offer dirty products. In practice, this means that the firm ignores the green customers and targets basically the traditional market. However, this strategy may lead to a bad image of the firm in the market, which may impact on firm's competitiveness in the future. Other factors can also make this strategy questionable such as the future market changes (e.g., more green customers) and the environmental regulations/restrictions that are being imposed by an increasing number of countries. In order to deal with this situation, the firm can adopt a market segmentation policy (see e.g., Chen, 2001). In this case, the firm can offer a dirty product to the traditional market and a green product to the green market. However, this strategy has also some limitations as discussed in Chen (2001).

Observation 6: If the customers are willing to pay a higher price for the product then this can lead to reducing per unit emissions.

This observation is illustrated in Fig. 10 where we show the variation of per unit emissions as a function of the selling price. We consider the following setting: $D_k^{\min} = 100,000$, $D_k^{\max} = 200,000$, $E_k^{\min} = 400$ gCO_2 and $E_k^{\max} = 800$ gCO_2. In fact, if the price increases then it can become profitable to design a more expensive but greener SC. Indeed, in this case, even a small reduction in emissions (namely, a small increase in demand) can lead to significantly increased revenue thanks to the high price. Consequently, the higher cost resulting from the design of a greener SC can be offset by the increase in revenue.

Observation 7: For a firm facing a green market, the availability of clean production technologies and/or transportation modes alternatives can have a significant impact on firm's profit and strategic supply chain decisions. The availability of such clean alternatives can significantly enhance the firm's profit. In addition, this improvement generally goes up with an increase in green market size.

We firstly compare, for increasing values of $D_k^{\max}$, the firm's optimal profit given by model ($M2$) under the base parameters setting (presented earlier) with the profit obtained under each of these two scenarios: (1) only the dirty production technology is available and (2) only the road transportation is available. Results are illustrated in Fig. 11. One can observe that the consideration of the clean technology and the relatively clean rail and water transportation modes in the base scenario can lead to improve the optimal profit by up to 55% and 41%, respectively. As expected, the gain generated by considering the green alternatives generally goes up with an increase in the green market size. Indeed, when the green technologies and transportation modes are available, the model can use them to obtain a greener product and, consequently, a higher demand, even if a distant offshore facility is selected. However, in the absence of green technologies and transportation modes, the model has few options to adapt the SC strategy to the increase in green market size. These options are locating production facilities close to customers and selecting local suppliers, which generally increases considerably the supply chain cost. For instance, in cases of $D_k^{\max} = 200,000$ and 220,000, and when the clean technology is not available, the model opened the Tunisian facility to serve the Italian customer and the polish facility to serve the German customer, each of them is supplied by its local supplier, whereas only the Tunisian supplier and facility are selected in case of base scenario (i.e., when clean technology is available).

6. Conclusion

In this paper, we have shown that supply chain optimization models should evolve to capture the correlation between the environmental performance of a product (in terms of carbon emissions), customer demand, and supply chain decisions. We used mixed integer programming to develop supply chain design models where the demand for the final product depends on its per unit emissions. The amount of carbon emissions in the different arcs and nodes of the supply chain are used to calculate this. We considered the emissions associated with the upstream transportation (from suppliers to production facilities), the production process, and the downstream transportation (from production facilities to customers). The main decisions pertaining to the models are the selection of suppliers, the location of production facilities, the selection of production technologies, and the selection of transportation modes. We first dealt with the case of a single customer and then extended the model to consider multiple customers. We also discussed different modeling extensions.

We conducted numerical experiments on a case study and showed how important insights can be obtained and used to inform corporate decision making by operating firms. In particular, the insights relative to the impacts of integrating customers' environmental awareness in supply chain design models would be difficult to obtain without the support of optimization models like those developed in this paper. Here is a summary of the main findings:

- When the market comprises both ordinary and green customers, a firm that designs its supply chain without taking into account the sensitivity of green customers to carbon emissions can suffer significant loss.
- If demand is sensitive to carbon emissions then the optimal solution can be to bring the area of production close to the area of consumption and to select local suppliers.
- An emergence of green customers (sensitive to carbon emissions) can oblige firms to design greener supply chains in order to decrease per unit carbon emissions even when there is no environmental legislation.
- In some cases, total emissions can decrease when a small green market begins to grow but they can also paradoxically increase with the increase in green market size.
- If green customers are very demanding (in terms of reducing carbon emissions) then the best strategy can be to offer dirty products.
- When demand is sensitive to emissions, this can lead to lower per unit emissions if the customers are willing to pay a higher price for the product (with all other factors remaining constant).
- For a firm facing a green market, the availability of clean production technologies and/or transportation modes alternatives can considerably increase the firm's profit and impact the strategic supply chain decisions.

This work can be considered as an initial contribution to the development of SC design models integrating emissions-sensitive demand. We highlight that the proposed models are particularly relevant for industries where the emissions associated with the logistics activities (basically, transportation) are predominant with comparison to the other types of emissions, such as for textile and automotive industries. Although we considered the emissions generated by the manufacturing activities, our models are less suited for the cases of energy-intensive industries where the emissions from production technologies are predominant.

Furthermore, there are some risks associated with each one of the decisions considered in our model. If the location is offshore, there might be highly impacted with financial fluctuations of currencies and states of the economy, and so forth. Also, there might be associated risks with fluctuating demands due to the stochastic nature of the demand as well as due to risks such as natural disasters. The location of suppliers and transportation mode of raw materials and subcomponents, as well as the transportation of finished goods becomes critical in such situations and mitigation strategies should be a topic of future research to minimize the impact of such situations. In order to cope with supply chain risks, managers can proceed by different approaches such as the evaluation of different scenario of input parameters and the use of a two-stage selection process where the risk factors are evaluated by a qualitative method in the first stage. The complexity of our proposed model merits an in-depth analysis associated with risks. The authors see the potential for future expansion of such extension.

The proposed models offer other avenues for further exploration. Future research might use other approaches to calculate per unit emissions or study other types of relations between per unit emissions and demand. It is also worthwhile to compare the results of our base models with the results given by the model extensions since this may lead to interesting insights. However, this may require some changes in the proposed extensions in order to harmonize the demand structure between the different models and to obtain a relevant comparison framework.

Appendix A

Tables 5–20.

Table 5
Emissions Ω_{pmsj} (gCO_2) and purchasing cost PC_{pmsj} (€) of item $P1$ by Tunisian facility.

	Chinese supplier		Tunisian supplier		Italian supplier		Polish supplier	
	Emission	Cost	Emission	Cost	Emission	Cost	Emission	Cost
Road	900	11.1	19	6.16	320	9.7	366.2	8.98
Rail	Impossible		7.2	6.06	Impossible		Impossible	
Air	6916	23	Impossible		1252.5	8.23	2558.9	9.94
Water	131	5.61	Impossible		22.6	7.1	103	6.63

Table 6
Emissions Ω_{pmsj} (gCO_2) and purchasing cost PC_{pmsj} (€) of item $P1$ by Italian facility.

	Chinese supplier		Tunisian supplier		Italian supplier		Polish supplier	
	Emission	Cost	Emission	Cost	Emission	Cost	Emission	Cost
Road	760	9.61	300	7.65	47	7.42	89.4	6.5
Rail	240	5.68	Impossible		18	7.16	24	5.97
Air	6502	21.38	1705.8	7.48	1030	8.18	1371.3	7.72
Water	82.1	5.65	31	5.34	15	7.27	86.2	6.9

Table 7
Emissions Ω_{pmsj} (gCO_2) and purchasing cost PC_{pmsj} (€) of item $P1$ by Polish facility.

	Chinese supplier		Tunisian supplier		Italian supplier		Polish supplier	
	Emission	Cost	Emission	Cost	Emission	Cost	Emission	Cost
Road	694	8.96	369.3	8.29	146.76	10.94	20.83	5.88
Rail	229	5.49	Impossible		49.74	7.49	12.62	5.78
Air	5742	19.29	2817.8	9.55	2044.08	10.12	787.23	6.65
Water	190	6.61	138.1	6.06	53.26	7.93	20.57	5.75

Table 8
Emissions Ω_{pmsj} (gCO_2) and purchasing cost PC_{pmsj} (€) of item $P2$ by Chinese facility.

	Chinese supplier		Tunisian supplier		Italian supplier		Polish supplier	
	Emission	Cost	Emission	Cost	Emission	Cost	Emission	Cost
Road	47	3.82	410	12.28	368	13.29	298	10.87
Rail	23.5	3.31	Impossible		108	9.56	91	7.87
Air	780.1	5.3	3125	23.04	2907	23.4	2523	19.25
Water	12	3.24	75	7.86	48.5	9.8	86	9.38

Table 9
Emissions Ω_{pmsj} (gCO_2) and purchasing cost PC_{pmsj} (€) of item $P2$ by Tunisian facility.

	Chinese supplier		Tunisian supplier		Italian supplier		Polish supplier	
	Emission	Cost	Emission	Cost	Emission	Cost	Emission	Cost
Road	450	11.1	9.5	6.16	160	9.7	183.1	8.98
Rail	Impossible		3.6	6.06	Impossible		Impossible	
Air	3408	23	Impossible		626.5	8.23	1274.4	9.94
Water	65.1	5.61	Impossible		11.3	7.1	51.5	6.63

Table 10
Emissions Ω_{pmsj} (gCO_2) and purchasing cost PC_{pmsj} (€) of item $P2$ by Italian facility.

	Chinese supplier		Tunisian supplier		Italian supplier		Polish supplier	
	Emission	Cost	Emission	Cost	Emission	Cost	Emission	Cost
Road	380	9.61	150	7.65	24	7.42	45.2	6.5
Rail	240	5.68	Impossible		9	7.16	12	5.97
Air	3251	21.38	852.4	7.48	515	8.18	685.1	7.72
Water	41	5.65	15	5.34	7	7.27	43	6.9

Table 11
Emissions Ω_{pmsj} (gCO_2) and purchasing cost PC_{pmsj} (€) of item $P2$ by Polish facility.

	Chinese supplier		Tunisian supplier		Italian supplier		Polish supplier	
	Emission	Cost	Emission	Cost	Emission	Cost	Emission	Cost
Road	347	8.96	184.3	8.29	73.76	10.94	10.4	5.88
Rail	229	5.49	Impossible		25.74	7.49	6.31	5.78
Air	2871	19.29	1408.9	9.55	1022.04	10.12	393.6	6.65
Water	95	6.61	69	6.06	26	7.93	10.2	5.75

Table 12
Emissions Ω_{pmsj} (gCO_2) and purchasing cost PC_{pmsj} (€) of item $P3$ by Chinese facility.

	Chinese supplier		Tunisian supplier		Italian supplier		Polish supplier	
	Emission	Cost	Emission	Cost	Emission	Cost	Emission	Cost
Road	47	3.82	410	12.28	368	13.29	298	10.87
Rail	23.5	3.31	Impossible		108	9.56	91	7.87
Air	780.1	5.3	3125	23.04	2907	23.4	2523	19.25
Water	12	3.24	75	7.86	48.5	9.8	86	9.38

Table 13
Emissions Ω_{pmsj} (gCO_2) and purchasing cost PC_{pmsj} (€) of item $P3$ by Tunisian facility.

	Chinese supplier		Tunisian supplier		Italian supplier		Polish supplier	
	Emission	Cost	Emission	Cost	Emission	Cost	Emission	Cost
Road	450	11.1	9.5	6.16	160	9.7	183.1	8.98
Rail	Impossible		3.6	6.06	Impossible		Impossible	
Air	3408	23	Impossible		626.5	8.23	1274.4	9.94
Water	65.1	5.61	Impossible		11.3	7.1	51.5	6.63

Table 14
Emissions Ω_{pmsj} (gCO_2) and purchasing cost PC_{pmsj} (€) of item $P3$ by Italian facility.

	Chinese supplier		Tunisian supplier		Italian supplier		Polish supplier	
	Emission	Cost	Emission	Cost	Emission	Cost	Emission	Cost
Road	380	9.61	150	7.65	24	7.42	45.2	6.5
Rail	240	5.68	Impossible		9	7.16	12	5.97
Air	3251	21.38	852.4	7.48	515	8.18	685.1	7.72
Water	41	5.65	15	5.34	7	7.27	43	6.9

Table 15
Emissions Ω_{pmsj} (gCO_2) and purchasing cost PC_{pmsj} (€) of item $P3$ by Polish facility.

	Chinese supplier		Tunisian supplier		Italian supplier		Polish supplier	
	Emission	Cost	Emission	Cost	Emission	Cost	Emission	Cost
Road	347	8.96	184.3	8.29	73.76	10.94	10.4	5.88
Rail	229	5.49	Impossible		25.74	7.49	6.31	5.78
Air	2871	19.29	1408.9	9.55	1022.04	10.12	393.6	6.65
Water	95	6.61	69	6.06	26	7.93	10.2	5.75

Table 16
Emissions Ω_{pmsj} (gCO_2) and purchasing cost PC_{pmsj} (€) of item $P4$ by Chinese facility.

	Chinese supplier		Tunisian supplier		Italian supplier		Polish supplier	
	Emission	Cost	Emission	Cost	Emission	Cost	Emission	Cost
Road	47	3.82	410	12.28	368	13.29	298	10.87
Rail	23.5	3.31	Impossible		108	9.56	91	7.87
Air	780.1	5.3	3125	23.04	2907	23.4	2523	19.25
Water	12	3.24	75	7.86	48.5	9.8	86	9.38

Table 17
Emissions Ω_{pmsj} (gCO_2) and purchasing cost PC_{pmsj} (€) of item $P4$ by Tunisian facility.

	Chinese supplier		Tunisian supplier		Italian supplier		Polish supplier	
	Emission	Cost	Emission	Cost	Emission	Cost	Emission	Cost
Road	450	11.1	9.5	6.16	160	9.7	183.1	8.98
Rail	Impossible		3.6	6.06	Impossible		Impossible	
Air	3408	23	Impossible		626.5	8.23	1274.4	9.94
Water	65.1	5.61	Impossible		11.3	7.1	51.5	6.63

Table 18
Emissions Ω_{pmsj} (gCO_2) and purchasing cost PC_{pmsj} (€) of item $P4$ by Italian facility.

	Chinese supplier		Tunisian supplier		Italian supplier		Polish supplier	
	Emission	Cost	Emission	Cost	Emission	Cost	Emission	Cost
Road	380	9.61	150	7.65	24	7.42	45.2	6.5
Rail	240	5.68	Impossible		9	7.16	12	5.97
Air	3251	21.38	852.4	7.48	515	8.18	685.1	7.72
Water	41	5.65	15	5.34	7	7.27	43	6.9

Table 19
Emissions Ω_{pmsj} (gCO_2) and purchasing cost PC_{pmsj} (€) of item $P4$ by Polish facility.

	Chinese supplier		Tunisian supplier		Italian supplier		Polish supplier	
	Emission	Cost	Emission	Cost	Emission	Cost	Emission	Cost
Road	347	8.96	184.3	8.29	73.76	10.94	10.4	5.88
Rail	229	5.49	Impossible		25.74	7.49	6.31	5.78
Air	2871	19.29	1408.9	9.55	1022.04	10.12	393.6	6.65
Water	95	6.61	69	6.06	26	7.93	10.2	5.75

Table 20
Emissions Ω_{mj} (gCO_2) and transp. cost TC_{mj} (€) per unit from facilities to German customer.

	Chinese facility		Tunisian facility		Italian facility		Polish facility	
	Emission	Cost	Emission	Cost	Emission	Cost	Emission	Cost
Road	1324.3	11.5	600.6	5.2	109.4	0.79	88.6	0.5
Rail	385.7	4	Impossible		30	0.37	22.9	0.25
Air	11,001	31	3422.1	5	3421.4	2	1778.4	3.12
Water	209	5	65.02	1.23	123.6	0.76	60.5	0.3

References

Altmann, M., 2015. A supply chain design approach considering environmentally sensitive customers: the case of a German manufacturing SME. International Journal Production Research 53 (21), 6534–6550.

Arikan, E., Fichtinger, J., Ries, J.M., 2014. Impact of transportation lead-time variability on the economic and environmental performance of inventory systems. Int. J. Prod. Econ. 157, 279–288.

Benjaafar, S., Li, Y., Daskin, M., 2013. Carbon footprint and the management of supply chains: insights from simple models. IEEE Trans. Autom. Sci. Eng. 10 (1).

Bjorklund, M., Martinsen, U., Abrahamsson, M., 2012. Performance measurements in the greening of supply chains. Supply Chain Manag.: Int. J. 17 (1), 29–39.

Bozorgi, A., Pazour, J., Nazzal, D., 2014. A new inventory model for cold items that considers costs and emissions. Int. J. Prod. Econ. 155, 114–125.

Cachon, G.P., 2011. Supply Chain Design and the Cost of Greenhouse Gas Emissions. Working Paper, The Wharton School, University of Pennsylvania, PA.

Chaabane, A., Ramudhin, A., Paquet, M., 2011. Designing supply chains with sustainability considerations. Prod. Plan. Control 22 (8), 727–741.

Chaabane, A., Ramudhin, A., Paquet, M., 2012. Design of sustainable supply chains under the emission trading scheme. Int. J. Prod. Econ. 135, 37–49.

Chen, C., 2001. Design for the environment: a quality-based model for green product development. Manag. Sci. 47, 250–263.

Comas Martí, J.M., Tancrez, J.S., Seifert, R.W., 2015. Carbon footprint and responsiveness trade-offs in supply chain network design. Int. J. Prod. Econ. 166, 129–142.

Dekker, R., Bloemhof, J., Mallidis, I., 2012. Operations research for green logistics – an overview of aspects, issues, contributions and challenges. Eur. J. Oper. Res. 219, 671–679.

Diabat, A., Simchi-Levi, D., 2010. A carbon-capped supply chain network problem. In: IEEE International Conference on Industrial Engineering and Engineering Management, IEEE, Piscataway, NJ, pp. 523–527.

Diabat, A., Al-Salem, M., 2015. An integrated supply chain problem with environmental considerations. Int. J. Prod. Econ. 164, 330–338.

Drake, D., Kleindorfer, P.R., Van Wassenhove, L.N., 2012. Technology Choice and Capacity Portfolios Under Emissions Regulation. INSEAD Working Paper No. 2010/93/TOM/INSEAD Social Innovation Centre, Harvard Business School Technology & Operations Management, Unit Working Paper No. 12-079.

Erdogan, S., Miller-Hooks, E., 2012. A green vehicle routing problem. Transp. Res. Part E 48, 100–114.

European Commission, 2008. Attitudes of Europeans citizens towards the environment. Eurobarometer 295.

European Commission, 2009. Europeans' attitudes towards the issue of sustainable consumption and production. Flash Eurobarom. 256.

Glock, C.H., Jaber, M.H., Searcy, C., 2012. Sustainability strategies in an EPQ model with price- and quality-sensitive demand. Int. J. Logist. Manag. 23 (3), 340–359.
Hammami, R., Frein, Y., Hadj-Alouane, A.B., 2009. A strategic-tactical model for the supply chain design in the delocalization context: Mathematical formulation and a case study. International Journal of Production Economics 122, 351–365.
Hammami, R., Nouira, I., Frein, Y., 2015. Carbon emissions in a multi-echelon production-inventory model with lead time constraints. International Journal of Production Economics 164, 292–307.
Hammami, R., Frein, Y., 2013. An optimisation model for the design of global multi-echelon supply chains under lead time constraints. Int. J. Prod. Res. 51 (9), 2760–2775.
Hassini, E., Surti, C., Searcy, C., 2012. A literature review and a case study of sustainable supply chains with a focus on metrics. Int. J. Prod. Econ. 140, 69–82.
Hoen, K.M.R., Tan, T., Fransoo, J.C., van Houtum, G.J., 2014. Effect of carbon emission regulations on transport mode selection under stochastic demand. Flex. Serv. Manuf. J. 26 (1–2), 170–195.
Hovelaque, V., Bironneau, L., 2015. The carbon-constrained EOQ model with carbon emission dependent demand. Int. J. Prod. Econ. 164, 285–291.
Hugo, A., Pistikopoulos, E., 2005. Environmentally conscious long-range planning and design of supply chain networks. J. Clean. Prod. 13 (15) 1471–149.
Jayaraman, V., Singh, R., Anandnarayan, A., 2012. Impact of Sustainable Manufacturing Practices on Consumer Perception and Revenue Growth: An Emerging Economy Perspective. International Journal of Production Research 50 (5), 1395–1410.
Jensen, P.A., Bard, J.F., 2003. Operations Research Models and Methods. John Wiley & Sons, Hoboken, NJ.
Kannan, D., Khodaverdi, R., Olfat, L., Jafarian, A., Diabat, A., 2013. Integrated fuzzy multi criteria decision making method and multi-objective programming approach for supplier selection and order allocation in a green supply chain. J. Clean. Prod. 47, 355–367.
Krass, D., Nedorezov, T., Ovchinnikov, A., 2013. Environmental taxes and the choice of green Technology. Production and Operations Management 22 (5), 1035–1055.
Letmathe, P., Balakrishnan, N., 2005. Environmental considerations on the optimal product mix. Eur. J. Oper. Res. 167, 398–412.
Mafakheri, F., Breton, M., Ghoniem, A., 2011. Supplier selection-order allocation: a two-stage multiple criteria dynamic programming approach. Int. J. Prod. Econ. 132, 52–57.
Mahenc, P., 2008. Signaling the environmental performance of polluting products to green consumers. Int. J. Ind. Organ. 26, 59–68.
Nouira, I., Frein, Y., Hadj-Alouane, A.B., 2014. Optimization of manufacturing systems under environmental considerations for a greenness-dependent demand. Int. J. Prod. Econ. 150, 188–198.
Paksoy, T., Bektas, T., Ozceylan, E., 2011. Operational and environmental performance measures in a multi-product closed-loop supply chain. Transp. Res. Part E 47, 532–546.
Palak, G., Eksioglu, S.D., Geunes, J., 2014. Analyzing the impacts of carbon regulatory mechanisms on supplier and mode selection decisions: an application to a biofuel supply chain. Int. J. Prod. Econ. 154, 198–216.
Radulescu, M., Radulescu, S., Radulescu, C.Z., 2009. Sustainable production technologies which take into account environmental constraints. Eur. J. Oper. Res. 193, 730–740.
Ramudhin, A., Chaabane, A., 2010. Carbon market sensitive sustainable supply chain network design. Int. J. Manag. Sci. Eng. Manag. 5, 30–38.
Sarkis, J., 2003. A strategic decision framework for green supply chain management. J. Clean. Prod. 11, 397–409.
Shaw, K., Shankar, R., Yadav, S.S., Thakur, L.S., 2012. Supplier selection using fuzzy AHP and fuzzy multi-objective linear programming for developing low carbon supply chain. Expert Syst. Appl. 39, 8182–8192.
Tang, C.S., Zhou, S., 2012. Research advances in environmentally and socially sustainable operations. Eur. J. Oper. Res. 223, 585–594.
Tate, W.L., MEllram, L., Kirchoff, J.F., 2010. Corporate social responsibility reports: a thematic analysis related to supply chain management. J. Supply Chain Manag. 46 (1), 19–44.
Wang, F., Lai, X., Shi, N., 2011. A multi-objective optimization for green supply chain network design. Decis. Support Syst. 51, 262–269.
Young, W., Hwang, K., McDonalds, S., Oates, C.J., 2010. Sustainable consumption: green consumer behavior when purchasing products. Sustain. Dev. J. 18, 20–31.
Zanoni, S., Mazzoldi, L., Zavanella, L.E., Jaber, M.Y., 2014. A joint economic lot size model with price and environmentally sensitive demand. Prod. Manuf. Res.: Open Access J. 2 (1), 341–354.
Zhang, L., Wang, J., You, J., 2015. Consumer environmental awareness and channel coordination with two substitutable products. Eur. J. Oper. Res. 241, 63–73.
Zhu, Q., Sarkis, J., Geng, Y., 2005. Green Supply Chain Management in China: Pressures, Practices and Performance.''. International Journal of Operations and Production Management 25 (5), 449–468.

Further reading

Aronsson, H., Huge-Brodin, M., 2006. The environmental impact of changing logistics structure. Int. J. Logist. Manag. 17, 394–415.
David, O.W., Clark, C.D., Jensen, K.L., Yen, S.T., 2011. Consumer willingness to pay for appliances produced by Green Power Partners. Energy Econ. 33 (6), 1095–1102.
Mewton, R.T., Cacho, O.J., 2012. Green Power voluntary purchases: price elasticity and policy analysis. Int. J. Prod. Econ. 140, 69–82.
Pan, S., Ballot, E., Fontane, F., 2013. The reduction of greenhouse gas emissions from freight transport by pooling supply chains. Int. J. Prod. Econ. 143, 86–94.