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Economic and environmental considerations in a stochastic inventory control model with order splitting under different delivery schedules among suppliers

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ABSTRACT

This study analyzes an integrated inventory control and delivery scheduling problem in a stochastic demand environment with economic and environmental considerations. In particular, we examine a bi-objective continuous review inventory control model with order splitting among multiple suppliers, where both expected costs and carbon emissions per unit time are minimized. For this problem, two different delivery scheduling policies are considered for the split orders: sequential splitting and sequential delivery. First, we formulate the problem under each delivery scheduling policy as bi-objective mixed-integer nonlinear models. Then, an adaptive ϵ-constraint algorithm and an evolutionary search algorithm are proposed to approximate the Pareto front of these models. A numerical study is conducted to compare the two approximation algorithms. Another numerical study demonstrates the effects of the demand variance on the expected costs and carbon emissions per unit time under each delivery scheduling policy. Finally, examples are presented to show how the tools provided in this study can be used to compare different scheduling policies. Our results show that the delivery policy and supplier selection both have strong effects on the economic and environmental performance, and also that a good approximation of the Pareto front is crucial to accurately compare delivery scheduling policies.

1. Introduction

There is a growing consensus that carbon emissions are a leading contributor to global climate change, which has increased pressure around the world to enact legislation to curb these emissions. Carbon emission regulations have emerged to address these issues and incentivize firms to limit greenhouse gas (GHG) emissions, primarily carbon-dioxide (other GHG emissions can be measured in terms of carbon-dioxide, see, e.g., [47]). Environmental regulations, however, are not the only motivation for companies to replan their operations with environmental considerations. The increased environmental awareness of consumers encourages firms to "green" their operations to stay competitive, as is discussed in surveys by Loebich et al. [89] and Kiron et al. [78].

Industrial and transportation sectors are the largest contributors to GHG emissions. The industrial and transportation sectors generated 21% and 14%, respectively, of the global GHG emissions in 2010 [71] and 21% and 27%, respectively, of the U.S. GHG emissions in 2013 [48]. Thus, a very large fraction of carbon emissions are due to supply chain activities including manufacturing, inventory holding, freight transportation, logistics and warehousing activities.

Inventory management is particularly important for a company as this determines not only the level of inventory carried and warehousing activities, but also impacts the amount and the frequency of freight shipments and logistical operations. The inventory control policy of a company, therefore, is inextricably linked with its environmental performance. There is a growing body of literature that analyzes inventory control models with environmental considerations. As will be reviewed in Section 2, these studies include environmental aspects of the inventory related operations using different approaches. One approach is to associate direct costs with the environmental damage due to the inventory related operations. Another approach models the inventory control policies under environmental regulations such as carbon cap, carbon tax, carbon trading, or carbon offsetting. Considering environmental objectives such as emission minimization along with the classical economic objectives such as cost minimization (profit maximization) is another approach. In this

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study, we incorporate the environmental aspects of inventory related operations by formulating an inventory control model with environmental objectives.

Sawik [104,106] notes that jointly determining supplier selection, order allocation, and order scheduling decisions increases the supply chain performance. Particularly, our focus is on a retailer's integrated inventory control, supplier selection, and delivery scheduling problem with economic (cost minimization) and environmental (emission minimization) objectives. We study the case of stochastic continuous demand and assume a continuous review inventory control system. The retailer can split his/her order among an arbitrary number of heterogeneous suppliers. Furthermore, we consider that the retailer can arrange when the split orders will be received by scheduling the deliveries from the suppliers.

It should be noted that different delivery scheduling policies are generally modeled for the supplier (or manufacturer) in two-echelon supply chains in the context of shipment consolidation (see, e.g., [25]) or multi-item inventory systems in the context of joint replenishment problems (see, e.g., [76]). Unlike shipment consolidation and joint replenishment problems, this study analyzes a single-echelon (retailer) and single-item stochastic inventory system with order splitting among multiple heterogeneous suppliers. With order splitting among multiple suppliers allowed, the retailer can control different suppliers' delivery schedules by changing the order release times to the suppliers. For instance, in a single buyer-multiple suppliers setting, Kim and Goyal [77] consider two different delivery schedules, which they refer to as lumpy and phased deliveries. In case of lumpy deliveries, the orders from different suppliers are delivered simultaneously, while different suppliers' orders are delivered alternately in case of phased deliveries. Glock [57] defines six delivery schedules regarding the production cycles of two manufacturers with delivery at the single buyer. Both studies consider two-echelons (buyer and vendor) simultaneously and assume deterministic demand.

Single-echelon single-item stochastic inventory control models with order splitting among multiple suppliers have been studied in the literature (see, e.g., the reviews by [95,119]). In most of these studies, the split orders are assumed to be delivered sequentially (see, e.g., [32–35,110–112,42,1]). That is, the retailer places his/her order with all selected suppliers at the same time, so that the supplier with the shortest realized lead time delivers first, the supplier with the second shortest realized lead time delivers second, and so on. Sawik [105] emphasizes the importance of multiple sourcing along supply chains subject to uncertainties and, as noted by Glock [57] as well, the delivery schedule of the orders from multiple sources affects the inventory related costs. Furthermore, as discussed in this study, different delivery schedules have different environmental performance. Therefore, it is important to account for different delivery scheduling policies within inventory control models with environmental considerations.

In this study, we model a single retailer's stochastic inventory control problem with order splitting decisions among multiple suppliers under two different delivery scheduling policies, namely sequential splitting and sequential delivery. Under sequential delivery, the retailer splits each order among the selected suppliers and places all these orders simultaneously; thus the retailer receives the split orders from different suppliers sequentially due to the suppliers' varying lead times (similar to phased deliveries defined in Kim and Goyal [77] as well as the aforementioned single-item stochastic inventory control models with order splitting). On the other hand, under sequential splitting, the retailer splits each order among different suppliers and places them such that all the split orders from the different suppliers are delivered at the retailer simultaneously (similar to lumpy deliveries defined in Kim and Goyal [77]).

Specifically, given identical split orders and re-order points, the average inventory held will be lower under sequential splitting,

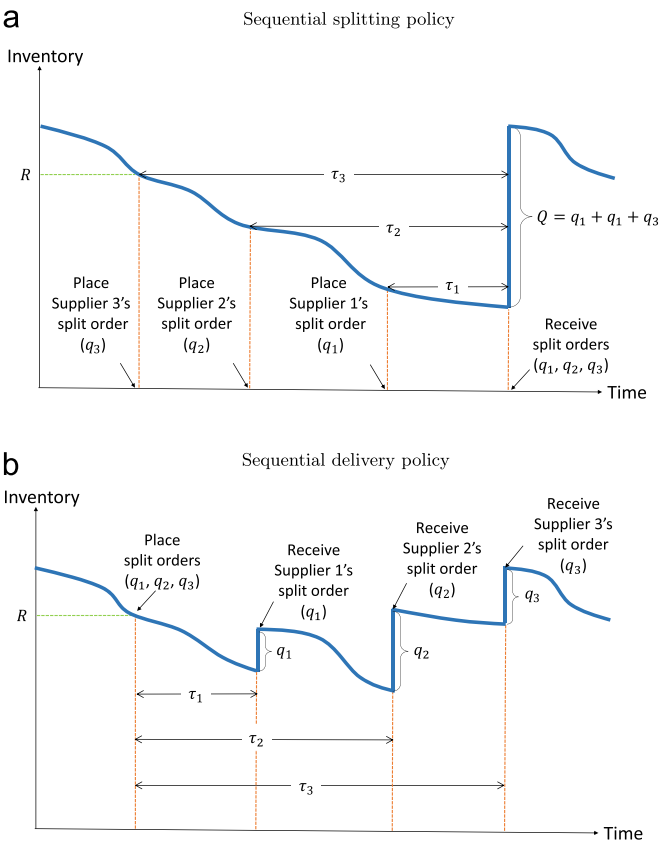

Fig. 1. Inventory vs. time.

because by delaying order delivery it allows inventory to fall to a lower level before all orders arrive together. This is shown in Fig. 1, which illustrates the retailer's inventory over time under sequential splitting (Fig. 1a) and sequential delivery (Fig. 1b) when an order is split among three suppliers such that $\tau_1 < \tau_2 < \tau_3$ and q_i is the part of the order to be delivered by supplier i. However, the average number of units short is expected to be smaller under sequential delivery due to the higher average inventory level (see Fig. 1b vs. Fig. 1a). Because both inventories held and units short will have an impact on the economic and environmental performance of a retailer, it is essential to analyze the inventory control system under each scheduling policy regarding their economic and environmental tradeoffs.

Most of the studies on the stochastic inventory control models with order splitting focus on economically comparing order splitting under sequential delivery to single sourcing, i.e., when order splitting is not allowed. The focus of our study is to assess not only the economic but also the environmental effects of a retailer's inventory control, order splitting, and delivery scheduling decisions. Because different suppliers can have distinct points of origin and/or transportation units used for delivery, we allow suppliers to vary in their shipping specifications (delivery lead times and shipment capacities) and transportation costs (unit transportation and fixed delivery costs), as well as environmental characteristics (per unit and fixed emissions generation from deliveries). We first formulate the retailer's inventory control, order splitting, and supplier selection decisions as a bi-objective mixed-integer nonlinear programming model under each delivery scheduling policy. To solve these models, we discuss application of an adaptive ϵ-constraint algorithm and propose an evolutionary search algorithm to approximate the Pareto fronts of these bi-objective models. Our numerical studies indicate that the proposed evolutionary search algorithm is more efficient than the adaptive ϵ-constraint algorithm. Another set

of numerical studies shows the effects of the stochastic demand on the retailer's costs and emissions. Finally, through sample scenarios, we demonstrate how a retailer can use the tools provided in this study to select a delivery scheduling policy in consideration of both economic and environmental targets.

The rest of the paper is organized as follows. In Section 2, we review inventory control models with environmental considerations and related studies. Section 3 discusses the settings of the problem and formulates the retailer's bi-objective optimization problems under sequential splitting and sequential delivery policies. Section 4 discusses the application of the adaptive ϵ-constraint algorithm and provides the details of the evolutionary search algorithm as Pareto front approximation methods. Numerical studies are presented in Section 5 and concluding remarks, a summary of contributions, and future research directions are given in Section 6.

2. Literature review

In a broad sense, our research considers inventory control models with multiple sources of supply, supplier selection, and order splitting. Minner [95], Thomas and Tyworth [119], and Aissaoui et al. [5] provide reviews of inventory control models with supplier selection and order splitting. Inventory control models with supplier selection under stochastic demand are grouped into two classes: models with deterministic and stochastic lead times [95,101]. Similar to Moinzadeh and Nahmias [96], Moinzadeh and Schmidt [97], Zhang [127], Chiang and Gutierrez [35], and Jain et al. [73], we assume that the suppliers have deterministic lead times, i.e., they are reliable.

Sustainability has been considered in various operations and supply chain management settings (see, e.g., the reviews by [38,39,87,115,49]) and supplier evaluation and selection models have been intensively studied in the literature (see, e.g., the reviews by [65,26]). With the increasing sustainability concerns along supply chains, environmental considerations have also been incorporated in supplier selection models (see, e.g., [85] for a comprehensive approach and [56,59,70,130] for reviews of green supplier selection models). In this study, we integrate sustainability in an inventory control model with order splitting allowed among multiple sources of supply (i.e., suppliers).

Environmental aspects of the inventory related operations are commonly integrated into deterministic models, such as the economic order quantity (EOQ) or deterministic economic lot sizing (ELS) models and their variations, through either modeling environmental regulations such as carbon cap, taxing, trading, and offsetting (see, e.g., [69,72,10,29,120,83,79,108,63,68] for EOQ models and [14,2,3,100,64,67,129] for ELS models with environmental regulations), or by associating direct costs with environmental pollution generated from inventory control related operations (see, e.g., [19,125,12] for EOQ models with environmental costs), or incorporating environmental objectives along with the classical economic objectives (see, e.g., [20,27,21,7,84] for EOQ models and [90,11,46] for ELS models with environmental objectives). Our study analyzes a stochastic demand continuous review inventory control model with multiple suppliers and environmental considerations. Therefore, in the following review, our focus is on the stochastic inventory control studies that account for environmental aspects of the inventory related operations and, among those, we distinguish the ones that consider multiple supply sources.

Most of the stochastic inventory control models with environmental considerations revisit the classical single-period stochastic demand model, i.e., the Newsvendor model. The Newsvendor model maximizes the expected profits due to a single order by considering the costs associated with unsold items in case of overage and unmet demand in case of underage. Chen and Monahan [28], Song and Leng [113], Zhang and Xu [126], Choi [36,37], Liu et al. [88], Rosic and Jammernegg [103], Hoen et al. [66], Arikan and Jammernegg [9], Chen and Wang [31], Chen et al. [30] and Manikas and Kroes [92] study the Newsvendor model and its variations (including multi-mode, multi-item, and multi-period settings) under environmental regulations. Brito and de Almeida [22] model a multi-objective Newsvendor model with environmental objectives. Among these studies, Hoen et al. [66] and Chen and Wang [31] consider different modes of transportation and Choi [36,37], Rosic and Jammernegg [103], and Arikan and Jammernegg [9] integrate different sourcing channels (dual sourcing with a local and an off-shore supplier) as alternative options.

Other than the Newsvendor model, variants of the economic lot-sizing (ELS) model with stochastic demand have been recently analyzed with environmental regulations (see [58,54,102,128]) and environmental objectives (see [107]). Except Purohit et al. [102], all of these studies consider multiple modes for either transportation or production.

In this study, unlike the single-period Newsvendor or multi-period ELS models with stochastic demand, we study an inventory control model over an infinite planning horizon. In particular, we analyze a continuous review inventory control model with order splitting allowed among an arbitrary number of capacitated heterogeneous suppliers. There are a limited number of studies integrating environmental considerations over infinite planning horizons. Arikan et al. [8] numerically demonstrate how the costs and carbon emissions generated change with different transportation modes and delivery lead times when a cost or an emission minimizing order quantity re-order point policy (i.e, (Q,R) model) is used for ordering decisions. Fichtinger et al. [51] use simulation to evaluate the effects of integrated inventory and warehouse management activities assuming a (Q,R) model with a fixed safety stock (which basically reduces the model to an EOQ formulation). Mallidis et al. [91] study a bi-objective integrated periodic review inventory control and network design model with cost and emission minimization objectives and Tang et al. [118] study a periodic review inventory control model with an emission target.

This study is most related to Schaefer and Konur [109], which analyzes two bi-objective (Q,R) models, where costs and emissions are jointly minimized: one with less-than-truckload transportation and one with truckload transportation. For each model, they propose a method to approximate the Pareto frontier and then numerically evaluate the effects of demand variability and lead time on the costs and emissions with each transportation mode. Finally, they discuss that a retailer can prefer either mode depending on his/her economic and environmental targets. Similar to Schaefer and Konur [109], we formulate bi-objective (Q,R) models with cost and emission minimization objectives; however, we allow order splitting among multiple suppliers, who have distinct cost, delivery, and environmental characteristics. As noted by Aguezzoul [4], these characteristics are the most commonly used evaluation criteria for selecting third-party logistics providers. Furthermore, we consider two different delivery scheduling policies for the selected suppliers.

To the best knowledge of the authors, the integrated continuous review inventory control and delivery scheduling problem under stochastic demand with environmental considerations has not been analyzed in the literature. As noted above, while there is a growing body of literature on environmental inventory control models, most of these studies assume deterministic demand or stochastic demand in the single period or finite planning horizon. Furthermore, while stochastic inventory control models with order splitting have been analyzed extensively, different delivery scheduling policies are not considered in such models in terms of both economic and environmental aspects. This study, therefore, contributes to the body of literature on inventory control models with environmental considerations by (i) integrating supplier

selection and order splitting decisions in continuous review inventory systems, (ii) modeling different delivery scheduling policies, (iii) providing efficient solution methods for the problem of interest, and (iv) investigating how different scheduling policies compare in terms of economic and environmental performance. In the next section, we explain the details of the settings and formulation of the models.

3. Problem formulation

We consider a retailer's inventory control and delivery scheduling problem for a single item which has stochastic demand. It is assumed that the inventory is continuously reviewed, i.e., the retailer knows the inventory level at any moment. In case of continuous inventory review, a common inventory control policy adopted is the (Q,R) model, where Q denotes the order quantity and R denotes the re-order point. That is, whenever the inventory on hand falls to R, an order of Q units is placed. Therefore, we analyze a (Q,R) model with supplier selection under different delivery schedules and consider that the basic assumptions of continuous review inventory control models hold: stationary continuous demand, full backorders, and at most one outstanding order (see [60]). Further, we use the normal distribution for modeling the stochastic demand as it is appropriate in many retail scenarios (with the exception of slow-moving products; see, e.g., [16]), and is robust in continuous review inventory systems (see, e.g., [98,123,112]). Later, in Section 3.3, we discuss generalizations to other demand distributions such as gamma and Poisson. However, the solution methods discussed in Section 4 are rather generic.

In particular, let the demand per unit time for the item be a normally distributed random variable with mean λ and standard deviation υ. We therefore assume that the demand during a time period of t is normally distributed with mean λt and standard deviation $\upsilon\sqrt{t}$ (see, e.g., [99]). Let $f_t(y)$ and $F_t(y)$ denote the probability density and cumulative probability functions, respectively, of the normally distributed random variable y with mean λt and standard deviation $\upsilon\sqrt{t}$. Due to stochastic demand, there might be shortages and let $n(r,t)$ be the expected number of units short over a time period t when the starting inventory is r. It then follows that $n(r,t)=\int_r^\infty (y-r)f_t(y)dy$. As noted before, we assume that all of the shortages are backordered.

In the settings of the classical (Q,R) model, the retailer incurs inventory holding, penalty, procurement, and order setup costs, and carbon emissions are generated due to inventory holding, backordering, procurement, and order setup operations (see, e.g., [109]). Similar to [109], we define $\tilde{h}\geq 0$, $\tilde{p}\geq 0$, $\tilde{c}\geq 0$, and $\tilde{A}\geq 0$ as the inventory holding cost per unit per unit time, penalty cost per unit backordered, purchase cost per unit, and order setup cost, respectively; and analogously, $\widehat{h}\geq 0$, $\widehat{p}\geq 0$, $\widehat{c}\geq 0$, and $\widehat{A}\geq 0$ as the carbon emissions generated from inventory holding per unit per unit time, per unit backorder, per unit procurement, and order setup, respectively. We note that similar parameters are commonly used in the literature and we refer the reader to the cited studies for justifications of using these parameters. It should be further noted that when the carbon emissions are only due to freight transportation, or only some of the above activities contribute to the retailer's carbon emissions, one can define the parameters of the other activities to be zero. However, in order to have more generalized settings, we formulate the retailer's problem with all of the above parameters. In this study, we explicitly model the costs and carbon emissions of order delivery assuming that the retailer can use a set of suppliers for delivering his/her order.

Suppose that the retailer can split and, thereby, partially deliver his/her order quantity with a set of n suppliers, indexed by i such that $i\in I$ where $I=\{1,2,\ldots,n\}$ (these suppliers can also be considered to represent the carriers in freight carrier selection context and different transportation modes in mode selection context). As different suppliers might have distinct characteristics with regard to their vehicles, shipment requirements, pricing schemes, and environmental impacts, we assume that the retailer incurs different costs and that varying carbon emissions are generated for each supplier. We define $\tilde{a}_i$ and $\tilde{e}_i$, respectively, as the fixed and variable delivery cost with supplier i (similar to the approach in [73,109]). The fixed delivery cost $\tilde{a}_i$ may vary as noted by [117] due to different geographical locations of suppliers. The variable delivery cost $\tilde{e}_i$ is the additional transportation cost for each unit delivered by supplier i. Similarly, we define $\widehat{a}_i$ and $\widehat{e}_i$, respectively, as the retailer's fixed and variable carbon emissions due to delivery with supplier i. Here, $\widehat{a}_i$ can be considered as the carbon emissions generated due to the empty weight of the transportation unit (e.g., a truck) and $\widehat{e}_i$ is the carbon emissions generated from each additional unit loaded to the truck (similar parameters are defined in [69,29,79,83,109]). Furthermore, we assume that the suppliers' shipment capacities and lead times vary and we define w_i and τ_i as supplier i's transportation capacity and delivery lead time, respectively.

The retailer's order can be split among different suppliers and the deliveries by different suppliers can be scheduled by the retailer in order to reduce costs and/or carbon emissions. As noted in Section 1, we consider two delivery scheduling policies: sequential splitting and sequential delivery. Under sequential splitting, the retailer sequentially splits his/her order among different suppliers considering their lead times such that the split orders are delivered at the same time (see Fig. 1a). Here, the retailer will start splitting his/her order (i.e., place the first order) when the inventory level is R. This schedule is defined similar to lumpy deliveries explained in Kim and Goyal [77]. Under sequential delivery, the retailer splits his/her order among different suppliers at the same time (when the inventory level falls to R); hence, the split orders are delivered sequentially due to varying lead times of the suppliers (see Fig. 1b). As noted in Section 1, single-item stochastic inventory control models with order splitting typically assume sequential delivery. Under sequential delivery, we assume that the next order is not placed until the partial order allocated to the last supplier is delivered.

Under both sequential splitting and sequential delivery, the retailer must determine which supplier to use, how much to deliver with each supplier, and when to start order splitting among the suppliers. Let

$$x_i=\begin{cases}1 & \text{if supplier } i \text{ is used for delivery,}\\ 0 & \text{otherwise}\end{cases}$$

and $\mathbf{x}$ be the binary n-vector of x_i values. Furthermore, recall that q_i is the quantity delivered by supplier i at each replenishment and let $\mathbf{q}$ denote the n-vector of q_i values. Note that if $x_i=0$ then $q_i=0$, and if $x_i=1$ then $q_i\leq w_i$. As defined previously, R is the re-order point, which defines the point when order splitting starts under sequential splitting and the point when all orders are placed under sequential delivery. Also, $Q=\sum_{i\in I}q_i$. In what follows, we formulate the retailer's inventory control, supplier selection, and order splitting problem under each delivery scheduling policy as a bi-objective optimization problem, where the expected costs and carbon emissions per unit time are minimized (Section 3.3 discusses how to modify these models as single-objective optimization problems that associate direct costs to emissions or consider environmental regulations). Table 1 summarizes the notation used and possible metrics for each parameter. Additional notation will be defined as needed.

Table 1
Notation.

Notation	Description	Metric
Demand parameters		
λ	Expected demand rate	units/year
υ	Standard deviation of demand rate	units
y	Normally distributed random variable with λt and $\upsilon\sqrt{t}$	units
$f_t(y)$	Probability density function of y	
$F_t(y)$	Cumulative distribution function of y	
Retailer parameters		
$\tilde{h}$	Inventory holding cost per unit per unit time	\$/unit/year
$\tilde{p}$	Unit backorder cost	\$/unit
$\tilde{c}$	Unit procurement cost	\$/unit
$\tilde{A}$	Fixed order setup cost	\$/order
$\widehat{h}$	Emissions due to inventory holding per unit per unit time	CO_2 lbs/unit/year
$\widehat{p}$	Emissions due to per unit backorder	CO_2 lbs/unit
$\widehat{c}$	Emissions due to per unit procurement	CO_2 lbs/unit
$\widehat{A}$	Emissions due to order placement	CO_2 lbs/order
Retailer's decision variables		
x_i	1 if supplier i is used for delivery, 0 otherwise	
$\mathbf{x}$	n-vector of x_i values	
q_i	Partial order delivered by supplier i	units
$\mathbf{q}$	n-vector of q_i values	
R	Re-order point for starting order splitting	units
Supplier parameters		
τ_i	Delivery lead time of supplier i	year
w_i	Transportation capacity of supplier i per order	units
$\tilde{a}_i$	Fixed delivery charge by supplier i	\$/order
$\tilde{e}_i$	Variable transportation cost of supplier i	\$/unit
$\widehat{a}_i$	Fixed delivery emissions due to supplier i	CO_2 lbs/order
$\widehat{e}_i$	Variable transportation emissions of supplier i	CO_2 lbs/unit

3.1. Sequential splitting

If the retailer adopts the sequential splitting policy, we define the effective lead time as the maximum of the lead times of the selected suppliers, i.e., the time from when the retailer starts splitting his/her order among the selected suppliers until the split orders are simultaneously received (in other studies, where sequential delivery is assumed, effective lead time is commonly defined as the minimum lead time of the selected suppliers, see, e.g., [111,110,52]). Let $\tau(\mathbf{x})$ denote the effective lead time when the supplier selection decision is given by $\mathbf{x}$. It then follows that

$$\tau(\mathbf{x}) = \max_{i \in I}\{\tau_i x_i\}. \tag{1}$$

The retailer's expected procurement cost per unit time amounts to $\tilde{c}\lambda$. Furthermore, the expected inventory level with sequential splitting is defined similar to the classical (Q,R) model and one can derive that $\tilde{h}\left(R-\lambda\tau(\mathbf{x})+\frac{1}{2}\sum_{i\in I}q_i\right)$ is the expected inventory holding cost per unit time, as the average inventory varies between $R+Q-\lambda\tau(\mathbf{x})$ and $R-\lambda\tau(\mathbf{x})$ (see, e.g., [60]). Similarly, it can be argued that the expected cycle length is $\frac{1}{\lambda}\sum_{i\in I}q_i$; thus, the expected order setup cost per unit time equals $\frac{\lambda\tilde{A}}{\sum_{i\in I}q_i}$. Furthermore, since shortages can occur during the effective lead time, the expected number of units short per cycle is $n(R,\tau(\mathbf{x}))$. As the demand per unit time is normally distributed with λ and υ, it can be shown that $n(R,\tau(\mathbf{x})) = \upsilon\sqrt{\tau(\mathbf{x})}L((R-\lambda\tau(x))/\upsilon\sqrt{\tau(\mathbf{x})})$, where $L(z)$ is the standard loss function (see, e.g., [99]). It then follows that the expected backordering cost per unit time is equal to $\frac{\tilde{p}\lambda n(R,\tau(\mathbf{x}))}{\sum_{i\in I}q_i}$. In addition to these costs, the retailer incurs delivery costs. Note that $\tilde{a}_i x_i$ is the fixed delivery cost paid to supplier i in each cycle; therefore, the total expected fixed delivery cost per unit time amounts to $\frac{\lambda\sum_{i\in I}\tilde{a}_i x_i}{\sum_{i\in I}q_i}$. Moreover, $\tilde{e}_i q_i$ is the variable transportation cost charged by supplier i per order; hence, $\frac{\lambda\sum_{i\in I}\tilde{e}_i q_i}{\sum_{i\in I}q_i}$ is the total expected variable transportation cost per unit time. Putting all these together, the retailer's expected cost per unit time under sequential splitting as a function of the decision variables R, $\mathbf{q}$, and $\mathbf{x}$, denoted by $C^1(R,\mathbf{q},\mathbf{x})$, is

$$C^1(R,\mathbf{q},\mathbf{x}) = \tilde{c}\lambda + \frac{\lambda\sum_{i\in I}\tilde{e}_i q_i}{\sum_{i\in I}q_i} + \tilde{h}\left(R-\lambda\tau(\mathbf{x})+\frac{1}{2}\sum_{i\in I}q_i\right) + \frac{\lambda\left(\tilde{A}+\sum_{i\in I}\tilde{a}_i x_i\right)}{\sum_{i\in I}q_i} + \frac{\tilde{p}\lambda n(R,\tau(\mathbf{x}))}{\sum_{i\in I}q_i}, \tag{2}$$

where the first, second, third, fourth, and the last terms are the expected procurement, transportation, inventory holding, order setup and fixed delivery, and backordering cost per unit time, respectively, with $\tau(\mathbf{x})$ defined in Eq. (1).

The expected carbon emissions generated from inventory related operations can be defined similar to the expected inventory related costs given in Eq. (2). Particularly, it can be shown that the retailer's expected carbon emissions per unit time under sequential splitting as a function of the decision variables R, $\mathbf{q}$, and $\mathbf{x}$, denoted by $E^1(R,\mathbf{q},\mathbf{x})$, is

$$E^1(R,\mathbf{q},\mathbf{x}) = \widehat{c}\lambda + \frac{\lambda\sum_{i\in I}\widehat{e}_i q_i}{\sum_{i\in I}q_i} + \widehat{h}\left(R-\lambda\tau(\mathbf{x})+\frac{1}{2}\sum_{i\in I}q_i\right) + \frac{\lambda\left(\widehat{A}+\sum_{i\in I}\widehat{a}_i x_i\right)}{\sum_{i\in I}q_i} + \frac{\widehat{p}\lambda n(R,\tau(\mathbf{x}))}{\sum_{i\in I}q_i}, \tag{3}$$

where the first, second, third, fourth, and the last terms are the expected carbon emissions generated per unit time from procurement, transportation, inventory holding, order setup and deliveries, and backordering operations, respectively, such that $\tau(\mathbf{x})$ is defined in Eq. (1).

Here we consider that the retailer has the objectives of minimizing his/her expected total costs and expected total carbon emissions per unit time. Then the retailer's bi-objective optimization problem under sequential splitting (**P1**) can be formulated as follows:

$$\begin{aligned}
(\mathbf{P1}):\quad & \min \quad C^1(R,\mathbf{q},\mathbf{x}) \\
& \min \quad E^1(R,\mathbf{q},\mathbf{x}) \\
& \text{s.t.} \quad 0 \le q_i \le x_i w_i \quad \forall i \in I \\
& \qquad x_i \in \{0,1\} \quad \forall i \in I \\
& \qquad R > 0.
\end{aligned}$$

In **P1**, the first set of constraints guarantees that the retailer allocates the order among the selected suppliers only, and that the split order quantities are non-negative and less than or equal to the supplier's transportation capacity. The second set of constraints is the binary definitions of x_i values and the third constraint is the non-negativity of the re-order point.

3.2. Sequential delivery

In the case the retailer adopts the sequential delivery policy, the retailer's expected procurement cost per unit time amounts to $\tilde{c}\lambda$ as in the case of sequential splitting. Under sequential delivery policy, we define a cycle as the time between placing two consecutive (split) orders; therefore, the expected cycle length can be defined similar to the classical (Q,R) model. That is, the expected cycle length is $\frac{1}{\lambda}\sum_{i\in I}q_i$. Similar to the case of sequential splitting, it then follows that the expected order setup cost per unit time is equal to $\frac{\lambda\tilde{A}}{\sum_{i\in I}q_i}$, total expected fixed delivery cost per unit time amounts to $\frac{\lambda\sum_{i\in I}\tilde{a}_i x_i}{\sum_{i\in I}q_i}$, and total expected variable transportation cost per unit time is equal to $\frac{\lambda\sum_{i\in I}\tilde{e}_i q_i}{\sum_{i\in I}q_i}$. Defining the expected

inventory holding cost and expected penalty cost per unit time, on the other hand, is different than the sequential splitting policy. To do so, without loss of generality, let us assume that the suppliers are sorted such that $\tau_1 < \tau_2 < \cdots < \tau_n$.

Given that $x_i=1 \ \forall i \in I$, for instance, note that the average inventory varies between R and $R-\lambda\tau_1$ from the moment orders are placed (say $\bar{t}$) until the moment right before the first split order is delivered, i.e., over time $[\bar{t}, \bar{t}+\tau_1)$ (see Fig. 1b). Similarly, the inventory level between receiving the first and second split orders varies between $R-\lambda\tau_1+q_1$ and $R-\lambda\tau_2+q_1$ over time $[\bar{t}+\tau_1, \bar{t}+\tau_2)$. Now, let τ_{n+1} denote the average cycle length, i.e., $\tau_{n+1}=\sum_{i\in I} q_i/\lambda$ and $\tau_0=0$. For a normally distributed demand rate, the average inventory held over a cycle will be equal to the sum of the areas under $n+1$ right-trapezoids, where the ith trapezoid has edges of length $R-\lambda\tau_{i-1}+\sum_{j\le i-1} q_j$ and $R-\lambda\tau_i+\sum_{j\le i-1} q_j$ and width (height) of length $\tau_i-\tau_{i-1}$ for $i \in I$. This is illustrated in Appendix A.1 for $n=3$. After simplifications, the sum of the areas of these trapezoids totals $\tau_{n+1}\left(R+\frac{1}{2}\sum_{i\in I} q_i\right)-\sum_{i\in I}\tau_i q_i$. Then, multiplying this total area by $\tilde{h}$ and dividing by the cycle length $\tau_{n+1}=\sum_{i\in I} q_i/\lambda$, the expected inventory holding cost per unit time for any $\mathbf{x}$ is equal to $\tilde{h}\left(R-\frac{\lambda\sum_{i\in I}\tau_i q_i}{\sum_{i\in I} q_i}+\frac{1}{2}\sum_{i\in I} q_i\right)$, where we guarantee that $q_i=0$ if $x_i=0$ by adding constraints in the retailer's optimization problem. The expected carbon emission generated due to inventory holding is defined similarly. It is worthwhile to note that given the same $(R,\mathbf{q},\mathbf{x})$, $\tau(\mathbf{x}) \ge \frac{\sum_{i\in I}\tau_i q_i}{\sum_{i\in I} q_i}$; and thus, $\tilde{h}\left(R-\lambda\tau(\mathbf{x})+\frac{1}{2}\sum_{i\in I} q_i\right) \le \tilde{h}\left(R-\frac{\lambda\sum_{i\in I}\tau_i q_i}{\sum_{i\in I} q_i}+\frac{1}{2}\sum_{i\in I} q_i\right)$, i.e., sequential delivery results in the same or higher level of expected inventory holding cost compared to sequential splitting.

Now, we focus on defining the expected penalty cost per unit time. To do so, we first calculate the expected number of units short within one cycle. Shortages can occur during the time periods from the moment the order is split until the first delivery is received, from the moment the first delivery is received until the second delivery is received, and so on. Let y_i be the random variable defining the inventory right before receiving supplier i's delivery. Furthermore, let us define $z_{ij}=\max\{0,(\tau_i-\tau_j)/|\tau_i-\tau_j|\}$. That is,

$$z_{ij}=\begin{cases}1 & \text{if } \tau_i>\tau_j,\\ 0 & \text{otherwise,}\end{cases}$$

such that $z_{ii}=0$. Then, one can show that y_i is a normally distributed random variable with mean $\mu_i(R,\mathbf{q},\mathbf{x})=x_i(R+\sum_{j\in I} z_{ij}q_j-\lambda\tau_i)$ and $\sigma_i(\mathbf{x})=x_i v\sqrt{\tau_i}$. By definition of y_i, it follows that the expected number of units short right after the previous supplier's delivery is received until right before supplier i's delivery is received is $n_i(R,\mathbf{q},\mathbf{x})=-\int_{-\infty}^{0} y_i f^i(y_i)dy_i$, where $f^i(y_i)$ is the normal density function with mean $\mu_i(R,\mathbf{q},\mathbf{x})$ and standard deviation $\sigma_i(\mathbf{x})$. It then follows that

$$n_i(R,\mathbf{q},\mathbf{x})=-\mu_i(R,\mathbf{q},\mathbf{x})+\sigma_i(\mathbf{x})L\left(-\mu_i(R,\mathbf{q},\mathbf{x})/\sigma_i(\mathbf{x})\right), \tag{4}$$

where $L(z)$ is the standard loss function. That is, the expected number of total units short within one replenishment cycle is $\sum_{i\in I} n_i(R,\mathbf{q},\mathbf{x})$. One can note that, given the same $(R,\mathbf{q},\mathbf{x})$, for any demand realization, the units of short under sequential delivery will be less than or equal to the units of short under sequential splitting because more inventory will be available under sequential delivery right after receiving the split order from the first supplier.

From the above discussion, the retailer's expected costs per unit time under sequential delivery as a function of the decision variables R, $\mathbf{q}$, and $\mathbf{x}$, denoted by $C^2(R,\mathbf{q},\mathbf{x})$, is

$$C^2(R,\mathbf{q},\mathbf{x})=\tilde{c}\lambda+\frac{\lambda\sum_{i\in I}\tilde{e}_i q_i}{\sum_{i\in I} q_i}+\tilde{h}\left(R-\frac{\lambda\sum_{i\in I}\tau_i q_i}{\sum_{i\in I} q_i}+\frac{1}{2}\sum_{i\in I} q_i\right)+\frac{\lambda\left(\tilde{A}+\sum_{i\in I}\tilde{a}_i x_i\right)}{\sum_{i\in I} q_i}+\frac{\tilde{p}\lambda\sum_{i\in I} n_i(R,\mathbf{q},\mathbf{x})}{\sum_{i\in I} q_i}, \tag{5}$$

where the first, second, third, fourth and the last terms are the expected procurement, inventory holding, order setup and fixed delivery, and penalty cost per unit time, respectively, such that $n_i(R,\mathbf{q},\mathbf{x})$ is defined in Eq. (4).

The expected carbon emissions generated from inventory related operations can be defined similar to the expected inventory related costs given in Eq. (5). Particularly, it can be shown that the retailer's expected carbon emissions per unit time under sequential delivery as a function of the decision variables R, $\mathbf{q}$, and $\mathbf{x}$, denoted by $E^2(R,\mathbf{q},\mathbf{x})$, is

$$E^2(R,\mathbf{q},\mathbf{x})=\hat{c}\lambda+\frac{\lambda\sum_{i\in I}\hat{e}_i q_i}{\sum_{i\in I} q_i}+\hat{h}\left(R-\frac{\lambda\sum_{i\in I}\tau_i q_i}{\sum_{i\in I} q_i}+\frac{1}{2}\sum_{i\in I} q_i\right)+\frac{\lambda\left(\hat{A}+\sum_{i\in I}\hat{a}_i x_i\right)}{\sum_{i\in I} q_i}+\frac{\hat{p}\lambda\sum_{i\in I} n_i(R,\mathbf{q},\mathbf{x})}{\sum_{i\in I} q_i}, \tag{6}$$

where the first, second, third, fourth and the last terms are the expected carbon emissions generated per unit time from procurement, transportation, inventory holding, order setup and deliveries, and backordering operations, respectively, such that $n_i(R,\mathbf{q},\mathbf{x})$ is defined in Eq. (4).

Similar to **P1**, the retailer's bi-objective optimization problem under sequential delivery can be formulated as follows:

$$\begin{aligned}(\mathbf{P2}):\quad &\min \quad C^2(R,\mathbf{q},\mathbf{x})\\ &\min \quad E^2(R,\mathbf{q},\mathbf{x})\\ &\text{s.t.} \quad 0\le q_i\le x_i w_i \quad \forall i\in I\\ &\qquad x_i\in\{0,1\} \quad \forall i\in I\\ &\qquad R>0.\end{aligned}$$

The constraints are identical to those in **P1**.

3.3. Generalizations of the models

This section provides generalizations of **P1** and **P2** to consider different approaches to integrate environmental considerations and different demand distributions.

As noted in Section 1, there are several approaches to model environmental considerations. In **P1** and **P2**, we consider environmental objectives in addition to the classical economic objectives. Other common approaches are associating costs with the emissions generated and modeling environmental regulations. In particular, let us define $B^j(R,\mathbf{q},\mathbf{x})=C^j(R,\mathbf{q},\mathbf{x})+\psi\left(E^j(R,\mathbf{q},\mathbf{x})-\Phi\right)$ and let $\mathbf{P'J}$ be the following single-objective optimization problem: $\min\{B^j(R,\mathbf{q},\mathbf{x}): 0\le q_i\le x_i w_i \ \ \forall i\in I,\ x_i\in\{0,1\} \ \ \forall i\in I,\ R>0\}$. Now, letting $\Phi=0$ and ψ be the cost of unit emission generated, $\mathbf{P'J}$ is the model adapting the approach of associating costs to the emissions. Similarly, letting $\Phi=0$ and ψ define the tax per unit emission generated, $\mathbf{P'J}$ represents the tax regulation model. Finally, by letting $\Phi>0$ denote the emission cap and ψ be the emission trading price, then $\mathbf{P'J}$ is the cap-and-trade model. Also, we note that both the costs and emissions are defined per unit time as it is the common approach considering an infinite planning horizon (see, e.g., [109]). Since the average demand rate (number of units per unit time) is λ, one can use $C^j(R,\mathbf{q},\mathbf{x})/\lambda$ and $E^j(R,\mathbf{q},\mathbf{x})/\lambda$ as the expected cost and expected emissions per unit, respectively. Therefore, when λ is a constant, defining the costs and emissions per unit of product will not change the analyses.

Next, we discuss how to modify **P1** and **P2** for different demand distributions, and specifically the gamma and Poisson distributions. To do so, let us define $f_t(y_t)$ and $F_t(y_t)$ as the probability density and cumulative probability functions, respectively, of the random variable y_t such that y_t denotes the demand over t time units ($f_t(y)$, $F_t(y)$, and y are still defined per unit time). Furthermore, let λ_t and υ_t be the mean and standard deviation of y_t, respectively. Since the cycle length definition will not change, only the third and fifth terms of the objective functions, i.e., inventory holding and backordering related costs and emissions, will change under each scheduling policy. In particular, for sequential splitting, it is easily shown that the expected inventory held per unit time will be $\left(R-\lambda_{\tau(\mathbf{x})}+\frac{1}{2}\sum_{i\in I}q_i\right)$ and the expected number of units short per cycle will be $n(R,\tau(\mathbf{x}))=\int_R^{\infty}(y_{\tau(\mathbf{x})}-R)f_{\tau(\mathbf{x})}(y_{\tau(\mathbf{x})})dy_{\tau(\mathbf{x})}$, where $\tau(\mathbf{x})$ is still given by Eq. (1).

For sequential delivery, the expected inventory held per unit time will be similarly defined as the sum of the areas of $n+1$ trapezoids (see Appendix A.1). Specifically, given $\tau_i<\tau_{i+1}\,\forall i\le n-1$, $\tau_0=0$, and $\tau_{n+1}=\sum_{i\in I}q_i/\lambda$, the ith trapezoid will have edges of length $r^{ia}=R-\sum_{1\le j\le i-1}\lambda_{(\tau_j-\tau_{j-1})}+\sum_{1\le j\le i-1}q_j$ and $r^{ib}=R-\sum_{1\le j\le i}\lambda_{(\tau_j-\tau_{j-1})}+\sum_{1\le j\le i-1}q_j$, and width (height) of length $\tau_i-\tau_{i-1}$ for $i\in I$. Thus, the expected inventory held per cycle will be $\sum_{i=1}^{n}(r^{ia}+r^{ib})(\tau_i-\tau_{i-1})/2$ for any given $\mathbf{x}$ as long as $q_i=0$ when $x_i=0$ (note that when $\lambda_\tau=\lambda\tau$, we have the same equations as defined previously). Finally, the expected number of units short right before receiving the order from supplier i will be $n_i(R,\mathbf{q},\mathbf{x})=\int_{R+\sum_{j\in I}z_{ij}q_j}^{\infty}(y_{\tau_i}-R-\sum_{j\in I}z_{ij}q_j)f_{\tau_i}(y_{\tau_i})dy_{\tau_i}$, and therefore the total expected number of units short per cycle will be $\sum_{i\in I}n_i(R,\mathbf{q},\mathbf{x})$.

Now, suppose that the demand per unit time has a gamma distribution with α and β as the shape and scale parameters, respectively, and let this be denoted by $g(\alpha,\beta)$ (given that the demand per unit time has mean λ, standard deviation υ, and gamma distribution, the shape parameter α and the scale parameter β can be estimated as $\alpha=\lambda^2/\upsilon^2$ and $\beta=\upsilon^2/\lambda$, see, e.g., [24,121,75]). One can note that $\lambda=\alpha\beta$ and $\upsilon=\sqrt{\alpha}\beta$ (see, e.g., [112]). Then, the demand over τ discrete time units will be $g(\tau\alpha,\beta)$ with mean $\tau\lambda$. Therefore, the expressions for the expected inventory held per cycle will be identical to the case with normally distributed demand per unit time under both sequential splitting and sequential delivery. Furthermore, for normally distributed demand, we used the standard loss function ($L(z)$) for determining the expected number of units short per cycle. Similarly, for gamma distributed demand, one can use the so-called gamma loss function. In particular, given the demand per unit time has a gamma distribution $g(\alpha,\beta)$, then $n(R,\tau(\mathbf{x}))=\tau(\mathbf{x})\alpha\beta\left(1-G(R,\tau(\mathbf{x})\alpha+1,\beta)\right)-R\left(1-G(R,\tau(\mathbf{x})\alpha,\beta)\right)$ under sequential splitting, where $G(R,a,b)$ is the cumulative distribution function of $g(a,b)$ at R (see, e.g., [41,122,121]). For sequential delivery, following the same logic, we have $n_i(R,\mathbf{q},\mathbf{x})=\tau_i\alpha\beta\left(1-G\left(R+\sum_{j\in I}z_{ij}q_j,\tau_i\alpha+1,\beta\right)\right)-\left(R+\sum_{j\in I}z_{ij}q_j\right)\left(1-G\left(R+\sum_{j\in I}z_{ij}q_j,\tau_i\alpha,\beta\right)\right)$.

Finally, the Poisson distribution is typically used for modeling the discrete demand of slow-moving items such as spare parts (see, e.g., [112,99]). When the unit demand is discrete, the analysis of the classical (Q,R) model is typically based on renewal processes (see, e.g., [60,50,74]). As noted in [112], the expressions for the expected inventory held and expected number of units short can be modified for a Poisson demand process. Specifically, given the demand per unit time is a Poisson process with rate λ, the demand over τ discrete time units will have Poisson distribution with rate $\tau\lambda$ such that $f_\tau(y_\tau)=e^{-\tau\lambda}(\tau\lambda)^{y_\tau}/y_\tau!$ (see, e.g., [96,112]).

4. Solution analysis

Two common solution approaches for solving multi-objective optimization problems are reduction to a single-objective optimization problem (via weighting or min-max deviation methods) and generation of Pareto efficient solutions. In this study, we use the latter approach as this gives the decision maker a set of alternative solutions and illustrates how the objective functions change with respect to each other. Note that both **P1** and **P2** are bi-objective mixed-integer nonlinear programming models. Furthermore, even with one of the objective functions as the single objective, both **P1** and **P2** are NP-hard problems. Therefore, we focus on developing an efficient algorithm to approximate the set of Pareto efficient solutions for **P1** and **P2**. To do so, we first discuss an implementation of the well-known adaptive ϵ-constraint algorithm. After that, we characterize properties of the Pareto efficient solutions and construct an evolutionary search algorithm that utilizes these properties.

It should be noted that both the adaptive ϵ-constraint and evolutionary search algorithms are approximation algorithms as both **P1** and **P2** have continuous decision variables. Furthermore, both of the objective functions are not necessarily convex (see, e.g., [23,62] for convexity conditions on the classical (Q,R) model). Many exact methods have been recently developed for multi-objective pure integer models. One may refer to the review papers by Ehrgott and Gandibleux [44,45] and Alves and Climaco [6] and the book by Ehrgott [43] for reviews of such methods. Also, Dächert and Klamroth [40] present a substantial review of the exact methods. On the other hand, in the case of multi-objective mixed-integer models, the exact methods aim to generate the exact set of integer parts of the Pareto efficient solutions. Most of the previous methods for solving multi-objective mixed-integer models such as branch-and-bound algorithms (see, e.g., [93,94,124,13,116]), the triangular splitting method [17,18], and other methods (see, e.g., [114]) are studied for multi-objective mixed-integer linear programming models.

In this study, the problems of interest are multi-objective mixed-integer nonlinear programming models; hence, one cannot directly apply the current solution methods. In what follows, we first give some preliminaries, then discuss the implementation details of the adaptive ϵ-constraint algorithm of Laumanns et al. [86], and finally, explain the evolutionary search algorithm, which utilizes properties similar to the ones used in the triangle splitting method proposed by Boland et al. [18] for mixed-integer-linear programming models. Throughout the rest of this section, cost and emission refer to expected costs and expected carbon emissions per unit time, respectively.

4.1. Preliminaries

Let $j=1$ and $j=2$ be the indices defining the sequential splitting and sequential delivery policies, respectively. Furthermore, let PF^j denote the Pareto front, the set of Pareto efficient points, of problem $\mathbf{P}_j$. We will use the following definition of Pareto efficient solution.

Definition 1. A feasible solution $(R,\mathbf{q},\mathbf{x})$ is in PF^j if and only if there does not exist another feasible solution $(\overline{R},\overline{\mathbf{q}},\overline{\mathbf{x}})$ such that $C^j(R,\mathbf{q},\mathbf{x})\ge C^j(\overline{R},\overline{\mathbf{q}},\overline{\mathbf{x}})$ and $E^j(R,\mathbf{q},\mathbf{x})\ge E^j(\overline{R},\overline{\mathbf{q}},\overline{\mathbf{x}})$, where at least one of these inequalities is strict ([15]).

Now, let us define $\left(\tilde{R}^j,\tilde{\mathbf{q}}^j,\tilde{\mathbf{x}}^j\right)=\arg\min\left\{C^j(R,\mathbf{q},\mathbf{x}):0\le q_i\le x_i w_i\ \forall i\in I,x_i\in\{0,1\}\ \forall i\in I,R>0\right\}$ and $\left(\widehat{R}^j,\widehat{\mathbf{q}}^j,\widehat{\mathbf{x}}^j\right)=\arg\min\{E^j(R,\mathbf{q},\mathbf{x}):0\le q_i\le x_i w_i\ \forall i\in I,x_i\in\{0,1\}\ \forall i\in I,R>0\}$. That is, $\left(\tilde{R}^j,\tilde{\mathbf{q}}^j,\tilde{\mathbf{x}}^j\right)$ is the cost minimizing and $\left(\widehat{R}^j,\widehat{\mathbf{q}}^j,\widehat{\mathbf{x}}^j\right)$ is the emission minimizing

solution of problem $\mathbf{P}_j$. For notational simplicity, let $\tilde{C}^j = C^j\left(\tilde{R}^j, \tilde{\mathbf{q}}^j, \tilde{\mathbf{x}}^j\right)$, $\tilde{E}^j = E^j\left(\tilde{R}^j, \tilde{\mathbf{q}}^j, \tilde{\mathbf{x}}^j\right)$, $\widehat{C}^j = C^j\left(\widehat{R}^j, \widehat{\mathbf{q}}^j, \widehat{\mathbf{x}}^j\right)$, and $\widehat{E}^j = E^j\left(\widehat{R}^j, \widehat{\mathbf{q}}^j, \widehat{\mathbf{x}}^j\right)$.

Remark 1. If $(R, \mathbf{q}, \mathbf{x}) \in PF^j$, then $\tilde{C}^j \leq C^j(R, \mathbf{q}, \mathbf{x}) \leq \widehat{C}^j$ and $\widehat{E}^j \leq E^j(R, \mathbf{q}, \mathbf{x}) \leq \tilde{E}^j$.

Remark 1 is a direct implication of Definition 1 and it is a well-known result (see, e.g., [61]). It directly follows from Remark 1 that $\left(\tilde{R}^j, \tilde{\mathbf{q}}^j, \tilde{\mathbf{x}}^j\right) \in PF^j$ and $\left(\widehat{R}^j, \widehat{\mathbf{q}}^j, \widehat{\mathbf{x}}^j\right) \in PF^j$. Now, suppose that $\mathbf{x}$ is given and consider the following bi-objective optimization problem:

$$
\begin{array}{lll}
(\mathbf{P}_j|\mathbf{x}): & \min & C^j(R, \mathbf{q}|\mathbf{x}) \\
& \min & E^j(R, \mathbf{q}|\mathbf{x}) \\
& \text{s.t.} & 0 \leq q_i \leq x_i w_i \quad \forall i \in I \\
& & R > 0,
\end{array}
$$

Let $PF^j(\mathbf{x})$ be the set of $(R, \mathbf{q}, \mathbf{x})$ solutions such that $(R, \mathbf{q})$ is Pareto efficient to problem $\mathbf{P}_j|\mathbf{x}$. Note that $PF^j(\mathbf{x})$ can be approximated with the classical ϵ-constraint algorithm [61], which does not need to be adaptive as $\mathbf{P}_j|\mathbf{x}$ does not have any integer decision variables. Appendix A.2 gives the implementation details of the ϵ-constraint algorithm for approximating $PF^j(\mathbf{x})$. Furthermore, let us define $\left(\tilde{R}^j(\mathbf{x}), \tilde{\mathbf{q}}^j(\mathbf{x})\right) = \arg\min\left\{C^j(R, \mathbf{q}|\mathbf{x}) : 0 \leq q_i \leq x_i w_i \ \forall i \in I, R > 0\right\}$ and $\left(\widehat{R}^j(\mathbf{x}), \widehat{\mathbf{q}}^j(\mathbf{x})\right) = \arg\min\left\{C^j(R, \mathbf{q}|\mathbf{x}) : 0 \leq q_i \leq x_i w_i \ \forall i \in I, R > 0\right\}$. That is, $\left(\tilde{R}^j(\mathbf{x}), \tilde{\mathbf{q}}^j(\mathbf{x})\right)$ and $\left(\widehat{R}^j(\mathbf{x}), \widehat{\mathbf{q}}^j(\mathbf{x})\right)$ are the optimum re-order point and split orders of $\mathbf{P}_j|\mathbf{x}$ with only cost ($C^j(R, \mathbf{q}|\mathbf{x})$) and only emission ($E^j(R, \mathbf{q}|\mathbf{x})$) minimization objectives, respectively, given the supplier selection $\mathbf{x}$ under policy j. For notational simplicity, let $\tilde{C}^j(\mathbf{x}) = C^j\left(\tilde{R}^j(\mathbf{x}), \tilde{\mathbf{q}}^j(\mathbf{x}), \mathbf{x}\right)$, $\tilde{E}^j(\mathbf{x}) = E^j\left(\tilde{R}^j(\mathbf{x}), \tilde{\mathbf{q}}^j(\mathbf{x}), \mathbf{x}\right)$, $\widehat{C}^j(\mathbf{x}) = C^j\left(\widehat{R}^j(\mathbf{x}), \widehat{\mathbf{q}}^j(\mathbf{x}), \mathbf{x}\right)$, and $\widehat{E}^j(\mathbf{x}) = E^j\left(\widehat{R}^j(\mathbf{x}), \widehat{\mathbf{q}}^j(\mathbf{x}), \mathbf{x}\right)$.

Remark 2. (i) If $(R, \mathbf{q}, \mathbf{x}) \in PF^j(\mathbf{x})$, then $\tilde{C}^j(\mathbf{x}) \leq C^j(R, \mathbf{q}, \mathbf{x}) \leq \widehat{C}^j(\mathbf{x})$ and $\widehat{E}^j(\mathbf{x}) \leq E^j(R, \mathbf{q}, \mathbf{x}) \leq \tilde{E}^j(\mathbf{x})$; and (ii) if $(R, \mathbf{q}, \mathbf{x}) \notin PF^j(\mathbf{x})$, then $(R, \mathbf{q}, \mathbf{x}) \notin PF^j$.

Remark 2(i) is defined similar to Remark 1. Remark 2(ii) follows from Definition 1 and it indicates that $PF^j \subseteq \bigcup_{\mathbf{x} \in [0,1]^n} PF^j(\mathbf{x})$, where $[0, 1]^n$ denotes the set of all binary n-vectors. In fact, it follows from Remark 2(ii) that $PF^j = PE\left(\bigcup_{\mathbf{x} \in [0,1]^n} PF^j(\mathbf{x})\right)$, where $PE(\Phi)$ denotes the set of Pareto efficient solutions within a given set of $(R, \mathbf{q}, \mathbf{x})$ solutions Φ (see, also, [55] for a similar result). Appendix A.3 states an iterative procedure to determine $PE(\Phi)$ out of Φ. This further suggests the following total enumeration approach to approximate PF^j: approximate $PF^j(\mathbf{x})$ for each $\mathbf{x}$ (using the classical ϵ-constraint method given in Appendix A.2) and extract $PF^j = PE\left(\bigcup_{\mathbf{x} \in [0,1]^n} PF^j(\mathbf{x})\right)$ (using the iterative method given in Appendix A.3). An algorithmic description of this total enumeration algorithm is given in Appendix A.4. We will use the total enumeration algorithm as a benchmark for the adaptive ϵ-constraint and evolutionary search algorithms.

However, one does not need to approximate $PF^j(\mathbf{x})$ for each possible $\mathbf{x} \in [0, 1]^n$ in order to approximate PF^j. Particularly, let us define $Z^j = \{\mathbf{x} : PF^j(\mathbf{x}) \cap PF^j \neq \emptyset, \mathbf{x} \in [0, 1]^n\}$, that is, Z^j is the set of binary supplier selection decision vectors, which produce Pareto efficient $(R, \mathbf{q}, \mathbf{x})$ solutions for problem $\mathbf{P}_j$. It then follows from Remark 2(ii) that $PF^j = PE\left(\bigcup_{\mathbf{x} \in Z^j} PF^j(\mathbf{x})\right)$. The idea of the adaptive ϵ-constraint method is to use the cost and emission minimizing solutions of a $\mathbf{x} \in Z^j$ to partially approximate $PF^j(\mathbf{x})$, whereas the evolutionary search algorithm tries to directly determine a good approximation of Z^j without a need to fully approximate $PF^j(\mathbf{x})$ for each possible $\mathbf{x} \in [0, 1]^n$. We will use the following definition within the algorithms for comparing two sets of solutions S^1 and S^2.

Definition 2. S^1 Pareto dominates S^2 if $S^2 \cap PE(S^1 \cup S^2) = \emptyset$ [84].

That is, if all of the solutions within S^2 are Pareto dominated by at least one solution within S^1, then S^1 Pareto dominates S^2, represented as $S^1 \ll S^2$ as we have two minimization objectives. The case when neither S^1 nor S^2 Pareto dominates the other is represented as $S^1 \lesseqgtr S^2$. Next, we explain the implementation details of the adaptive ϵ-constraint algorithm.

4.2. Adaptive ϵ-constraint algorithm

Similar to the classical ϵ-constraint algorithm, the main idea of the adaptive ϵ-constraint algorithm is to move one of the objective functions to the constraints as an upper bound. In particular, let $(R^{j\delta_E}, \mathbf{q}^{j\delta_E}, \mathbf{x}^{j\delta_E}) = \arg\min\{C^j(R, \mathbf{q}, \mathbf{x}) : E^j(R, \mathbf{q}, \mathbf{x}) \leq \delta_E, \ 0 \leq q_i \leq x_i w_i \ \forall i \in I, x_i \in \{0, 1\} \ \forall i \in I, R > 0\}$ and $(R^{j\delta_C}, \mathbf{q}^{j\delta_C}, \mathbf{x}^{j\delta_C}) = \arg\min\{E^j(R, \mathbf{q}, \mathbf{x}) : C^j(R, \mathbf{q}, \mathbf{x}) \leq \delta_C, 0 \leq q_i \leq x_i w_i \ \forall i \in I, x_i \in \{0, 1\} \ \forall i \in I, R > 0\}$. That is, $(R^{j\delta_E}, \mathbf{q}^{j\delta_E}, \mathbf{x}^{j\delta_E})$ minimizes the cost such that the emissions are less than or equal to δ_E and $(R^{j\delta_C}, \mathbf{q}^{j\delta_C}, \mathbf{x}^{j\delta_C})$ minimizes the emissions such that the cost is less than or equal to δ_C. The next remark follows from Definition 1 and Remark 1.

Remark 3. (i) If $\widehat{E}^j \leq \delta_E \leq \tilde{E}^j$, then $(R^{j\delta_E}, \mathbf{q}^{j\delta_E}, \mathbf{x}^{j\delta_E}) \in PF^j$. (ii) If $\tilde{C}^j \leq \delta_C \leq \widehat{C}^j$, then $(R^{j\delta_C}, \mathbf{q}^{j\delta_C}, \mathbf{x}^{j\delta_C}) \in PF^j$.

Remarks 1 and 3 constitute the main framework of the ϵ-constraint algorithm. In the ϵ-constraint algorithm, starting with $\delta_E = \tilde{E}^j$ (or $\delta_C = \widehat{C}^j$), one iteratively determines solutions in the form of $(R^{j\delta_E}, \mathbf{q}^{j\delta_E}, \mathbf{x}^{j\delta_E})$ (or $(R^{j\delta_C}, \mathbf{q}^{j\delta_C}, \mathbf{x}^{j\delta_C})$) by reducing δ_E (or δ_C) values by ϵ at each iteration until $\delta_E = \widehat{E}^j$ (or $\delta_C = \tilde{C}^j$), where ϵ is a small number. However, since $\mathbf{P}_j$ is a mixed-integer nonlinear programming model, it is not guaranteed that $E^j(R^{j\delta_E}, \mathbf{q}^{j\delta_E}, \mathbf{x}^{j\delta_E}) = \delta_E$ (or $C^j(R^{j\delta_C}, \mathbf{q}^{j\delta_C}, \mathbf{x}^{j\delta_C}) = \delta_C$). Therefore, one might end up with the same $(R^{j\delta_E}, \mathbf{q}^{j\delta_E}, \mathbf{x}^{j\delta_E})$ (or $(R^{j\delta_C}, \mathbf{q}^{j\delta_C}, \mathbf{x}^{j\delta_C})$) for different δ_E (or δ_C) values when ϵ is too small. On the other hand, if ϵ is too large, the approximation will not be sufficient and might miss a $\mathbf{x}$ such that there exist many Pareto efficient $(R, \mathbf{q}, \mathbf{x})$ solutions. To avoid these drawbacks of the ϵ-constraint algorithm [86], we adaptively select δ_E (or δ_C) and ϵ values considering $\mathbf{x}^{j\delta_E}$ (or $\mathbf{x}^{j\delta_C}$) and Remark 2(i).

In particular, suppose that the ϵ-constraint algorithm is to be implemented with the cost minimization objective and the emissions constraint. At an intermediate iteration, let us assume that $\mathbf{x}^{j\delta_E} \neq \mathbf{x}^{j(\delta_E + \epsilon)}$. In such a case, we first replace δ_E with $E^j(R^{j\delta_E}, \mathbf{q}^{j\delta_E}, \mathbf{x}^{j\delta_E})$ instead of $\delta_E - \epsilon$. This will prevent consideration of δ_E values that would return the same solution. Then, we set $\epsilon = [\delta_E - \widehat{E}^j(\mathbf{x}^{j\delta_E})]/M$, where M is a predetermined number defining the maximum number of solutions to generate for a given $\mathbf{x}$. Depending on how large M is, the adaptive updates of δ_E and ϵ will avoid missing Pareto efficient solutions due to large ϵ values and avoid solving unnecessary optimization problems due to small ϵ values.

Using the adaptive ϵ-constraint method with specific objective and constraint choices might result in an approximation of PF^j with low diversity. To increase the diversity of the approximation, one can also execute the adaptive ϵ-constraint method by switching the function choices. Specifically, if the adaptive ϵ-constraint method is to be implemented with the emission mini-

mization objective and the cost constraint, we update δ_C and ϵ as follows. At an intermediate iteration, suppose that $\mathbf{x}^{j(\delta_C+\epsilon)} \neq \mathbf{x}^{j\delta_C}$. In such a case, we first set $\delta_C = C^j(R^{j\delta_C}, \mathbf{q}^{j\delta_C}, \mathbf{x}^{j\delta_C})$. Then, we set $\epsilon = \left[\hat{\delta}_C - \tilde{C}^j(\mathbf{x}^{j\delta_C})\right]/M$.

Appendix A.5 gives the algorithmic description of the adaptive ϵ-constraint algorithm with both possible executions for problem $\mathbf{P}_j$ to approximate PF^j. We note that one needs to solve mixed-integer nonlinear programming models to determine $(R^{j\delta_E}, \mathbf{q}^{j\delta_E}, \mathbf{x}^{j\delta_E})$ and $(R^{j\delta_C}, \mathbf{q}^{j\delta_C}, \mathbf{x}^{j\delta_C})$, and these models are NP-hard; therefore, we devise a multi-start local search heuristic to solve them. The details of this multi-start search heuristic are given in Appendix A.6. Furthermore, $\widehat{E}^j(\mathbf{x}^{j\delta_E})$ and $\tilde{C}^j(\mathbf{x}^{j\delta_C})$ should be determined throughout the adaptive ϵ-constraint algorithm, and, therefore, non-linear programming models should be solved. To solve any non-linear programming model required to be solved with the algorithms, we use an interior point method (see, e.g., [53]). Next, we characterize further properties of a Pareto efficient solution of $\mathbf{P}_j$ and propose an evolutionary search algorithm.

4.3. Properties and evolutionary search algorithm

The evolutionary search algorithm is based on approximating Z^j directly. To do so, we compare different supplier selection vectors and check which ones can potentially belong to Z^j using Properties 1–3. The proofs of Properties 1–3 are given in Appendix A.7.

Property 1. *Suppose that* $\mathbf{x}^1$ *and* $\mathbf{x}^2$ *define two supplier selection decisions such that* $\mathbf{x}^1 \neq \mathbf{x}^2$. $\mathbf{x}^2 \notin Z^j$ *if* (*i*) $\tilde{C}^j(\mathbf{x}^1) \leq \tilde{C}^j(\mathbf{x}^2) \leq \widehat{C}^j(\mathbf{x}^1)$ *and* $\tilde{E}^j(\mathbf{x}^1) < \widehat{E}^j(\mathbf{x}^2)$ *or* (*ii*) $\widehat{C}^j(\mathbf{x}^1) < \tilde{C}^j(\mathbf{x}^2)$ *and* $\widehat{E}^j(\mathbf{x}^1) \leq \widehat{E}^j(\mathbf{x}^2)$.

Property 1 suggests that if there exists an $\mathbf{x}^1$ satisfying the stated conditions, one should not include $\mathbf{x}^2$ within Z^j. In particular, the stated conditions guarantee that $PF^j(\mathbf{x}^1)$ Pareto dominates $PF^j(\mathbf{x}^2)$, i.e., $PF^j(\mathbf{x}^1) \ll PF^j(\mathbf{x}^2)$. Furthermore, it is sufficient to calculate only the cost and emissions minimizing re-order point and split orders under the given supplier selection decisions instead of generating more than two points on $PF^j(\mathbf{x}^2)$. We note that Property 1 gives sufficient but not necessary conditions for $PF^j(\mathbf{x}^1) \ll PF^j(\mathbf{x}^2)$. The following property is a direct implication of Property 1.

Property 2. *Suppose that S is a set of supplier selection decisions and* $\overrightarrow{\mathbf{x}} \notin S$. $\overrightarrow{\mathbf{x}} \notin Z^j$ *if* (*i*) $\widehat{E}^j(\overrightarrow{\mathbf{x}}) > \min_{\mathbf{x} \in S}\{\tilde{E}^j(\mathbf{x}) : \tilde{C}^j(\mathbf{x}) \leq \tilde{C}^j(\overrightarrow{\mathbf{x}}), \tilde{C}^j(\overrightarrow{\mathbf{x}}) \leq \widehat{C}^j(\mathbf{x})\}$ *or* (*ii*) $\widehat{E}^j(\overrightarrow{\mathbf{x}}) \geq \min_{\mathbf{x} \in S}\{\widehat{E}^j(\mathbf{x}) : \widehat{C}^j(\mathbf{x}) < \tilde{C}^j(\overrightarrow{\mathbf{x}})\}$.

While Property 1 compares a given supplier selection decisions vector to another one, Property 2 compares a given supplier selection decisions vector to a set of other supplier selection decisions vectors. Properties 1 and 2 will be both used within the evolutionary search algorithm to determine supplier selection decisions, for which we do not need to generate $PF^j(\mathbf{x})$. Particularly, the evolutionary search algorithm first approximates Z^j and then gets the PF^j approximation as $PE\left(\bigcup_{\mathbf{x} \in Z^j} PF^j(\mathbf{x})\right)$. Additionally, even if one cannot state that it is not unnecessary to approximate $PF^j(\mathbf{x})$, it is still important to determine that $\mathbf{x} \notin Z^j$ after approximating $PF^j(\mathbf{x})$ because doing so would reduce the size of $\bigcup_{\mathbf{x} \in Z^j} PF^j(\mathbf{x})$, and thereby, reduce the computational time to determine $PE\left(\bigcup_{\mathbf{x} \in Z^j} PF^j(\mathbf{x})\right)$. Next, we state an intuitive property that can be used for this purpose.

Property 3. *Suppose that* $PF^j(\mathbf{x})$ *is given. If* $\exists i \in I$ *with* $\tilde{a}_i > 0$ *or* $\widehat{a}_i > 0$ *such that* $x_i = 1$ *and* $q_i = 0$ $\forall (R, \mathbf{q}, \mathbf{x}) \in PF^j(\mathbf{x})$, *then* $\mathbf{x} \notin Z^j$.

Property 3 simply notes that the retailer will not use a supplier for delivery unless the supplier delivers a positive percentage of the total order quantity. This result is expected as the retailer will neither pay the fixed delivery charge nor claim the fixed portion of the carbon emissions due to using a supplier who is not delivering anything. Therefore, if at least one of the suppliers selected under $\mathbf{x}$ is not needed for each Pareto efficient solution within $PF^j(\mathbf{x})$, $\mathbf{x}$ will not produce any Pareto efficient solution within PF^j.

At this point, we are ready to propose the evolutionary search algorithm for problem $\mathbf{P}_j$ to approximate PF^j. This algorithm uses 4 steps described below: it starts with step (i) and repeats steps (ii) and (iii) until the criterion defined in step (iv) is satisfied. The algorithmic description of the evolutionary search algorithm is given in Appendix A.8.

(i) *Chromosome representation and initialization*: Note that a solution for $\mathbf{P}_j$ is in the form of $(R, \mathbf{q}, \mathbf{x})$, where R and $\mathbf{q}$ are the continuous variables and $\mathbf{x}$ is the vector of binary variables. In the evolutionary search algorithm, instead of analyzing $(R, \mathbf{q}, \mathbf{x})$, we focus on analyzing $\mathbf{x}$. Here, $\mathbf{x}$ is used as a chromosome. To analyze $\mathbf{x}$, we will approximate $PF^j(\mathbf{x})$ with the ϵ-constraint method (see Appendix A.2) as needed instead of generating $PF^j(\mathbf{x})$ for every $\mathbf{x}$. To start the algorithm, α chromosomes are randomly generated as the initial population.

(ii) *Fitness evaluation*: The purpose of the fitness evaluation step is to determine the best chromosomes in a given set of chromosomes, i.e., parent chromosomes of a population. Suppose that a set of ℓ chromosomes, S, is given. We use Properties 2 and 3 to determine the best chromosomes within population S, denoted by S^* as follows. First, the chromosomes are sorted such that $\tilde{C}^j(\mathbf{x}^1) \geq \tilde{C}^j(\mathbf{x}^2) \geq \cdots \geq \tilde{C}^j(\mathbf{x}^\ell)$. Then, for each chromosome $\mathbf{x}^g \in S$ such that $1 \leq g \leq \ell$, if $\widehat{E}^j(\mathbf{x}^g) > \min\left\{\tilde{E}^j(\mathbf{x}^1), \tilde{E}^j(\mathbf{x}^2), \ldots, \tilde{E}^j(\mathbf{x}^{g-1})\right\}$, we exclude it from S and let $S := S \setminus \{\mathbf{x}^g\}$. Note that the remaining chromosomes in S will still be sorted in decreasing order of their $\tilde{C}^j(\mathbf{x})$ values. Without loss of generality, suppose that we have $k \leq \ell$ chromosomes remaining in S such that $\tilde{C}^j(\mathbf{x}^1) \geq \tilde{C}^j(\mathbf{x}^2) \geq \cdots \geq \tilde{C}^j(\mathbf{x}^k)$. Then, for each chromosome $\mathbf{x}^g \in S$ such that $1 \leq g \leq \ell$, if $\widehat{E}^j(\mathbf{x}^g) \geq \min\left\{\tilde{E}^j(\mathbf{x}^f) : f \leq g-1, \widehat{C}^j(\mathbf{x}^f) < \tilde{C}^j(\mathbf{x}^f)\right\}$, we exclude it from S and let $S := S \setminus \{\mathbf{x}^g\}$. So far, we have checked the conditions in Property 2. Finally, for the remaining chromosomes, we generate $PF^j(\mathbf{x})$, and check whether the condition in Property 3 is being satisfied; if so, we eliminate the chromosome from S. The remaining chromosomes constitute the set of parent chromosomes, S^*, of the initially given population S.

(iii) *Mutation operations*: Mutation operations are used to generate the next population using the set of parent chromosomes of the current population. We use three mutation operations: add-drop mutation, neighbor mutation, and random mutation. Add-drop mutation is executed on each gene of each parent chromosome such that if $x_i = 1$ ($x_i = 0$) for a given parent chromosome $\mathbf{x}$, a mutant is generated by making $x_i = 0$ ($x_i = 1$) and not changing other genes. With add-drop mutation, n mutant chromosomes are generated from each parent chromosome. Neighbor mutation generates the neighbors of a parent chromosome such that each neighbor has the same number of suppliers selected. Specifically, given a parent chromosome $\mathbf{x}$, its (a,b)-neighbor, denoted by $\mathbf{x}^{(a,b)}$ such that $1 \leq a \leq n$, $1 \leq b \leq n$, $a \neq b$, exists if $x_a + x_b = 1$ and is defined by swapping x_a and x_b values. With neighbor mutation, we generate all neighbors of each parent chromosome. Finally, we randomly generate a set of β chromosomes. The next population consists of the parent chromosomes and the newly generated chromosomes. By including the parent chromosomes of the current population within the next population, it is guaranteed that the populations are not worsening. Also, by keeping a list of the chromosomes evaluated, we exclude already evaluated chromosomes (other than the parent chromosomes) from the population.

This avoids evaluating a chromosome twice and assures that we generate $PF^j(\mathbf{x})$ for a chromosome $\mathbf{x}$ at most once.

(iv) *Termination*: We terminate generating new populations if the set of parent chromosomes is not changing over a pre-specified number (γ) of consecutive populations. At termination, let S^* be the set of parent chromosomes. Then, based on Property 2, PF^j is approximated as $PE\left(\bigcup_{\mathbf{x}\in S^*} PF^j(\mathbf{x})\right)$.

5. Numerical studies

This section focuses on three sets of numerical analysis: (i) efficiency of the proposed algorithms with each delivery scheduling policy, (ii) effects of the demand variance on the retailer's expected costs and carbon emissions under each delivery scheduling policy, and (iii) comparison of the delivery scheduling policies. In these analyses, we use similar data ranges to those of Schaefer and Konur [109]. Refer to Appendix A.9 for the details of the parameter ranges used for problem instance generation as well as the parameter specifications for the algorithms. The algorithms are coded in Matlab 2014 and executed on a personal computer with 3 GHz dual-core processor and 16 GB RAM. Tables of analyses (i) and (ii) are presented in Appendix A.10.

5.1. Efficiency of the algorithms

Here, we compare the adaptive ϵ-constraint algorithm (AE) with the evolutionary search algorithm (ES) under each delivery scheduling policy. In comparing AE and ES, we use the total enumeration algorithm (TE) as a benchmark. In particular, we randomly generate 10 problem instances with the number of suppliers n increasing from 3 to 10 in increments of 1 and we solve each problem instance under each delivery scheduling policy using each algorithm (i.e., 80 problem instances are generated and a problem instance is solved 6 times) and then, we compare the set of unique $\mathbf{x}$'s within the solutions returned by each algorithm, denoted by Z^j_{TE}, Z^j_{AE}, and Z^j_{ES} for the TE, AE, and ES algorithms, respectively, under delivery scheduling policy j. For comparison, we use the following statistics for each algorithm: the number of unique $\mathbf{x}$'s, i.e., $\left|Z^j_{TE}\right|$, $\left|Z^j_{AE}\right|$, and $\left|Z^j_{ES}\right|$, and computational time in seconds (*cpu*). Furthermore, for AE, we calculate the percentage of the solutions in Z^j_{AE} which are also in Z^j_{TE}, i.e., $\left|Z^j_{TE}\cap Z^j_{AE}\right|\Big/\left|Z^j_{AE}\right|$ (denoted by $AE\cap TE$) and the percentage of the solutions in Z^j_{AE} which are also in Z^j_{ES}, i.e., $\left|Z^j_{ES}\cap Z^j_{AE}\right|\Big/\left|Z^j_{AE}\right|$ (denoted by $AE\cap ES$). Similarly, for ES, we calculate the percentage of the solutions in Z^j_{ES} which are also in Z^j_{TE}, i.e., $\left|Z^j_{TE}\cap Z^j_{ES}\right|\Big/\left|Z^j_{ES}\right|$ (denoted by $ES\cap TE$) and the percentage of the solutions in Z^j_{ES} which are also in Z^j_{AE}, i.e., $\left|Z^j_{AE}\cap Z^j_{ES}\right|\Big/\left|Z^j_{ES}\right|$ (denoted by $ES\cap AE$). Tables 2 and 3 in Appendix A.10 present the averages of these statistics over the 10 problem instances solved for each n for sequential splitting and sequential delivery, respectively. We have the following observations based on Tables 2 and 3:

- ES is much faster than AE, with the relative speed advantage increasing with the number of suppliers n. As expected, TE required more computational time than the other two algorithms for every instance and it did find more solutions.
- Compared with TE, ES was able to find more common solutions than AE did under each delivery scheduling policy on average, and furthermore, ES returned more solutions than AE. On average, ES was able to find 97.3% and 96.1% of the solutions returned by AE under sequential splitting and sequential delivery, respectively, while AE was able find 91.5% and 92.2% of the solutions returned by ES under sequential splitting and sequential delivery, respectively.
- On average, sequential splitting requires less computational time than sequential delivery (with all algorithms) and this advantage increases with the number of suppliers.

While the total enumeration algorithm gives the best approximation for both PF^1 and PF^2, it is computationally burdensome and its computational time increases drastically with the problem size n. Based on the above observations, it can be concluded that the evolutionary search algorithm is a better approximation method than the adaptive ϵ-constraint algorithm for both PF^1 and PF^2 as it is able to find more common solutions with TE in less computational time. Therefore, the evolutionary search algorithm can be considered as an efficient approximation algorithm for practical problem sizes and we use it as a solution tool to analyze the effects of demand variance.

5.2. Effects of the demand variance

In this analysis, our goal is to demonstrate the effects of the demand variance on the retailer's expected costs and carbon emissions per unit time under each delivery scheduling policy as well as how PF^1 compares to PF^2 as υ increases. To do so, we randomly generate 10 problem instances for each number of suppliers $n\in\{3,5,7,9\}$ and we solve each problem instance with 8 different values of the standard deviation of the demand rate, υ, increasing from 200 to 1600 in increments of 200 (i.e., 40 problem instances are generated and a problem instance is solved 8 times) under both delivery scheduling policies using the ES algorithm.

To demonstrate the effects of the increase in υ under each delivery scheduling policy, we calculate the mean of the costs and emissions of the solutions within the approximated Pareto front of a problem instance under each delivery scheduling policy for a given υ. We refer to this average point of a given Pareto front, PF^j, as the mean-Pareto-solution with costs defined by $\overline{C}^j=\sum_{(R,\mathbf{q},\mathbf{x})\in PF^j} C^j(R,\mathbf{q},\mathbf{x})/|PF^j|$ and emissions defined by $\overline{E}^j=\sum_{(R,\mathbf{q},\mathbf{x})\in PF^j} E^j(R,\mathbf{q},\mathbf{x})/|PF^j|$. Table 4 in Appendix A.10 documents the averages of $\overline{C}^j$ and $\overline{E}^j$ values over the 40 problem instances solved with each υ for sequential splitting and sequential delivery and Fig. 2a illustrates these averages (Table 5 in Appendix A.10 reports more details with the averages of $\overline{C}^j$ and $\overline{E}^j$ values over the 10 problem instances solved with each n and υ for sequential splitting and sequential delivery). As expected, it can be observed from Table 4 and seen in Fig. 2a that both $\overline{C}^j$ and $\overline{E}^j$ increase as υ increases under both delivery scheduling policies. This result generalizes the observations of Schaefer and Konur [109] on the effects of demand variability to the case with multiple suppliers and different scheduling policies. Furthermore, recalling the alternative models defined in Section 3.3 with $B^j(R,\mathbf{q},\mathbf{x})=C^j(R,\mathbf{q},\mathbf{x})+\psi\left(E^j(R,\mathbf{q},\mathbf{x})-\Phi\right)$, it can also be argued that the total cost (including environmental costs or tax or trading costs/revenues) will increase with υ.

Table 4 also provides the averages of the percent differences between $\overline{C}^1$ and $\overline{C}^2$ and between $\overline{E}^1$ and $\overline{E}^2$, where $\Delta C=(\overline{C}^2-\overline{C}^1)/\overline{C}^2$ and $\Delta E=\left(\overline{E}^2-\overline{E}^1\right)/\overline{E}^2$. That is, ΔC and ΔE measure the savings in costs and emissions, respectively, due to switching from sequential delivery to sequential splitting. Fig. 2b shows the averages ΔC and ΔE, as well as $\Delta C+\Delta E$ solved with each υ. We have the following observations based on Table 4 and Fig. 2b. For lower υ values ($\upsilon\le 800$), ΔC and ΔE do not follow a strictly increasing or decreasing trend; however, the total change ($\Delta C+\Delta E$) is slightly negative, i.e., sequential delivery can be slightly more preferable. On the other hand, for higher υ values ($\upsilon>800$), ΔC and ΔE (and thus $\Delta C+\Delta E$) increase as υ increases and the total change is positive.

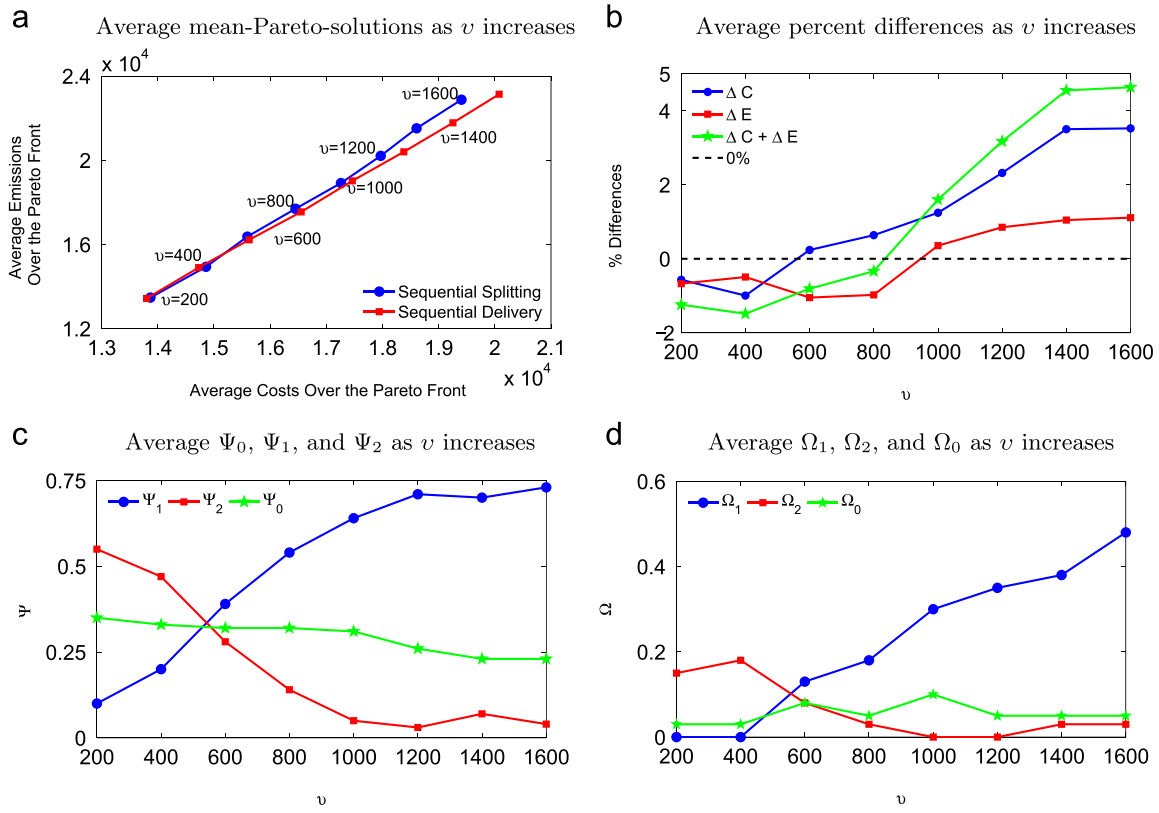

Fig. 2. Illustration of the effects of increases in υ.

That is, for higher υ values, sequential splitting is more preferable and its advantage over sequential delivery increases with υ.

To further demonstrate the effects of the increase in υ on comparison of the delivery scheduling policies, we first compare PF^1 and PF^2 to $PF = PE(PF^1 \cup PF^2)$ over the problem instances solved with different υ values. For comparing PF^1 and PF^2 to PF, we look at the following three percentages: the percentage of solutions in PF coming from both PF^1 and PF^2, denoted by Ψ_0 such that $\Psi_0 = |PF \cap PF^1 \cap PF^2| / |PF|$, the percentage of solutions in PF coming only from PF^1, denoted by Ψ_1 such that $\Psi_1 = |PF \cap PF^1| / |PF| - \Psi_0$, and the percentage of solutions in PF coming only from PF^2, denoted by Ψ_2 such that $\Psi_2 = |PF \cap PF^2| / |PF| - \Psi_0$. Table 6 in Appendix A.10 summarizes the averages of Ψ_0, Ψ_1, and Ψ_2 values over the 10 problem instances solved with each n and υ and Fig. 2c illustrates the averages of the Ψ_0, Ψ_1, and Ψ_2 over the 40 problem instances solved with each υ. Furthermore, we compare the percentage of the problem instances where $PF^1 \ll PF^2$ (denoted by Ω_1), $PF^2 \ll PF^1$ (denoted by Ω_2), and $PF^1 \equiv PF^1$ (denoted by Ω_0). Note that $100\% - \Omega_1 - \Omega_2 - \Omega_0$ defines the percentage of the problem instances where $PF^1 \lesseqgtr PF^2$. Table 7 in Appendix A.10 summarizes the averages of Ω_0, Ω_1, and Ω_2 values over the 10 problem instances solved with each n and υ and Fig. 2d illustrates their averages over the 40 problem instances solved with each υ.

Table 6 and Fig. 2c show that as υ increases, Ψ_1 tends to increase while Ψ_0 and Ψ_2 tend to decrease. This suggests that the retailer might change his/her delivery scheduling policy and sequential splitting might become more preferable as υ increases. In particular, since Ψ_1 tends to increase with υ, it means that the sequential splitting returns more solutions that are Pareto superior compared to the solutions returned with sequential delivery when the demand variance is higher. That is, the retailer can find more solutions with lower cost (emissions) under sequential splitting compared to the solutions with the same emissions (cost) levels under sequential delivery. Furthermore, it can be observed from Table 7 and Fig. 2d that the percentage of the problem instances where $PF^1 \ll PF^2$ tends to increase while the percentage of the problem instances where $PF^2 \ll PF^1$ tends to decrease as υ increases. This suggests that sequential splitting dominates sequential delivery for more problem instances as υ increases. Based on these observations and the previous observations from Table 4 and Fig. 2b, we can note that a retailer that observes increases in demand variance should consider switching from sequential delivery to sequential splitting. However, we recommend the use of tools provided here (as will be done next in Examples 1–3) for comparing PF^1 and PF^2.

5.3. Comparison of the scheduling policies

This section focuses on comparing sequential splitting and sequential delivery. Note that a retailer that wishes to purely minimize cost (emissions) would find the cost (emissions) minimizing solutions under each delivery scheduling policy, and then select the one which has lower value. On the other hand, a retailer that has both cost and emissions minimization objectives will need to compare the Pareto fronts under each scheduling policy, i.e., PF^1 and PF^2. Particularly, a retailer that has adopted a specific scheduling policy can select a solution from the corresponding Pareto front considering their economic as well as environmental targets. Nevertheless, if the retailer wishes to select a scheduling policy and then a solution under that policy considering their economic and environmental targets, then PF^1 and PF^2 should be compared. To do so, Definition 2 can be used.

Note that if $PF^1 \ll PF^2$ ($PF^2 \ll PF^1$), the retailer will prefer sequential splitting (sequential delivery) independent of their economic and environmental targets. On the other hand, if $PF^1 \lesseqgtr PF^2$, the retailer's delivery scheduling policy choice will depend on their economic and environmental targets. The next three examples illustrate that each of the following three cases is possible: $PF^1 \ll PF^2$ (in Example 1), $PF^1 \lesseqgtr PF^2$ (in Example 2), and $PF^2 \ll PF^1$ (in Example 3). Prior to discussing the implications of these examples, it is worthwhile to note that $PF^1(\mathbf{x}) \equiv PF^2(\mathbf{x})$ if

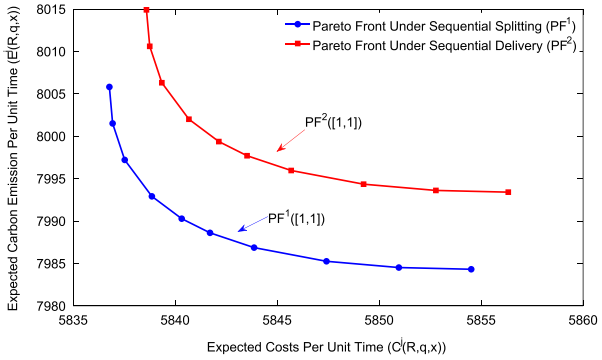

Fig. 3. Illustration of the Pareto fronts under delivery scheduling policies for Example 1.

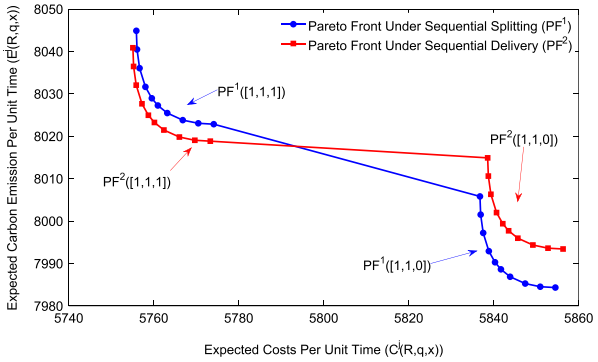

Fig. 4. Illustration of the Pareto fronts under delivery scheduling policies for Example 2.

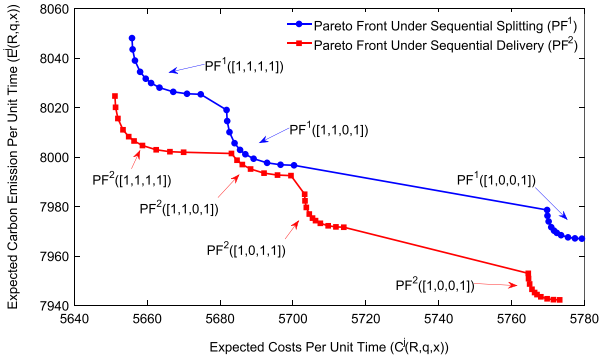

Fig. 5. Illustration of the Pareto fronts under delivery scheduling policies for Example 3.

$\sum_{i \in I} x_i = 1$. Thus, if $Z^1 = Z^2 = Z$ and Z consists of supplier selection decisions only with one supplier, then $PF^1 \equiv PF^2$.

The settings of the examples are as follows. Consider a retailer with the following parameters: normally distributed annual demand with $\lambda = 3000$, $\upsilon = 500$, and cost parameters such that $\tilde{h} = 0.1$/unit/year, $\tilde{p} = 15$, $\tilde{c} = 1$, and $\tilde{A} = 20$, and emission parameters such that $\widehat{h} = 0.5$/unit/year, $\widehat{p} = 10$, $\widehat{c} = 1$, and $\widehat{A} = 15$. Consider that there are four suppliers available with the characteristics as noted below.

Supplier	$\tilde{e}_i$	$\widehat{e}_i$	$\tilde{a}_i$	$\widehat{a}_i$	τ_i	w_i
1	0.5	1.1	9	12	0.02	50
2	0.6	1.3	12	14	0.07	60
3	0.55	1.2	11	17	0.03	40
4	0.65	1.4	10	13	0.01	70

In Example 1, the retailer can use only Suppliers 1 and 2 for delivery. Fig. 3 illustrates PF^1 and PF^2 and shows that $PF^1 \ll PF^2$ even if $Z^1 = Z^2 = \{[1,1]\}$; therefore, the retailer will prefer sequential splitting independent of their cost and/or emission targets.

In Example 2, the retailer can use only Suppliers 1, 2 and 3 for delivery. Fig. 4 shows PF^1 and PF^2, and while $Z^1 = Z^2 = \{[1,1,0],[1,1,1]\}$, $PF^1 \lesseqgtr PF^2$. Specifically, if the retailer sets a low cost target (< 5800), then they would prefer sequential delivery as that results in lower emissions for low cost solutions. Also, observe that all three suppliers are used and $PF^2([1,1,1]) \ll PF^1([1,1,1])$. However, if the retailer sets a low emissions target ($< \sim 8015$), then they would prefer sequential splitting with only Suppliers 1 and 2, as sequential splitting results in lower cost for low emission solutions (observe that $PF^1([1,1,0]) \ll PF^2([1,1,0])$). Note how the two curved parts of the Pareto front in Fig. 4 correspond to different supplier selections with the removal of Supplier 3 in the lower right, which allows lower emissions, but at greater costs.

Finally, in Example 3, the retailer can use all four suppliers for delivery. In this case, as can be observed from Fig. 5, $PF^2 \ll PF^1$, and therefore the retailer will prefer sequential delivery independent of their cost and/or carbon emissions targets. Specifically, the retailer can always find a solution under sequential delivery with a lower emission and/or cost level compared to sequential splitting (observe that $PF^2([1,1,1,1]) \cup PF^2([1,1,0,1]) \ll PF^1([1,1,1,1]) \cup PF^1([1,1,0,1])$ and $PF^2([1,0,0,1]) \ll PF^1([1,0,0,1])$). Furthermore, it is possible to achieve some specific cost and emissions targets only under sequential delivery (see $PF^2([1,0,1,1])$. Also note how moving along the Pareto front from upper left to lower right in Fig. 5 corresponds to removing suppliers, with the midsection corresponding to different supplier choices for sequential delivery and sequential splitting. This highlights the complex interactions between delivery scheduling policy and supplier selection decisions with multiple objectives.

In Appendix A.11, we present the results for Examples 1–3 when the daily demand has a gamma distribution. This shows that sequential splitting dominates in Examples 1 and 2, but either policy may be the best in Example 3, depending on the retailer's cost and emissions preferences.

It is clear from these examples that the delivery scheduling policy has significant effects on the economic and environmental performance of an inventory control system. Therefore, the models presented in this study will help decision makers to evaluate not only the costs but also the emissions of inventory related activities and supplier selection decisions. Furthermore, the above examples also demonstrate that a good approximation of the Pareto fronts is crucial for accurately comparing alternative delivery scheduling policies. The methods proposed in this study provide effective decision support tools for such comparative analysis. Finally, it is worthwhile to note that when environmental costs or regulations such as tax and cap-and-trade are considered instead of environmental objectives as discussed in the alternative models presented in Section 3.3, it is possible that sequential splitting is preferable over sequential delivery or vice versa.

6. Conclusions and future research

This paper studies an integrated stochastic inventory control, supplier selection, and order splitting problem under two different delivery scheduling policies with environmental considerations. We formulate and analyze a continuous review inventory control model with order splitting allowed among an arbitrary number of heterogeneous suppliers and with two objectives (cost and emission minimizations) under sequential splitting and sequential

delivery policies. The resulting models contribute to (i) the literature on environmental inventory control models by studying continuous review inventory control models with order splitting and environmental objectives and (ii) the literature on inventory control models with order splitting by comparing different delivery scheduling policies in terms of economic as well as environmental performance.

The resulting models are bi-objective mixed-integer nonlinear programming problems, for which there is a limited number of studies proposing exact methods to generate the Pareto fronts. Upon investigating the basic properties of Pareto efficient solutions, we first discuss an implementation of the adaptive ϵ-constraint method. Then, further properties, which extend the results for multi-objective mixed-integer linear programming problems, are used within an evolutionary search algorithm. Our numerical studies indicate that the evolutionary search algorithm is efficient compared to the adaptive ϵ-constraint algorithm. Another contribution of this study is, therefore, in providing some characteristics of bi-objective mixed-integer nonlinear programming problems.

Finally, the use of the models and the tools presented are demonstrated with numerical analyses. First, we illustrate the effects of demand variability on the costs and carbon emissions under each delivery scheduling policy. As expected, both costs and carbon emissions tend to increase as demand variance increases. In addition, we note that sequential splitting can become more preferable in case of high demand variance. Then, we show with three sample scenarios that a retailer's delivery scheduling policy can be either independent of, or dependent on, their cost and/or emissions targets.

One of the future research directions is to analyze similar models with stochastic delivery lead times. Furthermore, the literature review reveals that there are a limited number of studies that investigate multi-item inventory control systems with environmental considerations. Economic and environmental analyses of multi-item/multi-echelon inventory systems subject to deterministic and stochastic demand under different delivery scheduling policies remain as future research questions. The models in such studies will correspond to multi-objective mixed-integer nonlinear programming problems, which lack detailed research. Another important future direction is, therefore, to investigate further properties of the multi-objective mixed-integer nonlinear programming problems.

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Appendix A

A.1. Illustration of inventory calculation for sequential delivery

Here, we demonstrate how to calculate the total expected inventory held per cycle under sequential delivery with three selected suppliers such that $\tau_1 < \tau_2 < \tau_3$. Fig. 6 illustrates the average inventory over time. $A1$, $A2$, $A3$, and $A4$ are the areas under each right-trapezoid. The area calculation for each trapezoid is given under the figure. The expression after the first $=$ sign is for any demand distribution (as in Section 3.3), while the expression after the second $=$ sign is for normal demand distribution. The total expected inventory held per cycle under sequential delivery is found by summing the areas of the trapezoids.

A.2. ϵ-constraint algorithm for $\mathbf{P}_j|\mathbf{x}$

Here, we give the algorithmic description of the classical ϵ-constraint algorithm for problem $\mathbf{P}_j|\mathbf{x}$. Recall that $\left(\tilde{R}^j(\mathbf{x}),\tilde{\mathbf{q}}^j(\mathbf{x})\right) = \arg\min\left\{C^j(R,\mathbf{q}|\mathbf{x}) : 0 \le q_i \le x_i w_i \ \forall i \in I, R>0\right\}$, $\left(\widehat{R}^j(\mathbf{x}),\widehat{\mathbf{q}}^j(\mathbf{x})\right) = \arg\min\left\{C^j(R,\mathbf{q}|\mathbf{x}) : 0 \le q_i \le x_i w_i \ \forall i \in I, R>0\right\}$, $\tilde{C}^j(\mathbf{x}) = C^j\left(\tilde{R}^j(\mathbf{x}),\tilde{\mathbf{q}}^j(\mathbf{x}),\mathbf{x}\right)$, $\tilde{E}^j(\mathbf{x}) = E^j(\tilde{R}^j(\mathbf{x}),\tilde{\mathbf{q}}^j(\mathbf{x}),\mathbf{x})$, $\widehat{C}^j(\mathbf{x}) = C^j\left(\widehat{R}^j(\mathbf{x}),\widehat{\mathbf{q}}^j(\mathbf{x}),\mathbf{x}\right)$, and $\widehat{E}^j(\mathbf{x}) = E^j\left(\widehat{R}^j(\mathbf{x}),\widehat{\mathbf{q}}^j(\mathbf{x}),\mathbf{x}\right)$.

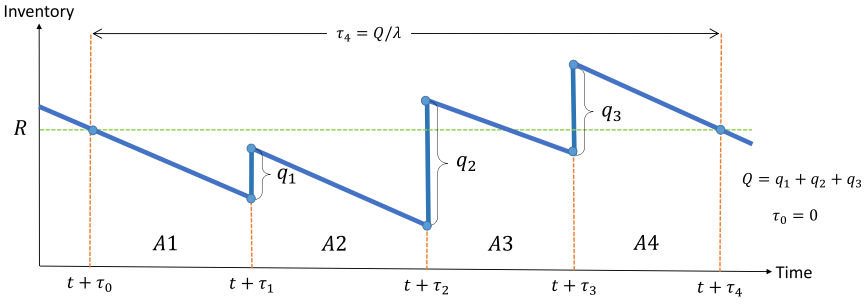
ϵ-constraint algorithm for $\mathbf{P}_j|\mathbf{x}$:

Step 1: Given M and $\mathbf{x}$, set $PF^j(\mathbf{x}) = \left\{(\tilde{R}^j(\mathbf{x}),\tilde{\mathbf{q}}^j(\mathbf{x})),(\widehat{R}^j(\mathbf{x}),\widehat{\mathbf{q}}^j(\mathbf{x}))\right\}$

Step 2: Set $\delta_E = \tilde{E}^j(\mathbf{x})$, $\epsilon_E = (\tilde{E}^j(\mathbf{x}) - \widehat{E}^j(\mathbf{x}))/M$, $\delta_C = \widehat{C}^j(\mathbf{x})$, and $\epsilon_C = \left(\widehat{C}^j(\mathbf{x}) - \tilde{C}^j(\mathbf{x})\right)/M$

Step 3: Let $\delta_E := \delta_E - \epsilon_E$ and $\delta_C := \delta_C - \epsilon_C$

Step 4:



$A1 = [R + (R - \lambda_{(\tau_1-\tau_0)})](\tau_1 - \tau_0)/2 = [R + (R - \lambda\tau_1)](\tau_1 - \tau_0)/2$

$A2 = [(R - \lambda_{(\tau_1-\tau_0)} + q_1) + (R - \lambda_{(\tau_1-\tau_0)} - \lambda_{(\tau_2-\tau_1)} + q_1)](\tau_2 - \tau_1)/2 = [(R - \lambda\tau_1 + q_1) + (R - \lambda\tau_2 + q_1)](\tau_2 - \tau_1)/2$

$A3 = [(R - \lambda_{(\tau_1-\tau_0)} - \lambda_{(\tau_2-\tau_1)} + q_1 + q_2) + (R - \lambda_{(\tau_1-\tau_0)} - \lambda_{(\tau_2-\tau_1)} - \lambda_{(\tau_3-\tau_2)} + q_1 + q_2)](\tau_3 - \tau_2)/2 = [(R - \lambda\tau_2 + q_1 + q_2) + (R - \lambda\tau_3 + q_1 + q_2)](\tau_3 - \tau_2)/2$

$A4 = [(R - \lambda_{(\tau_1-\tau_0)} - \lambda_{(\tau_2-\tau_1)} - \lambda_{(\tau_3-\tau_2)} + Q) + (R - \lambda_{(\tau_1-\tau_0)} - \lambda_{(\tau_2-\tau_1)} - \lambda_{(\tau_3-\tau_2)} - \lambda_{(\tau_4-\tau_3)} + Q)](\tau_4 - \tau_3)/2 = [(R - \lambda\tau_3 + Q) + (R)](\tau_4 - \tau_3)/2$

Fig. 6. Average inventory vs. time under sequential delivery.

Determine $(R^C, \mathbf{q}^C) = \text{argmin}\{C^j(R, \mathbf{q}|\mathbf{x}) : E^j(R, \mathbf{q}|\mathbf{x}) \leq \delta_E, 0 \leq q_i \leq x_i w_i \ \forall i \in I, R > 0\}$

Step 5: Determine $(R^E, \mathbf{q}^E) = \text{argmin}\{E^j(R, \mathbf{q}|\mathbf{x}) : C^j(R, \mathbf{q}|\mathbf{x}) \leq \delta_C, 0 \leq q_i \leq x_i w_i \ \forall i \in I, R > 0\}$

Step 6: Set $PF^j(\mathbf{x}) := PF^j(\mathbf{x}) \cup \{(R^C, \mathbf{q}^C), (R^E, \mathbf{q}^E)\}$

Step 7: If $\delta_E > \widehat{E}^j(\mathbf{x})$ and $\delta_C > \tilde{C}^j(\mathbf{x})$, go to Step 3; else, return $PF^j(\mathbf{x})$.

To increase the diversity of $PF^j(\mathbf{x})$, the above ϵ-constraint algorithm is executed with both possibilities: cost minimization and emissions constraint, and emissions minimization and cost constraint. Note that it will generate $2M+2$ solutions. In determining $\left(\tilde{R}^j(\mathbf{x}), \tilde{\mathbf{q}}^j(\mathbf{x})\right)$, $\left(\widehat{R}^j(\mathbf{x}), \widehat{\mathbf{q}}^j(\mathbf{x})\right)$, $(R^C, \mathbf{q}^C)$, and $(R^E, \mathbf{q}^E)$, the interior-point-method is used as one needs to solve nonlinear optimization models with continuous variables only.

A.3. Iterative procedure to determine $PE(\Phi)$

Here, we give the algorithmic description of an iterative method to determine $PE(\Phi)$, where $\Phi = \{(R, \mathbf{q}, \mathbf{x})^1, (R, \mathbf{q}, \mathbf{x})^2, \ldots, (R, \mathbf{q}, \mathbf{x})^\ell\}$. Similar procedures are given in the literature (see, e.g., [82,80,81]). For notational simplicity, let $C^j_o = C^j((R, \mathbf{q}, \mathbf{x})^o)$ and $E^j_o = E^j((R, \mathbf{q}, \mathbf{x})^o)$ for $1 \leq o \leq \ell$.

Iterative procedure to determine $PE(\Phi)$

Step 1: Set $o = 1$
Step 2: While $o \leq |\Phi| - 1$
Step 3: Set $w = \ell + 1$
Step 4: While $w \leq |\mathcal{S}|$
Step 5: If $C^j_o = C^j_w$ and $E^j_o = E^j_w$, set $w = w + 1$
Step 6: Else if $C^j_o \leq C^j_w$ and $E^j_o \leq E^j_w$, set $\Phi := \Phi \backslash \{(R, \mathbf{q}, \mathbf{x})^w\}$
Step 7: Else if $C^j_o \geq C^j_w$ and $E^j_o \geq E^j_w$, set $\Phi := \Phi \backslash \{(R, \mathbf{q}, \mathbf{x})^o\}$, $o = o - 1$, $w = |\Phi| + 1$
Step 8: End
Step 9: Set $o = o + 1$
Step 10: End
Step 11: Return $PE(\Phi) = \Phi$.

A.4. Total enumeration algorithm for PF^j

The algorithmic description of the total enumeration algorithm to approximate PF^j is as follows:

Total enumeration algorithm for $\mathbf{P}_j$:

Step 1: Let $L = [0, 1]^n$ and $\Phi = \varnothing$
Step 2: Pick a $\mathbf{x} \in L$ and generate approximated $PF^j(\mathbf{x})$
Step 3: Set $L := L \backslash \{\mathbf{x}\}$ and $\Phi := \Phi \cup PF^j(\mathbf{x})$
Step 4: If $L \neq \varnothing$, go to Step 2; else, go to Step 5
Step 5: Return $PF^j = PE(\phi)$.

A.5. Adaptive $\epsilon-$ constraint algorithm for $\mathbf{P}_j$

Below, we present the algorithmic description of the adaptive ϵ-constraint algorithm with both possible executions for problem $\mathbf{P}_j$ to approximate PF^j.

Adaptive ϵ**-constraint algorithm for** $\mathbf{P}_j$:

Step 1: Set $PF^j = \varnothing$, $\delta_E = \infty$, $\mathbf{x} = \mathbf{0}$, and $\epsilon = 0$
Step 2: If $\delta_E \geq \widehat{E}^j$, determine $(R^{j\delta_E}, \mathbf{q}^{j\delta_E}, \mathbf{x}^{j\delta_E})$ and set $PF^j := PF^j \cup (R^{j\delta_E}, \mathbf{q}^{j\delta_E}, \mathbf{x}^{j\delta_E})$
Step 3: If $\mathbf{x}^{j\delta_E} \neq \mathbf{x}$, set $\delta_E := E^j(R^{j\delta_E}, \mathbf{q}^{j\delta_E}, \mathbf{x}^{j\delta_E})$, $\epsilon := \left[\delta_E - \widehat{E}^j(\mathbf{x}^{j\delta_E})\right]/M$,
Step 4: Set $\delta_E := \delta_E - \epsilon$ and go to Step 2
Step 5: Else, set $\delta_C = \infty$, $\mathbf{x} = \mathbf{0}$, and $\epsilon = 0$
Step 6: If $\delta_C \geq \tilde{C}^j$, determine $(R^{j\delta_C}, \mathbf{q}^{j\delta_C}, \mathbf{x}^{j\delta_C})$ and set $PF^j := PF^j \cup (R^{j\delta_C}, \mathbf{q}^{j\delta_C}, \mathbf{x}^{j\delta_C})$
Step 7: If $\mathbf{x}^{j\delta_C} \neq \mathbf{x}$, set $\delta_C := C^j(R^{j\delta_C}, \mathbf{q}^{j\delta_C}, \mathbf{x}^{j\delta_C})$, $\epsilon := \left[\delta_C - \tilde{C}^j(\mathbf{x}^{j\delta_C})\right]/M$,
Step 8: Set $\delta_E := \delta_E - \epsilon$ and go to Step 6
Step 9: Else, return PF^j and $Z^j = \{\mathbf{x} : \exists (R, \mathbf{q}, \mathbf{x}) \in PF^j\}$.

Steps 1–5 are the execution of the adaptive ϵ-constraint algorithm with the cost minimization objective and Steps 5–9 are the execution of the adaptive ϵ-constraint algorithm with the emissions minimization objective.

A.6. Multi-start search heuristic

Here we give the details of the multi-start search heuristic for determining $(R^{j\delta_E}, \mathbf{q}^{j\delta_E}, \mathbf{x}^{j\delta_E}) = \arg\backslash\min\{C^j(R, \mathbf{q}, \mathbf{x}) : E^j(R, \mathbf{q}, \mathbf{x}) \leq \delta_E, 0 \leq q_i \leq x_i w_i \ \forall \ i \in I, x_i \in \{0, 1\} \ \forall \ i \in I, R > 0\}$ (the details are similar for determining $(R^{j\delta_C}, \mathbf{q}^{j\delta_C}, \mathbf{x}^{j\delta_C}) = \arg\backslash\min\{E^j(R, \mathbf{q}, \mathbf{x}) : C^j(R, \mathbf{q}, \mathbf{x}) \leq \delta_C, 0 \leq q_i \leq x_i w_i \ \forall \ i \in I, x_i \in \{0, 1\} \ \forall \ i \in I, R > 0\}$). In particular, given a starting solution, the search heuristic continuously moves to a better neighbor if one exists. If it cannot find a better neighbor, the search with the current starting solution terminates. Repeating this with multiple starting solutions, the final solution returned is the best out of the solutions achieved with the neighbor search. Let us define $(R^{j\delta_E}(\mathbf{x}), \mathbf{q}^{j\delta_E}(\mathbf{x})) = \arg\backslash\min\{C^j(R, \mathbf{q}|\mathbf{x}) : E^j(R, \mathbf{q}|\mathbf{x}) \leq \delta_E, \ 0 \leq q_i \leq x_i w_i \ \forall \ i \in I, R > 0\}$ as determined by the interior-point-method. Below, we give the algorithmic description of the multi-start search heuristic.

Multi-start search heuristic for $(R^{j\delta_E}, \mathbf{q}^{j\delta_E}, \mathbf{x}^{j\delta_E})$

Step 1: Given δ_E and starting solutions $\mathbf{x}^1, \mathbf{x}^2, \ldots, \mathbf{x}^\ell$, set $BN = \varnothing$
Step 2: For $o = 1 : \ell$
Step 3: Let $\mathbf{x} = \mathbf{x}^o$
Step 4: Given $\mathbf{x}$, set $N = \varnothing$ and determine $(R^{j\delta_E}(\mathbf{x}), \mathbf{q}^{j\delta_E}(\mathbf{x}))$
Step 5: For $i = 1 : n$
Step 6: Let $\mathbf{x}^{(i)} = \mathbf{x}$, set $\mathbf{x}^{(i)}_i = 1 - \mathbf{x}_i$, and determine $(R^{j\delta_E}(\mathbf{x}^{(i)}), \mathbf{q}^{j\delta_E}(\mathbf{x}^{(i)}))$
Step 7: If $(R^{j\delta_E}(\mathbf{x}^{(i)}), \mathbf{q}^{j\delta_E}(\mathbf{x}^{(i)}))$ exists, $N := N \cup \{(R^{j\delta_E}(\mathbf{x}^{(i)}), \mathbf{q}^{j\delta_E}(\mathbf{x}^{(i)}), \mathbf{x}^{(i)})\}$
Step 8: End
Step 9: Determine $(\overrightarrow{R}, \overrightarrow{\mathbf{q}}, \overrightarrow{\mathbf{x}}) = \arg\backslash\min\{C^j(\overline{R}, \overline{\mathbf{q}}, \overline{\mathbf{x}}) : (\overline{R}, \overline{\mathbf{q}}, \overline{\mathbf{x}}) \in N\}$
Step 10: If $C^j(R^{j\delta_E}(\mathbf{x}), \mathbf{q}^{j\delta_E}(\mathbf{x}), \mathbf{x}) \geq C^j(\overrightarrow{R}, \overrightarrow{\mathbf{q}}, \overrightarrow{\mathbf{x}})$, set $\mathbf{x} = \overrightarrow{\mathbf{x}}$ and go to Step 4
Step 11: Else, $BN := BN \cup \{(\overrightarrow{R}, \overrightarrow{\mathbf{q}}, \overrightarrow{\mathbf{x}})\}$
Step 12: End
Step 13: Return $(R^{j\delta_E}, \mathbf{q}^{j\delta_E}, \mathbf{x}^{j\delta_E}) = \arg\backslash\min\{C^j(R, \mathbf{q}, \mathbf{x}) : (R, \mathbf{q}, \mathbf{x}) \in BN\}$

A.7. Proofs of Properties 1–3

Proof of Property 1: Given $\mathbf{x}^1$ and $\mathbf{x}^2$ are two feasible supplier selection decisions such that $\mathbf{x}^1 \neq \mathbf{x}^2$, consider a solution $(R, \mathbf{q}, \mathbf{x}^2) \in PF^j(\mathbf{x}^2)$. From Property 2, we know that (i) $\tilde{C}^j(\mathbf{x}^2) \leq C^j(R, \mathbf{q}, \mathbf{x}^2) \leq \widehat{C}^j(\mathbf{x}^2)$ and (ii) $\widehat{E}^j(\mathbf{x}^2) \leq E^j(R, \mathbf{q}, \mathbf{x}^2) \leq \tilde{E}^j(\mathbf{x}^2)$. Now, suppose that (iii) $\tilde{C}^j(\mathbf{x}^1) \leq \tilde{C}^j(\mathbf{x}^2) \leq \widehat{C}^j(\mathbf{x}^1)$ and (iv) $\tilde{E}^j(\mathbf{x}^1) < \widehat{E}^j(\mathbf{x}^2)$ and consider $(\tilde{R}^j(\mathbf{x}^1), \tilde{\mathbf{q}}^j(\mathbf{x}^1), \mathbf{x}^1)$. Recall that $\tilde{C}^j(\mathbf{x}^1) = C^j(\tilde{R}^j(\mathbf{x}^1), \tilde{\mathbf{q}}^j(\mathbf{x}^1), \mathbf{x}^1)$ and $\tilde{E}^j(\mathbf{x}^1)$

$= E^j\left(\tilde{R}^j(\mathbf{x}^1), \tilde{\mathbf{q}}^j(\mathbf{x}^1), \mathbf{x}^1\right)$ by definition. It then follows that $C^j(\tilde{R}^j(\mathbf{x}^1), \tilde{\mathbf{q}}^j(\mathbf{x}^1), \mathbf{x}^1) \leq C^j(R, \mathbf{q}, \mathbf{x}^2)$ from (i) and (iii) and $E^j\left(\tilde{R}^j(\mathbf{x}^1), \tilde{\mathbf{q}}^j(\mathbf{x}^1), \mathbf{x}^1\right) < E^j(R, \mathbf{q}, \mathbf{x}^2)$ from (ii) and (iv). Therefore, any $(R, \mathbf{q}, \mathbf{x}^2) \in PF^j(\mathbf{x}^2)$ is not Pareto efficient by Definition 1; hence, $(R, \mathbf{q}, \mathbf{x}^2) \notin PF^j$ $\forall (R, \mathbf{q}, \mathbf{x}^2) \in PF^j(\mathbf{x}^2)$, which means that $\mathbf{x}^2 \notin Z^j$. Now, suppose that (v) $\widehat{C}^j(\mathbf{x}^1) < \tilde{C}^j(\mathbf{x}^2)$ and (vi) $\widehat{E}^j(\mathbf{x}^1) \leq \widehat{E}^j(\mathbf{x}^2)$ and consider $\left(\widehat{R}^j(\mathbf{x}^1), \widehat{\mathbf{q}}^j(\mathbf{x}^1), \mathbf{x}^1\right)$. Recall that $\widehat{C}^j(\mathbf{x}^1) = C^j\left(\widehat{R}^j(\mathbf{x}^1), \widehat{\mathbf{q}}^j(\mathbf{x}^1), \mathbf{x}^1\right)$, and $\widehat{E}^j(\mathbf{x}^1) = E^j\left(\widehat{R}^j(\mathbf{x}^1), \widehat{\mathbf{q}}^j(\mathbf{x}^1), \mathbf{x}^1\right)$ by definition. It then follows that $C^j\left(\widehat{R}^j(\mathbf{x}^1), \widehat{\mathbf{q}}^j(\mathbf{x}^1), \mathbf{x}^1\right) < C^j(R, \mathbf{q}, \mathbf{x}^2)$ from (i) and (v) and $E^j(\widehat{R}^j(\mathbf{x}^1), \widehat{\mathbf{q}}^j(\mathbf{x}^1), \mathbf{x}^1) \leq E^j(R, \mathbf{q}, \mathbf{x}^2)$ from (ii) and (vi). Therefore, any $(R, \mathbf{q}, \mathbf{x}^2) \in PF^j(\mathbf{x}^2)$ is not Pareto efficient by Definition 1; hence, $(R, \mathbf{q}, \mathbf{x}^2) \notin PF^j$ $\forall (R, \mathbf{q}, \mathbf{x}^2) \in PF^j(\mathbf{x}^2)$, which means that $\mathbf{x}^2 \notin Z^j$. □

Proof of Property 2: Suppose that S is a set of $\mathbf{x}$'s and $\overrightarrow{\mathbf{x}} \notin S$. Consider that $\widehat{E}^j(\overrightarrow{\mathbf{x}}) > \min_{\mathbf{x} \in S}\{\tilde{E}^j(\mathbf{x}) : \tilde{C}^j(\mathbf{x}) \leq \tilde{C}^j(\overrightarrow{\mathbf{x}}), \tilde{C}^j(\overrightarrow{\mathbf{x}}) \leq \widehat{C}^j(\mathbf{x})\}$ and let $\mathbf{x}' = \arg\min_{\mathbf{x} \in S}\{\tilde{E}^j(\mathbf{x}) : \tilde{C}^j(\mathbf{x}) \leq \tilde{C}^j(\overrightarrow{\mathbf{x}}), \tilde{C}^j(\overrightarrow{\mathbf{x}}) \leq \widehat{C}^j(\mathbf{x})\}$. These imply that $\tilde{C}^j(\mathbf{x}') \leq \tilde{C}^j(\overrightarrow{\mathbf{x}}) \leq \widehat{C}^j(\mathbf{x}')$ and $\tilde{E}^j(\mathbf{x}') < \widehat{E}^j(\overrightarrow{\mathbf{x}})$. It then follows from Property 1 that $\overrightarrow{\mathbf{x}} \notin Z^j$. Now, consider that $\widehat{E}^j(\overrightarrow{\mathbf{x}}) \geq \min_{\mathbf{x} \in \overline{Z}^j}\left\{\widehat{E}^j(\mathbf{x}) : \widehat{C}^j(\mathbf{x}) < \tilde{C}^j(\overrightarrow{\mathbf{x}})\right\}$ and let $\mathbf{x}'' = \arg\min_{\mathbf{x} \in \overline{Z}^j}\left\{\widehat{E}^j(\mathbf{x}) : \widehat{C}^j(\mathbf{x}) < \tilde{C}^j(\overrightarrow{\mathbf{x}})\right\}$. These imply that $\widehat{C}^j(\mathbf{x}'') < \tilde{C}^j(\overrightarrow{\mathbf{x}})$ and $\widehat{E}^j(\mathbf{x}'') \leq \widehat{E}^j(\overrightarrow{\mathbf{x}})$. It then follows from Property 1 that $\overrightarrow{\mathbf{x}} \notin Z^j$. □

Proof of Property 3: Suppose that $(R, \mathbf{q}, \mathbf{x}) \in PF^j(\mathbf{x})$ is such that $x_i = 1$ and $q_i = 0$ for a supplier $i \in I$ such that $\tilde{a}_i > 0$ or $\hat{a}_i > 0$. Now, consider the solution $(\overline{R}, \overline{\mathbf{q}}, \overline{\mathbf{x}})$ such that $\overline{R} = R$, $\mathbf{q} = \overline{\mathbf{q}}$, and $\overline{x}_j = x_j$ $\forall j \neq i, j \in I$ and $\overline{x}_i = 0$. Since $(R, \mathbf{q}, \mathbf{x})$ is feasible, it follows that $(\overline{R}, \overline{\mathbf{q}}, \overline{\mathbf{x}})$ is also feasible. Furthermore, since $\tilde{a}_i > 0$ or $\hat{a}_i > 0$, we have either $C^j(R, \mathbf{q}, \mathbf{x}) > C^j(\overline{R}, \overline{\mathbf{q}}, \overline{\mathbf{x}})$ and $E^j(R, \mathbf{q}, \mathbf{x}) \geq E^j(\overline{R}, \overline{\mathbf{q}}, \overline{\mathbf{x}})$ or $C^j(R, \mathbf{q}, \mathbf{x}) \geq C^j(\overline{R}, \overline{\mathbf{q}}, \overline{\mathbf{x}})$ and $E^j(R, \mathbf{q}, \mathbf{x}) > E^j(\overline{R}, \overline{\mathbf{q}}, \overline{\mathbf{x}})$. Therefore, it follows from Definition 1 that $(R, \mathbf{q}, \mathbf{x}) \notin PF^j$. Then, if this is the case $\forall (R, \mathbf{q}, \mathbf{x}) \in PF^j(\mathbf{x})$, then $PF^j(\mathbf{x}) \cap PF^j = \varnothing$; hence, $\mathbf{x} \notin Z^j$ by definition of Z^j. □

A.8. Evolutionary search algorithm to approximate PF^j

The algorithmic description of the evolutionary search algorithm to approximate PF^j is stated below:

Evolutionary search algorithm for $\mathbf{P}_j$:

Step 1: Given α, β, γ, randomly generate S with α chromosomes, set $S^0 = \varnothing$, and $\psi = 0$

Step 2: If $\psi \leq \gamma$

Step 3: Given S, determine S^* using fitness evaluation operations

Step 4: If $S^0 \equiv S^*$, set $\psi := \psi + 1$

Step 5: Else set $\psi := 0$ and $S^0 := S^*$

Step 6: Given S^*, generate a new S using mutation operations and go to Step 2

Step 7: Else, return $PF^j = PE(\bigcup_{\mathbf{x} \in S^*} PF^j(\mathbf{x}))$ and $Z^j = \{\mathbf{x} : \exists (R, \mathbf{q}, \mathbf{x}) \in PF^j\}$.

A.9. Details of the problem settings

The settings of the problem instances are defined similar to Schaefer and Konur [109]. In particular, we let $\lambda = 2000$ units and $\vartheta = 100$ in all problem instances. Furthermore, it is assumed that $\tilde{c} = \hat{c} = 1$ as expected costs and carbon emissions per unit time do not depend on the retailer's decision variables. The retailer's other cost and emissions parameters are generated from uniform distributions with the following ranges: $\tilde{h} \sim [2, 8]$, $\hat{h} \sim [5, 10]$, $\tilde{p} \sim [2, 8]$, $\hat{p} \sim [5, 10]$, $\tilde{A} \sim [50, 150]$, $\hat{A} \sim [50, 100]$. Similar parameter values are defined in environmental inventory control models (see, e.g., [69,29,120,79,83]).

Supplier parameters are generated as follows. We use the following uniform distribution ranges for delivery lead times, capacities, and fixed delivery costs: $\tau_i \sim [0.1, 0.5]$, $w_i \sim [100, 200]$ (rounded to the closest multiplier of 10 for practical purposes), and $\tilde{a}_i \sim [100, 250]$. We generate the other supplier costs and supplier emissions parameters as follows. First, we randomly generate a distance, g, such that $g \sim U[100, 500]$. Then, $\tilde{e}_i^E$ is generated assuming $\tilde{e}_i^E \sim U[0.005, 0.015]$. Here, $\tilde{e}_i^E$ is the per mile transportation cost of supplier i's empty vehicle. Then, $\tilde{e}_i^F = \beta \tilde{e}_i^E$, where beta is the empty-to-full ratio for a vehicle and it is generated assuming $\beta \sim U[0.2, 0.8]$. Here, $\tilde{e}_i^F / w_i$ represents the per mile per unit transportation cost of supplier i. Then, $\tilde{e}_i = g\left(\tilde{e}_i^E + \tilde{e}_i^F / w_i\right)$. $\hat{e}_i$ is generated similarly by letting $\hat{e}_i^E \sim U[1, 1.5]$ and we let $\hat{a}_i = g\hat{e}_i^E$.

In the ϵ-constraint algorithm given in Appendix A.2, which is used in the TE, AE, and ES algorithms, we set $M = 4$; thus, 10 Pareto efficient solutions are targeted to be generated for a given $\mathbf{x}$. In the multi-start search heuristic given in Appendix A.6, which is used within the AE algorithm, and initialization of the ES algorithm, we generate $2n$ starting solutions. That is $\ell = 2n$ in the multi-start search heuristic and $\alpha = 2n$ in the ES algorithm. Furthermore, in mutation operations of the ES algorithm, $2n$ chromosomes are randomly generated, i.e., $\beta = 2n$. Finally, we set $\gamma = n$ as the termination criteria in ES.

A.10. Tables of Sections 5.1 and 5.2

See Tables 2–7.

Table 2
Comparison of the algorithms for sequential splitting.

n	TE		AE				ES			
	$\lvert Z_{TE}^1 \rvert$	*cpu*	$\lvert Z_{AE}^1 \rvert$	*cpu*	*AE* ∩ *TE* (%)	*AE* ∩ *ES* (%)	$\lvert Z_{ES}^1 \rvert$	*cpu*	*ES* ∩ *TE* (%)	*ES* ∩ *AE* (%)
3	2.3	2.1	2.2	1.2	98.0	98.0	2.3	1.2	100.0	100.0
4	2.6	5.3	2.5	2.5	96.7	96.7	2.6	2.1	100.0	100.0
5	3.9	13.0	3.6	9.0	94.6	96.0	3.8	4.2	98.6	100.0
6	3.7	31.6	3.4	16.7	89.0	92.3	3.6	5.7	96.7	96.7
7	4.3	70.4	3.9	43.3	86.3	89.7	4.2	10.7	96.7	97.1
8	3.7	180.8	2.9	52.2	82.9	85.0	3.4	14.3	97.9	95.0
9	3.4	402.7	2.8	68.0	83.1	88.5	3.2	18.3	94.7	95.8
10	4.1	967.1	3.5	162.8	80.2	86.2	3.8	29.6	94.0	93.6
avg.	3.5	209.1	3.1	44.5	88.8	91.5	3.4	10.8	97.3	97.3

Table 3
Comparison of the algorithms for sequential delivery.

n	TE		AE				ES			
	$\lvert Z^2_{TE}\rvert$	*cpu*	$\lvert Z^2_{AE}\rvert$	*cpu*	$AE \cap TE$ (%)	$AE \cap ES$ (%)	$\lvert Z^2_{ES}\rvert$	*cpu*	$ES \cap TE$ (%)	$ES \cap AE$ (%)
3	2.4	2.5	2.4	1.8	100.0	100.0	2.4	1.5	100.0	100.0
4	2.6	6.8	2.3	2.9	92.2	92.2	2.6	2.4	100.0	100.0
5	3.7	17.0	3.3	9.8	88.1	88.1	3.7	5.4	100.0	95.0
6	3.9	45.9	3.6	25.6	86.7	86.7	3.8	10.5	98.0	93.0
7	5.7	106.5	5.5	97.5	97.2	97.2	5.7	19.2	100.0	98.9
8	4.3	310.0	3.9	73.4	89.8	89.8	4.3	32.9	100.0	96.7
9	3.8	661.7	3.8	264.9	95.6	97.2	3.6	47.2	95.0	92.1
10	5.9	1749.9	5.4	476.4	89.5	86.1	5.9	76.3	96.7	93.3
avg.	4.0	362.5	3.8	119.0	92.4	92.2	4.0	24.5	98.7	96.1

Table 4
Average mean-pareto-solutions and percent differences as υ increases.

υ	Avg.				% Diff.		
	$\overline{C}^1$	$\overline{E}^1$	$\overline{C}^2$	$\overline{E}^2$	ΔC	ΔE	$\Delta C+\Delta E$
200	13,868	13,470	13,800	13,430	−0.57	−0.67	−1.24
400	14,859	14,935	14,728	14,897	−0.99	−0.49	−1.49
600	15,595	16,365	15,627	16,219	0.24	−1.05	−0.81
800	16,452	17,690	16,552	17,543	0.64	−0.98	−0.34
1000	17,262	18,915	17,464	19,017	1.24	0.35	1.60
1200	17,970	20,204	18,380	20,394	2.32	0.85	3.18
1400	18,607	21,515	19,255	21,774	3.50	1.05	4.55
1600	19,407	22,871	20,077	23,134	3.53	1.11	4.64

Table 5
Mean-Pareto-solutions as υ increases for each n.

υ	$n=3$				$n=5$				$n=7$				$n=9$			
	$\overline{C}^1$	$\overline{E}^1$	$\overline{C}^2$	$\overline{E}^2$	$\overline{C}^1$	$\overline{E}^1$	$\overline{C}^2$	$\overline{E}^2$	$\overline{C}^1$	$\overline{E}^1$	$\overline{C}^2$	$\overline{E}^2$	$\overline{C}^1$	$\overline{E}^1$	$\overline{C}^2$	$\overline{E}^2$
200	13,850	12,658	13,676	12,722	13,622	13,233	13,601	13,138	13,508	13,509	13,451	13,467	14,492	14,479	14,473	14,3,3
400	14,862	14,338	14,796	14,344	14,538	14,578	14,478	14,718	14,534	15,053	14,639	14,885	15,503	15,770	15,000	15,641
600	15,803	16,018	15,869	16,074	15,265	15,920	15,315	15,778	15,433	16,428	15,516	16,319	15,879	17,095	15,809	16,703
800	16,791	17,642	16,963	17,811	16,166	17,065	16,276	16,637	16,175	17,833	16,262	17,828	16,677	18,221	16,706	17,896
1000	17,771	19,257	18,047	19,580	16,912	17,731	17,074	17,918	16,917	19,331	17,135	19,415	17,447	19,341	17,600	19,153
1200	18,778	20,793	19,131	21,215	17,574	18,954	17,927	19,220	17,399	20,684	17,976	20,774	18,128	20,384	18,485	20,367
1400	19,645	22,314	20,200	22,861	18,316	20,236	18,737	20,543	17,809	21,892	18,780	22,089	18,657	21,618	19,304	21,603
1600	20,649	23,857	21,257	24,403	19,079	22,141	19,542	21,837	18,511	22,923	19,331	23,477	19,387	22,561	20,177	22,818

Table 6
Comparison of PF^1 and PF^2 to PF as υ increases.

υ	$n=3$			$n=5$			$n=7$			$n=9$			Avg.		
	Ψ_1 (%)	Ψ_2 (%)	Ψ_0 (%)	Ψ_1 (%)	Ψ_2 (%)	Ψ_0 (%)	Ψ_1 (%)	Ψ_2 (%)	Ψ_0 (%)	Ψ_1	Ψ_2 (%)	Ψ_0 (%)	Ψ_1 (%)	Ψ_2 (%)	Ψ_0 (%)
200	5.9	55.9	38.2	18.7	59.0	22.3	14.8	44.9	40.3	1.9	59.5	38.6	10.3	54.8	34.9
400	16.6	38.6	44.8	20.4	55.2	24.4	29.3	34.3	36.4	14.1	58.9	27.0	20.1	46.7	33.1
600	47.2	11.7	41.1	28.9	44.0	27.1	56.9	8.2	34.9	23.7	49.4	26.9	39.2	28.3	32.5
800	59.0	2.2	38.8	51.8	15.1	33.1	66.3	1.2	32.6	38.5	36.8	24.7	53.9	13.8	32.3
1000	62.6	1.3	36.2	59.4	2.8	37.8	67.4	0.0	32.6	66.0	14.7	19.3	63.8	4.7	31.5
1200	62.6	1.3	36.1	66.2	3.0	30.8	67.7	5.6	26.7	87.3	2.2	10.5	70.9	3.0	26.0
1400	64.2	1.5	34.3	67.2	10.8	22.0	64.5	8.2	27.2	84.4	6.0	9.6	70.1	6.6	23.3
1600	64.5	1.1	34.4	66.0	11.5	22.5	71.6	2.9	25.5	91.7	0.0	8.3	73.4	3.9	22.7

Table 7
Dominance comparison of PF^1 and PF^2 as υ increases.

υ	$n=3$			$n=5$			$n=7$			$n=9$			Avg.		
	Ω_1 (%)	Ω_2 (%)	Ω_0 (%)	Ω_1 (%)	Ω_2 (%)	Ω_0 (%)	Ω_1 (%)	Ω_2 (%)	Ω_0 (%)	Ω_1 (%)	Ω_2 (%)	Ω_0 (%)	Ω_1 (%)	Ω_2 (%)	Ω_0 (%)
200	0	20	0	0	30	0	0	10	10	0	0	0	0.0	15.0	2.5
400	0	10	0	0	40	0	0	10	10	0	10	0	0.0	17.5	2.5
600	20	0	10	0	10	10	30	0	10	0	20	0	12.5	7.5	7.5
800	20	0	10	20	0	0	30	0	10	0	10	0	17.5	2.5	5.0
1000	30	0	10	40	0	20	30	0	10	20	0	0	30.0	0.0	10.0
1200	30	0	0	40	0	10	30	0	10	40	0	0	35.0	0.0	5.0
1400	30	0	0	50	10	10	20	0	10	50	0	0	37.5	2.5	5.0
1600	30	0	0	50	10	10	30	0	10	80	0	0	47.5	2.5	5.0

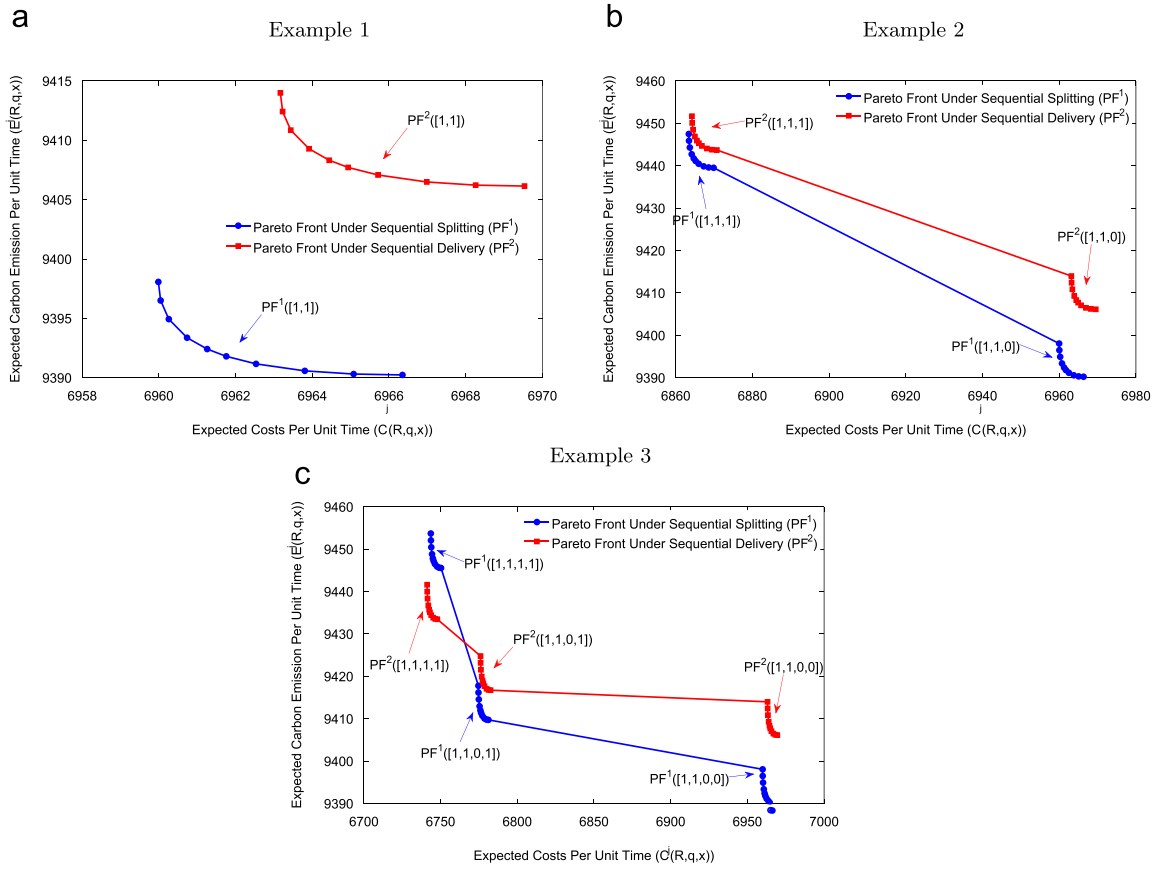


Fig. 7. Illustration of the Pareto fronts under delivery scheduling policies.

A.11. Examples of Section 5.3 with a gamma distribution

Here we give the illustrations of Pareto fronts for Examples 1–3 when the demand has a gamma distribution. Specifically, we assume that the daily demand has mean 12 and standard deviation 8. Then, we estimate the shape parameter $\alpha = 12^2/8^2 = 2.25$ and the scale parameter $\beta = 8^2/12 = 5.33$. Furthermore, we assume that a year has 300 days active, thus we let $[\tau_1, \tau_2, \tau_3, \tau_4] = [6, 21, 9, 3]$ days. The retailer has the same parameters but now $\tilde{h} = 0.00033$/unit/day and $\hat{h} = 0.00166$/unit/day. Finally, after calculating the daily cost and emission values, we multiply them by 300 to convert them to annual values. The results are illustrated in Fig. 7.

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