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Analyzing the impacts of carbon regulatory mechanisms on supplier and mode selection decisions: An application to a biofuel supply chain

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ABSTRACT

This paper analyzes the impacts of carbon regulatory mechanisms on replenishment decisions in a biofuel supply chain. We employ mathematical models for operations which integrate replenishment and supplier/transportation mode selection decisions. These models explicitly account for carbon emissions that may result from transportation and inventory storage activities. This research is motivated by observations indicating that nearly 19% of the energy consumption and 25% of the energy-related carbon dioxide emissions worldwide arise from transportation. Because freight transportation is expected to continue to grow, we consider the impacts of different carbon regulatory mechanisms on transportation and inventory replenishment decisions in a biofuel supply chain. A set of extensive numerical experiments uses the biofuel supply chain context to analyze the impacts of different regulatory mechanisms, including carbon cap, carbon tax, carbon cap and trade, and carbon offset, on performance. We use existing methodologies to calculate emissions as a function of distance traveled, load weight, and transportation mode used. We also use publicly available data to derive representative biomass transportation costs. As a consequence, our numerical results are meaningful, and give a realistic representation of the relationships between emissions from different transportation modes and the resulting costs. The results of our computational experiments indicate that carbon regulatory mechanisms have a non-trivial impact on replenishment schedules, and as a consequence, costs and emissions in the supply chain.

1. Introduction

Global climate change is an important contemporary issue that is being investigated from numerous perspectives. Many prominent world leaders and scientists have raised concerns in recent years regarding increased levels of greenhouse gas (GHG) emissions and the impacts these emissions have on climate change. The Intergovernmental Panel on Climate Change (IPCC) estimates an increase of 1.8–4 °C in Earth's temperature by the end of this century because of increased GHGs, such as carbon dioxide (CO_2), methane and nitrous oxide (Solomon et al., 2007). Of major concern is the burning of fossil fuels, since their extensive usage in areas ranging from power generation to transportation yields significant GHG emissions levels.

These concerns have inspired a worldwide debate about GHG emission reduction targets and regulations. Rogner et al. (2007) argue that in order to prevent global warming and climate change, GHG emissions should be reduced by 50% of their 1990 levels by 2050. Many countries and governments have accepted the premise that an urgent need exists to put policies into action, and have already set reduction targets. For example, through its European Climate Change Programme, the European Union aims to reduce its GHG emissions by at least 20% by 2020 compared to 1990 levels (European Commission, 2008). While the media has chronicled a fair amount of controversy regarding GHGs and climate change, our study does not weigh in on this debate; instead, our research assumes that reducing fossil fuel consumption will provide economic benefits and improve quality of life.

Transportation and other supply chain related activities are a major contributor to GHG emissions (International Transport Forum, 2010). The International Energy Agency (IEA) states that 19% of the energy consumption, and almost a quarter of the energy-related CO_2 emissions worldwide result from transportation (International Energy Agency, 2009). The US Environmental Protection Agency (EPA) estimates that during the period from 1990 to 2010, transportation-related emissions rose by 18% (Environmental Protection Agency, 2012). This is

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mainly due to the increased demand for travel, and the US vehicle fleet's stagnant fuel efficiency. Considering current worldwide trends in transportation mode usage, transportation demand is expected to increase by 50% by 2030 and by 80% by 2050. As a consequence, transportation related emissions are projected to nearly double, going from 7.5 Gigatonnes (Gt) in 2006 to about 14 Gt in 2050 (International Energy Agency, 2009). Given these trends, achieving the target of a 50% reduction in total carbon emissions by 2050 will be almost impossible, unless transportation-related emissions are reduced significantly.

The opportunities for reducing carbon emissions are multi-fold. A study by McKinsey & Company (2009) shows that improvements in energy efficiency, using alternative fuels (e.g., biofuels), and using alternative energy sources (e.g. wind and nuclear) can potentially reduce carbon emissions. In addition to developing new technologies, several studies advise modal shifts from energy intensive modes, such as road and air to rail, barge, and ship (International Transport Forum, 2008; Department of Transportation, 2010; International Energy Agency, 2010; McKinsey & Company, 2009). However, in the context of supply chain management, shifting from one transportation mode to another will impact costs and delivery lead times. Additionally, firms may not have access to a mode with lower emissions, such as rail or marine transportation, due to infrastructure and geographic limitations. Therefore, managers must identify the appropriate transportation mode(s) in a supply chain in order to address the tradeoffs between inventory and transportation costs, customer satisfaction (via on-time product delivery), and the carbon footprint of the product delivered. This study investigates whether decisions regarding which suppliers and transportation mode(s) are used and the degree of transportation vehicle utilization can greatly reduce energy usage without significantly impacting costs.

This paper contributes to the existing literature by providing model-based insights on the impacts that potential carbon regulatory policies, such as carbon cap, tax, cap-and-trade and offset have on supplier and transportation mode selection decisions. We propose economic lot-sizing models with multiple replenishment modes and carbon constraints for carbon regulatory policies. Through our numerical study we offer interesting observations with respect to the tradeoffs between costs and emissions. As models with carbon emission considerations are new in the literature, we also find it useful to provide insights about the complexity of the proposed models. We show that the problems with carbon cap and carbon offset mechanisms are NP-hard, while the problems with carbon tax and cap-and-trade mechanisms are easier problems and can be solved by a polynomial time algorithm. We also provide theoretical results about the relationships that exist between different carbon regulatory mechanisms. The main contribution of this paper, however, lies in applying the proposed models to a contemporary supply chain problem (biofuel supply chain) and deriving meaningful numerical results and insights.

In the numerical analysis we consider inventory replenishment decisions at a biorefinery which uses woody biomass for production of cellulosic ethanol. The US annually supplies 20% of the total 1.6 billion tons/year of biomass available for production of biofuels (US Department of Energy, 2011). Based on the Renewable Fuel Standard (RFS), the minimum level of renewable fuels used in the US transportation industry is expected to increase from 9.0 billion gallons per year (BGY) in 2008 to 36 BGY in 2022 (Renewable Fuels Association, 2012). We expect that, due to these requirements, the production of cellulosic ethanol will increase.

Inventory replenishment decisions at the biorefinery are very important because of the high in-bound logistics-related costs that occur as a result of the characteristics of the woody biomass which: (a) is bulky and difficult to transport, (b) has low energy density, and (c) is widely dispersed geographically. In addition to truck transportation, biorefineries consider receiving shipments by using high capacity transportation modes such as barge or unit rail. Using these modes of transportation has the potential to reduce transportation costs, decrease road traffic and improve road safety in the surrounding communities, and increase the pool of suppliers available. Increased biomass availability enables the establishment of large capacity plants, and consequently allows for economies of scale in production.

In our numerical experiments, we use a methodology for estimating emissions from transportation developed by Hoen et al. (2010). We selected this approach because of the soundness of their methodology and the similarity of the problem settings they consider to ours. Their equations account for factors such as the weights of transportation modes, associated fuel consumption, and load factors. As a result of this methodology, it is possible to calculate total transportation emissions as a function of distance traveled, product density, load volume, and the transportation mode used. We use publicly available data to derive transportation cost functions for rail, barge, and truck. As a consequence, our numerical results are meaningful and give a realistic representation of emissions levels and costs when using different transportation modes.

The rest of the paper is organized as follows. In Section 2, we use a simple Economic Order Quantity (EOQ) model to illustrate the tradeoffs between costs and emissions. Section 3 provides a review of the literature. Section 4 presents the formulation for the supplier selection problem. Section 5 presents models that capture carbon constraints and costs. In Sections 6 and 7, we discuss the data collection and analyze the results of our numerical experiments. We conclude with the observations from our study in Section 8.

2. An illustrative replenishment model

We use an illustrative example of the EOQ model in order to show how transportation mode selection decisions are affected by carbon regulatory mechanisms. The goal is to provide some insights about the impact of carbon emission limitations on inventory replenishment decisions.

Consider a facility that uses three different suppliers to replenish inventories. The annual requirements at the facility are 3000 tons. Suppliers are located 50, 150, and 400 miles away from the plant. Depending on transportation distance, and the availability of transportation infrastructures, these suppliers have access to different transportation modes. Table 1 lists the available transportation mode, unit variable cost (c), fixed order cost (K), unit inventory holding cost (h), and the unit emissions due to transportation (in kilograms (kg) of CO_2 per ton and per mile shipped) for each supplier. Total transportation-related emissions are a function of the

Table 1
Problem inputs for the EOQ model.

Supplier #	Transp. mode	Mode capacity (tons)	Distance (miles)	Var. costs (\$/(mile $*$ ton))	Fixed costs (\$/order)	Inv. hold. costs (\$/(ton $*$ year))	Emissions (kg CO_2/(mile $*$ ton))
1	Truck	30	50	10	20	0.005	0.06
2	Rail	100	150	5	400	0.005	0.03
3	Barge	1000	400	1	2000	0.005	0.01

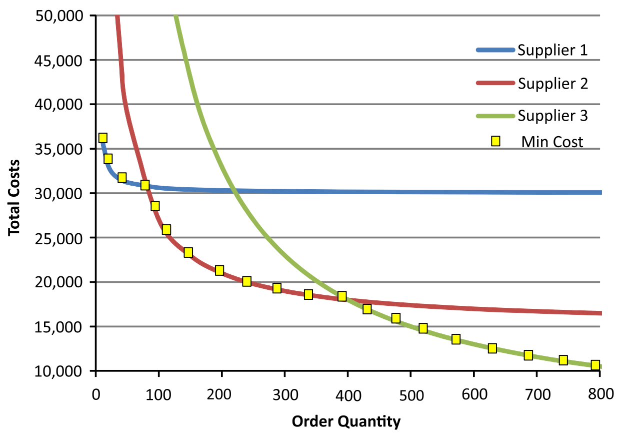

Fig. 1. Total costs.

distance traveled and transportation mode used. Emissions due to storage are considered to be fixed at 0.1 tons of CO_2 per year. Details about the methodology used for generating costs and emissions-related data are provided in Section 6.

Fig. 1 shows the total cost functions for all suppliers at different order quantities. Corresponding total emissions are 9, 13.5 and 12 tons per year for suppliers 1, 2, and 3, respectively. If emissions are not considered in this problem setting, then replenishment of inventory from supplier 3 using barge provides the minimum costs (see Fig. 1). Suppose that a carbon cap mechanism is used to control emissions in the supply chain which forces total emissions (over some time horizon) to be less than the cap. Consider the case when a carbon cap of 10 tons per year exists. In this case, only shipments from supplier 1 can meet the emissions requirement. Supplier 1 is located nearby the facility, and therefore, this supplier's total emissions are the smallest. Consider the scenario when the carbon cap is increased to 13 tons per year. Under such a scenario, only shipments from suppliers 1 and 3 can be considered due to their emission levels.

The results from this numerical example indicate that transportation mode selection decisions are not only impacted by the tradeoffs that exist between inventory and transportation costs, but also by the tradeoffs that exist between costs and carbon emissions in the supply chain. For example, emissions per ton and per mile traveled are highest for truck transportation as compared to barge and rail. However, emissions per ton shipped are smallest for supplier 1 who uses truck and is located 50 miles away from the plant. Consequently, total emissions are minimized when using supplier 1, who also has the highest inventory-related costs.

3. Literature review

The supply chain management (SCM) literature mostly focuses on improving the profitability and efficiency of the chain (Chopra and Meindl, 2007), where cost is an all-important measure of efficiency. More recently, because of increased public awareness of environmental issues, the SCM literature is expanding in a new direction which aims to limit the environmental impact of supply chain activities. One stream of research on "green" supply chain management (GSCM) has concentrated on topics involving product recycling, reuse, and disposal. We refer interested readers to Srivastava (2007), Dekker et al. (2012), and Tang and Zhou (2012) for a thorough literature review on GSCM.

A recent stream of literature within GSCM analyzes the carbon footprint of a product's supply chain. A number of papers analyze the impact of carbon emissions on global supply chains. These works focus on the factors and policies that impact emissions in different countries that are part of the chain (Aichele and Felbermayr, 2012; Fan et al., 2012; Rizet et al., 2012). At the supply chain level, a number of studies propose methods to measure and quantify carbon emissions due to processes such as transportation (Cadarso et al., 2010; Mtalaa et al., 2009; Piecyk and McKinnon, 2010; Sundarakani et al., 2010). A few studies analyze the role of carbon emissions as one of the drivers of sustainability in industries such as automobile and apparel (Lee, 2011; Caniato et al., 2012). Other studies propose optimization models to minimize the carbon footprint of a supply chain through changes in supply chain design and operations (Benjaafar et al., 2013). A number of these studies analyze the impact of carbon tax and carbon cap mechanisms on supplier selection decisions (Choi, 2013a, 2013b, 2013c; Zhang and Xu, 2013). The work presented in this paper falls in this stream of research, which identifies operational policy changes (e.g., in inventory replenishment schedules, transportation modes and supplier selection) that impact costs and emissions in the supply chain.

Production of fuels using renewable sources of energy (such as biomass) is experiencing growth in the US. The existing literature on biofuel supply chains has concentrated on identifying supply chain designs and management practices which optimize the system performance. A number of research articles utilize cost minimization models to determine optimal locations and capacities for biorefineries given the distribution of biomass and the location of final customers (Akgul et al., 2011; Dunnett et al., 2007, 2008; Eksioglu et al., 2009; Gunnarsson et al., 2004; Huang et al., 2010; Tembo et al., 2003; Zamboni et al., 2009). Other studies use models which identify supply chain management practices that maximize profits (Kim et al., 2010; Mansoornejad et al., 2010; Marvin et al., 2012; TittmannParker et al., 2010) and/or minimize risk associated with investments (Dal Mas et al., 2010). Stochastic programming and simulation models have been used to capture the uncertainties in biomass supply and costs in the supply chain (De Mol et al., 1997; Ileleji, 2007; Mahmoudi et al., 2009; Sokhansanj et al., 2006; Ravula et al., 2008; Tatsiopoulos and Tolis, 2003). This literature features a number of studies emphasizing the importance of minimizing transportation costs in biofuel supply chains (Eksioglu et al., 2010; Morrow et al., 2006; Yu et al., 2009). See An et al. (2011) and Iakovou et al. (2010) for a thorough review of the literature on biofuel and biomass supply chain design and management tools.

A number of studies in the area of GSCM have extended traditional inventory management models, such as the EOQ model, the newsvendor problem and the dynamic economic lot sizing model to account for carbon emissions due to production and inventory in the supply chain. For example, the EOQ model has been extended by Chen et al. (2013); Hua et al. (2011); Arslan and Turkay (2013) and Wahab et al. (2011) to address carbon cap, carbon tax, carbon cap and trade, and carbon offset mechanisms. Bouchery et al. (2012) present a multi-objective EOQ model which optimizes costs and emissions due to replenishment decisions. Song and Leng (2012) analyze the newsvendor problem under carbon cap, carbon tax and carbon cap and trade mechanisms. Rosič and Jammernegg (2013) integrate environmental regulations in a basic dual-sourcing newsvendor problem. This work evaluates the impact that carbon regulations have on transportation-related decisions.

The classical ELS problem assumes that a single supplier and a single transportation mode are used to replenish inventories. A number of studies have generalized the classical ELS model with various considerations. These extensions include finite production capacity models (Florian and Klein, 1971; Bitran and Yanasse, 1982), multi-echelon models (Kaminsky and Simchi-Levi, 2003) and multi-item models (Manne, 1958; Barany et al., 1984). Eksioglu (2009) and Jaruphongsa et al. (2005) studied the ELS problem with multi-mode replenishment costs and cargo capacity constraints. Choudhary and Shankar (2013) proposed a model to simultaneously determine lot-sizes and provide the optimal supplier and carrier selection decisions. In the GSCM area, Benjaafar et al. (2013) extend the ELS model to handle the carbon regulatory mechanisms. Helmrich et al. (2012), Mooij (2011) and Ty (2011) develop solution algorithms for the models proposed by Benjaafar et al. (2013). Absi et al. (2013) propose models and analyze the complexity for variations of the emissions constraint, such as time-cumulative emission cap, period-by-period cap, rolling cap, and global cap.

The general purpose of these extensions is to replicate real problems faced by manufacturing companies. However, because of current pressures on logistics activities to ensure sustainable practices, additional extensions of this problem class are practical and relevant. This is one of the motivations for this research, in addition to the need to develop replenishment planning decision models and policies that account for the carbon footprint of transportation modes. We contribute to these efforts by extending the ELS models to consider the impact of carbon regulatory mechanisms on replenishment decisions when a company has the option of using multiple suppliers and modes to replenish inventories. The models we develop can be used as sub-modules in MRP systems to help environmentally conscious companies with requirements planning when multi-mode and multi-supplier replenishment options are available. These tools enable companies to determine whether they should employ a single supplier and a single replenishment mode, or a combination of different suppliers and modes. We refer readers to Bonney and Jaber (2011) for a wide range of extensions to traditional inventory models.

A number of prior studies have focused on analyzing emissions from transportation activities in the supply chain. Bauer et al. (2010) propose an integer programming model to identify a transportation network design that minimizes total emissions due to transportation. Winebrake et al. (2008) present an energy and environmental network analysis model that explores the tradeoffs between costs, time and emissions resulting from freight transportation. Pan et al. (2013) and Ulku (2012) discuss how shipment consolidation in supply chains impacts emissions from freight transportation. Arikan et al. (2013) investigate the impacts of transportation lead time variability on the supply chain costs and emissions. The work by Hoen et al. (2012) focuses on measuring and analyzing carbon emissions due to transportation. They develop a methodology that can be used to quantify transportation carbon emissions. They use this methodology to compare emissions levels when shipping via different modes of transportation. Their results show that product characteristics, such as volume and density, impact transportation mode selection, and modal shifts can result in large emission reductions.

Several additional studies have addressed other supply chain network design decisions with carbon emission considerations. For example, Jaber et al. (2013) and El Saadany et al. (2011) discuss supply chain coordination decisions with environmental concerns. Chaabane et al. (2012), Kim et al. (2009), Wang et al. (2011), Neto et al. (2009), and Hugo and Pistikopoulos (2005) incorporate carbon emissions into multi-objective optimization models. Du et al. (2011) use game theoretic models for the supply chain network design.

Within the aforementioned literature, our research is most closely related to the work by Hoen et al. (2012). Their methodology generates data for our study's numerical experiments, and derives meaningful and realistic representations of the relationship between different transportation modes and consequent emissions levels. Our research is also closely related to studies by Benjaafar et al. (2013) and Helmrich et al. (2012) that assume that a single supplier is used to replenish inventories. Our work adds an important dimension to this problem, by accounting for supplier and transportation mode selection decisions. As a consequence, our models capture not only the tradeoffs that exist between costs and emissions due to inventory and transportation, but they also capture the tradeoffs between cost and emissions resulting from the use of different suppliers and transportation modes.

4. Supplier selection problem

This section discusses the mathematical model we propose in order to identify a replenishment schedule that minimizes total supply chain costs. In the following sections we define and formulate the problem; then we describe an algorithm that solves the problem in polynomial time.

4.1. Problem description

Our supply chain consists of a single facility and its suppliers. The facility could be a manufacturing facility, or a retailer making inventory replacement decisions every period within a fixed planning horizon of length T. A "supplier" in our model corresponds to a unique combination of a supply firm and a particular transportation mode. Thus, there may be multiple "suppliers" for a given supply firm but one for each transportation mode.

A facility can replenish its inventories using local or distant suppliers. Typically, if shipment delivery time is not a concern, a facility can increase the supplier pool size by considering suppliers located further away, which increases the likelihood that the facility will be able to identify suppliers (e.g., wholesalers) that can provide products at a competitive price. Depending on the distance traveled and transportation mode accessibility, barge, rail, or truck can be used to replenish inventories. The facility may, alternatively, replenish inventories using nearby suppliers who can respond in a timely manner. Because of short travel distances, these suppliers tend to use truck shipments. Shipments are initiated depending on the size of a shipment, e.g., full truck load (FTL) or less-than-full truck load (LTL). Somewhat paradoxically, replenishment costs from local suppliers are often higher compared to more distant suppliers, mainly due to frequent LTL shipments, as opposed to the FTL shipments from more distant suppliers. Our goal is to identify suppliers and a replenishment schedule that minimizes total replenishment (purchase and transportation) and inventory holding costs. Note that we will assume that demand must be satisfied in every time period, i.e., backorders are not allowed.

In this problem, operations costs consist of replenishment and inventory holding costs. Replenishment costs from supplier $i\,(i=1,\ldots,I)$ in period t consist of a fixed order cost (f_{it}) and a variable cost (c_{it}). The fixed order cost consists of the costs necessary to process an order as well as to load or unload a shipment. The variable cost consists of the purchasing cost and distance-dependent transportation costs. These costs are a function of quantity shipped. A unit inventory holding cost is charged per unit of inventory held at the facility at the end of each time period (h_t).

Fig. 2 provides a network representation of a two-tier supply chain problem with three suppliers and one facility. The time horizon consists of two time periods.

This network contains one dummy node, a total of T facility nodes (one node per time period), and $I*T$ supplier nodes. The dummy node has a supply equal to the total demand over the planning horizon. A facility node t has a demand equal to d_t. The supplier nodes correspond to each supplier in every time period. The network has $I*T$ replenishment arcs, $T-1$ inventory arcs and $I*T$ dummy arcs. Replenishment arcs connect suppliers with the facility in each time period. The cost per unit flow on a replenishment arc is c_{it} $(i=1,\ldots,I;\, t=1,\ldots,T)$. There is also a fixed cost for using supplier i

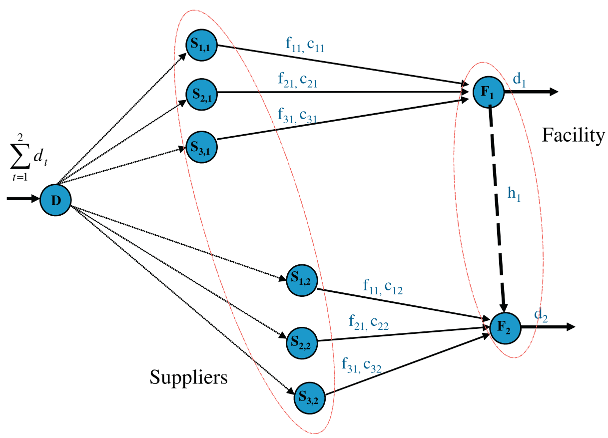

Fig. 2. Network representation of a two-period, three-supplier problem.

in period t equal to f_{it} $(i=1,\ldots,I; t=1,\ldots,T)$ which is incurred when using a replenishment arc. Inventory arcs connect the facility nodes in consecutive time periods. The cost per unit of flow on an inventory arc is h_t $(t=1,\ldots,T)$.

4.2. Problem formulation under cost minimization

We define the following decision variables for our models: y_{it} is a binary variable, which is equal to 1 if a shipment is received from supplier i in period t and 0 otherwise. q_{it} denotes the amount received from supplier i in period t and H_t represents the amount of inventory carried from period t to $t+1$.

The following is a mixed integer programming formulation of the cost minimization model. We refer to this as model (P).

$$\text{minimize} \quad \sum_{i=1}^{I}\sum_{t=1}^{T}\{f_{it}y_{it}+c_{it}q_{it}+h_tH_t\} \tag{P}$$

$$\sum_{i=1}^{I} q_{it}+H_{t-1}-d_t=H_t \tag{1}$$

$$H_0=0 \tag{2}$$

$$q_{it} \le \left(\sum_{\tau=t}^{T} d_\tau\right)y_{it} \tag{3}$$

$$y_{it}\in\{0,1\}, \quad \forall i, \ \forall t \tag{4}$$

$$q_{it}, H_t \ge 0, \quad \forall i, \ \forall t \tag{5}$$

The objective function of (P) minimizes total costs. Constraints (1) are the inventory balance constraints. Constraints (2) set the initial inventory to zero. Constraints (3) connect continuous and binary variables, and ensure that no flow is shipped from supplier i in period t, unless $y_{it}=1$. The remaining constraints are the binary and the nonnegativity constraints, respectively.

Proposition 1. *There exists an optimal solution to* (P) *such that*:

$$q^*_{it}q^*_{lt}=0, \quad \text{for } i,l=1,\ldots,I, \quad i\ne l, \quad \text{and}, \quad t=1,2,\ldots,T$$

$$q^*_{it}H^*_{t-1}=0, \quad \text{for } i=1,\ldots,I, \quad t=1,\ldots,T.$$

This proposition indicates that an optimal solution satisfies the zero-inventory ordering property and uses at most one supplier for replenishment in each period. This proposition is adapted from Balakrishnan and Geunes (2000). In the Appendix we provide a proof of this proposition. Model (P) is a special case of the ELS problem with multi-mode replenishment costs and cargo capacity constraints discussed by Eksioglu (2009). In that study, Eksioglu (2009) proposes an extension of the dynamic programming algorithm of Wagner and Whitin (1958) that solves the ELS model with multi-mode replenishment and fixed-charge cost functions, model (P).

Theorem 1. *There exists a dynamic programming algorithm that solves problem (P) in* $O(IT^2)$.

We provide details about this algorithm in the Appendix. Problem (P) is also a special case of the lot sizing problem with substitutions with a single end-product and multiple substitutable components (Balakrishnan and Geunes, 2000).

5. Modeling supply chain emissions constraints and costs

In this section we describe the supplier and transportation mode selection problem under a number of carbon regulatory mechanisms, including carbon cap, carbon tax, carbon cap-and-trade, and carbon offset. These models explore the tradeoffs between costs and emissions in this two-level supply chain.

5.1. Problem description

Consider the two-tier supply chain described above which consists of a facility and a number of suppliers (Fig. 2). The facility has the option to use nearby suppliers to replenish its inventories, or use suppliers located further away. In addition to costs, concerns about emissions now impact replenishment decisions made by the facility. Transportation-related emissions for shipments from local suppliers are typically low due to shorter distances traveled. Emissions per ton and per mile for barge and rail are smaller than those from trucks. However, depending on the transportation distance, the total emissions for long hauls using rail and barge may be higher. The objective of the models we propose is to identify a replenishment schedule that minimizes the total system costs and the carbon footprint of this supply chain.

We assume that carbon emissions in this supply chain result from transportation activities and holding inventory. We separate transportation related emissions into fixed $(\hat{f}_i)$ and variable $(\hat{c}_i)$ emissions. Fixed emissions are mainly due to loading and unloading of a shipment. These emissions depend on the transportation mode used since the equipment required to load and unload a barge, rail car, or truck, is different. Variable emissions also depend on the transportation mode used since the amount of carbon emitted per ton and per mile traveled by truck is different from that of rail or barge. Our model also considers emissions that may result from holding inventories. For example, the emissions per unit of inventory held in a time period $(\hat{h}_t)$ depend on the heating/cooling system at the facility (note that we do not consider perishable products, however).

5.2. Formulation with a carbon cap mechanism

We now discuss a first extension of model (P) that applies a carbon cap mechanism over the finite horizon. As a result, the total carbon emitted over the horizon due to transportation and inventory activities cannot surpass this cap. To represent the existence of such a mechanism mathematically, we add a constraint to our model. Constraint (6) limits the total emissions in the supply chain to C, the carbon cap level over the horizon. We refer to this as model (P_CC).

$$Z_{CC}=\min \sum_{i=1}^{I}\sum_{t=1}^{T}\{f_{it}y_{it}+c_{it}q_{it}+h_tH_t\} \tag{P\_CC}$$

subject to (1)–(5)

$$\sum_{i=1}^{I}\sum_{t=1}^{T}(\hat{f}_i y_{it}+\hat{c}_i q_{it}+\hat{h}_t H_t)\leq C \tag{6}$$

The objective function of (P_CC) minimizes total costs, subject to flow conservation constraints, setup forcing constraints and a carbon emission constraint (6). This model, in addition to cost, keeps track of emissions from inventory holding, transportation and loading/unloading activities. While the firm still minimizes supply chain related costs, it must ensure that the carbon constraint is not violated. This additional constraint can potentially increase total costs and impact supplier and transportation mode selection decisions.

Theorem 2. *Problem (P_CC) is NP-hard.*

In the Appendix we show that the problem is NP-hard even for a special case of model (P_CC) with a single supplier. The work by van den Heuvel et al. (2012) demonstrates that a special case of model (P_CC) with a single replenishment mode (single supplier), and non-speculative cost structure, is NP-complete. The work by Helmrich et al. (2012) shows yet another special case of (P_CC) with two replenishment modes, and time-invariant costs and emissions, is NP-hard. Since these special cases of (P_CC) are NP-hard, we conclude that problem (P_CC) is NP-hard.

Proposition 2. *One can identify whether problem (P_CC) has a feasible solution or not in $O(IT^2)$.*

In the Appendix we provide a proof of this proposition.

5.3. Formulation with a carbon tax mechanism

Under a carbon tax mechanism, a facility is charged a fee for each unit of CO_2 emitted. Let α denote the tax charged per unit of CO_2 emitted. The corresponding model formulation is called model (P_CT).

$$Z_{CT}=\min\sum_{i=1}^{I}\sum_{t=1}^{T}\{(f_{it}+\alpha\hat{f}_i)y_{it}+(c_{it}+\alpha\hat{c}_i)q_{it}+(h_t+\alpha\hat{h}_t)H_t\} \tag{P\_CT}$$

subject to (1)–(5)

The objective function minimizes the total replenishment costs, inventory costs, and emission taxes. Formulations (P_CT) and (P) have the same feasible region, but slightly different cost functions. However, both functions contain the same mathematical structure. Therefore, an optimal solution to (P_CT) (as discussed above for (P)) will satisfy the Zero Inventory and Single Source properties. The same dynamic programming algorithm can thus be used to solve this problem in $O(IT^2)$ time in the worst case.

Proposition 3. $Z_{CT}-\alpha C\leq Z_{CC}$

Proof. If we subtract the constant αC from the objective function of the carbon tax model, the resulting problem is equivalent to a Lagrangian relaxation of the carbon cap constraint in the carbon cap model, with a nonnegative Lagrangian multiplier α. Thus, at any fixed value of α, $Z_{CT}-\alpha C$ provides a lower bound on the optimal solution value of the carbon cap model. □

The value of α that maximizes the Lagrangian dual provides us an estimate of what we should be willing to pay for an additional unit of carbon cap in model P_CC, which relates to the model we discuss in the next subsection. The actual value of α used in the carbon tax mechanism relative to the value of α that maximizes the Lagrangian dual may provide an indication of the difference between the value the facility places on carbon emissions and the price it is required for its corresponding emissions under a carbon tax.

Proposition 3 also shows that if we eliminate the application of the carbon tax rate α to the base capacity, then the carbon tax mechanism is preferable to a carbon cap. Note that the resulting model would be equivalent to the carbon offset model, as discussed in Section 5.5, where a tax is only applied to emissions in excess of some base level.

Proposition 4. *If the optimal solution for the carbon tax model satisfies the carbon capacity constraint, then $Z_{CC}<Z_{CT}$.*

Proof. This holds trivially as the cost of the solution in the carbon capacity model is strictly less than that of the carbon tax model if $\alpha>0$ and, by assumption, the solution is feasible for the carbon capacity model. □

5.4. Formulation for carbon cap and trade mechanism

A carbon cap is imposed on the facility under a carbon cap-and-trade mechanism. However, a carbon market also exists, which allows the facility to sell unused carbon credits at a profit, or to purchase carbon credits if needed to satisfy customer demand (the European Union Emissions Trading system was the first large emission trading scheme in the world). Let e_t^+ (e_t^-) denote the amount of carbon credit purchased (sold) in period t. We denote the market price per unit of carbon by p. The following model minimizes total system costs under a carbon cap-and-trade mechanism. We refer to this as model (P_CCT).

$$Z_{CCT}=\min\sum_{i=1}^{I}\sum_{t=1}^{T}\{f_{it}y_{it}+c_{it}q_{it}+h_t H_t\}+p\sum_{t=1}^{T}(e_t^+-e_t^-) \tag{P\_CCT}$$

subject to (1)–(5)

$$\sum_{i=1}^{I}\sum_{t=1}^{T}(\hat{f}_i y_{it}+\hat{c}_i q_{it}+\hat{h}_t H_t)+\sum_{t=1}^{T}e_t^-\leq C+\sum_{t=1}^{T}e_t^+ \tag{7}$$

$$e_t^+,e_t^-\geq 0\quad t=1,\dots,T \tag{8}$$

Note that in an optimal solution of (P_CCT), constraint (7) is necessarily binding. For any solution such that the left-hand side is less than the right-hand side, we can decrease the objective (assuming $p>0$) by increasing the value of one or more e_t^- variables. We can thus re-write constraint (7) as follows:

$$\sum_{i=1}^{I}\sum_{t=1}^{T}(\hat{f}_i y_{it}+\hat{c}_i q_{it}+\hat{h}_t H_t)-C=\sum_{t=1}^{T}(e_t^+-e_t^-)$$

We can then substitute $\sum_{t=1}^{T}(e_t^+-e_t^-)$ out of the objective function of (P_CCT) and re-arrange the terms in the objective function to obtain:

$$\text{minimize}\sum_{i=1}^{I}\sum_{t=1}^{T}\{\tilde{f}_{it}y_{it}+\tilde{c}_{it}q_{it}+\tilde{h}_t H_t\}-pC,$$

where $\tilde{f}_{it}=f_{it}+p\hat{f}_i$, $\tilde{c}_i=c_{it}+p\hat{c}_i$, and $\tilde{h}_t=h_t+p\hat{h}_t$ for all $i=1,\dots,I$ and $t=1,\dots,T$. Note that in this objective function, pC is a constant, and so we can remove it from the objective without loss of optimality. After this transformation, the feasible regions of (P) and (P_CCT) are identical, as is the mathematical structure of the objective function in both cases. Therefore, we can use the dynamic programming approach detailed in the Appendix to solve this problem in $O(IT^2)$ time.

Model P_CCT is equivalent to a Lagrangian relaxation of the restricted version of problem P_CC in which constraint (6) must be satisfied at equality. In this Lagrangian relaxation, the Lagrangian multiplier is equivalent to p. If the value of p that maximizes the Lagrangian dual is positive, then this implies a price the facility would be willing to pay for additional carbon capacity; if it is negative, then this price corresponds to a value the facility should expect for selling excess carbon capacity to the market. The value of p relative to the value that maximizes the Lagrangian dual can indicate to the facility its value of carbon emissions relative to the market price.

Let $(\tilde{y}, \tilde{q}, \tilde{H})$ denote the solution that minimizes total emissions among all feasible solutions for the carbon cap and trade and carbon tax models, i.e., the feasible solution that minimizes $\tilde{C} = \sum_{i=1}^{I}\sum_{t=1}^{T}(\hat{f}_i y_{it} + \hat{c}_i q_{it} + \hat{h}_t H_t)$.

Proposition 5. *If $\alpha \le p(1 - C/\tilde{C})$ then $Z_{CT} \le Z_{CCT}$.*

Proof. Any feasible solution for the carbon cap and trade model is feasible for the carbon tax model, and vice versa. The result holds if, for any feasible solution $(\tilde{y}, \tilde{q}, \tilde{H})$, $\alpha(\sum_{i=1}^{I}\sum_{t=1}^{T}(\hat{f}_i y'_{it} + \hat{c}_i q'_{it} + \hat{h}_t H'_t)) \le p(\sum_{i=1}^{I}\sum_{t=1}^{T}(\hat{f}_i y'_{it} + \hat{c}_i q'_{it} + \hat{h}_t H'_t)) - pC$, i.e., if

$$\alpha \le p\left(1 - \frac{C}{\sum_{i=1}^{I}\sum_{t=1}^{T}(\hat{f}_i y'_{it} + \hat{c}_i q'_{it} + \hat{h}_t H'_t)}\right).$$

If this condition holds for the solution that minimizes the denominator of the second term in parentheses, it must hold for all feasible solutions. □

Note that Proposition 5 is only reasonable for cases in which $\tilde{C} > C$, i.e., when carbon capacity is always a constraining factor (otherwise only a negative tax would lead to an efficient carbon tax mechanism.

5.5. Formulation with a carbon offset mechanism

A carbon cap is imposed on the facility under a carbon offset mechanism, and a carbon market also exists that allows the facility to purchase carbon credits. However, under a carbon offset mechanism, a facility cannot sell unused carbon credits. The resulting problem formulation, which we denote by (P_CO), is as follows:

$$Z_{CO} = \min \sum_{i=1}^{I}\sum_{t=1}^{T}\{f_{it}y_{it} + c_{it}q_{it} + h_t H_t\} + \sum_{t=1}^{T} p e_t^+ \qquad \text{(P\_CO)}$$

subject to (1)–(5)

$$\sum_{i=1}^{I}\sum_{t=1}^{T}(\hat{f}_i y_{it} + \hat{c}_i q_{it} + \hat{h}_t H_t) \le C + \sum_{t=1}^{T} e_t^+ \qquad (9)$$

$$e_t^+ \ge 0 \quad t = 1, \ldots, T \qquad (10)$$

The objective function minimizes total costs, including the cost of purchasing offsets. A voluntarily carbon offset market exists in the US, wherein a variety of consumers buy offsets, including individuals, businesses, nonprofit organizations, governments, and universities. Major motivations for purchasing offsets are corporate responsibility and public relations (US Government Accountability Office, 2008). Observe that (P_CC) corresponds to the special case of (P_CO) in which p is a very large number. Because (P_CC) is NP-hard, the same therefore holds for (P_CO).

Consider, however, a carbon offset model with no base cap level, i.e., such that $C=0$. The resulting special case of P_CO is equivalent to one in which capacity is purchased in each period at a cost that is linear in the capacity level (with unit capacity price p). In this case, assuming $p > 0$, constraint (9) will be tight at optimality, which implies that we can substitute $\sum_{t=1}^{T} e_t^+$ out of the objective function, and the resulting problem is equivalent to a single-stage lot-sizing problem with modified cost coefficients.

For the following propositions,we assume that the value of p is the same for the P_CCT and P_CO models.

Proposition 6. $Z_{CCT} \le Z_{CO} \le Z_{CC}$.

Proof. For the first inequality, note that the feasible region of the carbon offset model is a strict subset of the feasible region of the carbon cap and trade model. In addition, any feasible solution for the carbon offset model has the same objective function value in both the carbon offset and carbon cap and trade model. For the second inequality, note that the feasible region of the carbon cap problem is a strict subset of the feasible region of the carbon offset problem, while the cost of any solution that is feasible for the carbon cap problem has the same objective function in both models. □

If the conditions of Proposition 5 hold, then because of Proposition 6 we have $Z_{CT} \le Z_{CCT} \le Z_{CO} \le Z_{CC}$. This implies that for sufficiently low carbon tax rates relative to market prices, a carbon tax may result in minimum total costs.

If the conditions of Proposition 4 hold, then $Z_{CCT} \le Z_{CO} \le Z_{CC} < Z_{CT}$, and a carbon tax only serves as a penalty.

Proposition 7. If $\alpha \ge p > 0$, then assuming $C > 0$, $Z_{CO} < Z_{CT}$.

Proof. Any feasible solution (y', q', H') for the carbon offset model is feasible for the carbon tax model, and vice versa. The objective function value for the carbon tax model less that of the carbon offset model for the solution (y', q', H') equals

$$\alpha\left(\sum_{i=1}^{I}\sum_{t=1}^{T}(\hat{f}_i y'_{it} + \hat{c}_i q'_{it} + \hat{h}_t H'_t)\right) - p\left\{\max\left\{\sum_{i=1}^{I}\sum_{t=1}^{T}(\hat{f}_i y'_{it} + \hat{c}_i q'_{it} + \hat{h}_t H'_t) - C, 0\right\}\right\}.$$

Because $\alpha \ge p$ and $\max\{\sum_{i=1}^{I}\sum_{t=1}^{T}(\hat{f}_i y'_{it} + \hat{c}_i q'_{it} + \hat{h}_t H'_t) - C, 0\} < \sum_{i=1}^{I}\sum_{t=1}^{T}(\hat{f}_i y'_{it} + \hat{c}_i q'_{it} + \hat{h}_t H'_t)$, the above quantity must be non-negative, implying the result. □

5.6. Summary of model formulations under carbon considerations

We propose four extensions of model (P) which capture the impact of carbon regulatory mechanisms on supplier and transportation mode selection decisions in the supply chain. The mechanisms we investigate are carbon cap, carbon tax, carbon cap-and-trade and carbon offset. The models for carbon tax and carbon cap-and-trade mechanisms are easily solvable. We present a dynamic programming algorithm in the Appendix which solves these problems in polynomial time. The models for carbon cap and carbon offset mechanisms are NP-hard. In our numerical analysis, we use CPLEX to solve small instances of these problems. The two NP-hard models imply that solution times, when the problems are solved using standard MILP solvers, will be impractical as the problem sizes grow. Both models include a single carbon cap constraint. In the absence of this constraint, the problems are shown to be polynomially solvable. Thus, relaxation of this constraint leads to easily solvable subproblems. Considering this fact, one can develop Lagrangian relaxation-based algorithms to generate good lower and upper bounds for these difficult problems, as well as insights regarding what facility might be willing to pay or receive with respect to carbon tax and offset mechanisms. It is also possible to generate upper bounds for these models by removing the carbon cap constraint, and changing the objective to minimizing the total carbon emissions. However, we do not provide details for these algorithms since this is beyond the scope of this paper, which focuses on demonstrating how carbon regulatory mechanisms influence costs and emissions in a biofuel supply chain.

6. Data collection and analysis

In this section we discuss our data collection and analysis. The models discussed above consider inventory replenishment decisions for a single commodity. The product on which we focus in this analysis is forest residue. Due to its physical characteristics of bulkiness, barge, rail, and truck may be used for shipping. The choice of the transportation mode depends on the travel distance and the associated level of carbon emissions. Forest residues are raw materials that can be used by biorefineries to produce cellulosic ethanol. We assume that such a biorefinery can meet its demand for forest residues using suppliers located nearby, or other suppliers around the nation. Canada is rich in forest, and therefore Canadian companies can be potential suppliers of forest residues. These suppliers may use rail or barge to ship their products to the US.

Table 2 summarizes some of the parameters our study used to generate data related to suppliers. We use uniform distributions to randomly generate transportation distances and variable replenishment costs. The selection of purchasing costs (at the roadside) is motivated by the following fact. The US Department of Energy (US DOE) estimates that for a price ranging from \$20 to \$80 per dry ton at the roadside, quantities of forest biomass currently available for production of biofuels would vary (at the national level) from 33 to 119 million dry tons (MDT) annually. However, for the biofuels industry to thrive, high levels of biomass should be available at lower prices. The US DOE is investigating a number of technology improvements, such as pre-processing of biomass, that would reduce these prices in the near future (Hess et al., 2009). The data in the table indicates a decrease in purchasing costs as we consider suppliers located further away. This is mainly because the pool of available suppliers increases as we consider suppliers located further away. A larger supplier pool provides the facility with more competitive prices.

Table 3 presents the scheme we use to assign transportation modes to suppliers. We assume that suppliers located within 25 miles of the facility will use truck shipments only. We assume that 50% of the suppliers located between 25 and 100 miles have access only to truck shipments, and the remaining 50% have access to both truck and rail. We assume that 50% of the suppliers located between 100 and 500 miles have access to truck and rail, and 50% have access to truck, rail and barge. As distance increases, the number of suppliers that has access to all modes of transportation increases. We use this scheme to also capture the reality that some suppliers may not have access to barge or rail due to the limited rail and barge infrastructure.

Table 4 presents the scheme we use to generate variable costs for truck transportation. Variable transportation costs depend on the distances traveled and the quantities shipped; therefore, the unit costs presented in the table are charged per ton and per mile traveled. The intervals that we use to calculate costs were generated by analyzing data made available by the Agricultural Marketing Service (AMS) of the US Department of Agriculture. The AMS publishes quarterly reports which present truck transportation trends for agricultural products in different regions of the US (Agricultural Marketing Services, 2012). The data in the table presents the average national rates charged during the last six quarters, beginning in January 2011.

Table 2
Input data generation.

Distance (in miles)	Number of suppliers	Purchasing costs (in \$)
U[5–25]	5	U[40–42]
U[25–100]	5	U[38–40]
U[100–500]	5	U[36–38]
U[500–1000]	15	U[34–36]
U[1000–1500]	15	U[30–35]

Table 3
Transportation mode assignment scheme.

Distance (in miles)	Truck (in %)	Truck&Rail (in %)	Truck & Rail & Barge (in %)
U[5–25]	100	0	0
U[25–100]	50	50	0
U[100–500]	0	50	50
U[500–1000]	0	30	70
U[1000–1500]	0	0	100

Table 4
Variable costs for truck transportation.

Distance (in miles)	Unit cost (in \$/(mile⁎ton))
[0–25]	U[0.0801–0.2401]
[25–100]	U[0.0457–0.1857]
> 100	U[0.0346–0.1746]

We randomly generated the fixed cost and variable costs for rail shipments. To identify these costs, we investigated the web-sites of Class I railway companies, such as CSX Transportation and BNSF Railway. These companies provide quotes (in \$ per rail car) for different products and different origin-destination pairs. We used the data provided for forest products to derive regression equations. The independent variable in these equations is the distance traveled, and the dependent variable is the price charged per rail car. The value of R^2 for these equations was 70% and the p-values of all independent variables were smaller than 0.1%. These values indicate that transportation distance has a great impact on the price charged. Based on these results, we decided to generate the fixed transportation cost using the uniform distribution $U[\$2500, \$3500]$ (in \$/shipment), and the unit variable cost using the uniform distribution $U[\$0.008, \$0.2]$ (in \$/(mile⁎ton)).

We also use data from AMS publications to derive transportation costs for barge. Based on this data, we generated the variable transportation cost using the uniform distribution $U[\$0.100, \$0.112]$ (in \$/(mile⁎ton)).

Our case study also considers the in-transit inventory costs. This is very important as the travel time differs substantially in different transportation modes. To calculate these costs, we first identify the travel time (in number of days) per shipment using information about travel distance and the average speed of the transportation vehicle. We assume the average speed for a truck is 65 mph, for rail 18 mph, and for barge 6.25 mph; vehicles operate for a total of 16 h per day, and vehicles operate for 350 days per year. The annual unit inventory holding cost (in \$/ton) is set equal to 20% of the unit purchase cost. We then use trip duration and unit inventory holding costs to calculate the inventory holding costs per ton shipped.

In our optimization model (P), the total unit replenishment cost for supplier i, c_i (in \$/ton), is the sum of the unit purchasing, transportation and in-transit inventory holding costs. The unit purchasing cost for supplier i is charged per ton of product replenished. Since variable transportation costs are provided in \$/(mile⁎ton), we multiply a supplier's transportation distance by the variable transportation cost in order to calculate a variable transportation cost per ton shipped from supplier i.

We consider a time horizon of $T=12$ months, with $t=1, \dots, 12$. We assume that demand for forest residues in each month is uniformly distributed between 80,000 and 100,000 tons. The conversion rate is estimated to be 60 gallons of ethanol per ton of residues (Center for Climate and Energy Solutions, 2009). Thus, the production capacity of the facility ranges between 57.6 and 72 MGY.

Let us now discuss the approach we used to collect emissions related data. In order to calculate emissions from material handling, we assume that loading and unloading of trucks, rail cars and barge are completed using loaders. The maximum allowable load for trucks (30 tons) is much smaller than rail (100 tons) or barge (1500 tons) (IOWA Department Of Transportation, 2012). For a

30 ton truck, the loading time of forest residue bundles takes about 45–50 min, and unloading takes about 50–55 min (Ranta and Rinne, 2006). We assume that a loader with a horsepower of 140 and a fuel consumption of 0.0217 gals/(hp*h) is used (McNeel et al., 2008). It is estimated that the consumption of one gallon of diesel fuel emits 9,922 g of CO_2 (Environmental Protection Agency, 2006). We assume that all modes of transportation use the same loading and unloading equipment, and therefore, we calculate the fixed emissions in tons of CO_2 per ton loaded and unloaded as follows: (duration of loading and unloading activities)$*0.0217*140*9922*10^{-6}/30$. Loading and unloading times are given in hours.

We also consider emissions due to storage of forest residues. A study by Wihersaari (2005) indicates that greenhouse gas emissions from storage can be much greater than emissions from the transportation of forest residues. The study indicates that "Greenhouse gas emissions are probably methane, when the temperature in the fuel stack is above the ambient temperature, and nitrous oxide, when the temperature is falling and the decaying process is slowing down". Following this study, we consider emissions due to storage and inventory to be uniformly distributed between 5 and 10 kg per ton of forest residues held in inventory every month.

We use the method developed by Hoen et al. (2010) to calculate emissions from transportation. Hoen et al. (2010) provide the following equations to calculate emissions for transportation via truck, rail and barge. In these equations, transportation distance D is in kilometers, the load weight w is in kilograms, v denotes volume, and ρ denotes density.

$$e_{truck} = v*\max(250, \rho)*(0.0002089 + 0.00003143D)$$
$$e_{rail} = 2.223*10^{-5}*D*w$$
$$e_{barge} = 1.3904*10^{-5}*D*w$$

7. Observations from our experiments

In this section, we discuss important observations related to the impact that different carbon regulatory mechanisms have on costs, emissions, and transportation mode decisions in this supply chain.

Below, we summarize the results from solving a wide variety of problems we generated using our data. Note that each point in any of the graphs represents the average results from solving 10 different randomly generated problem instances corresponding to the settings described for that particular problem.

Through our experiments we are also interested in investigating the impact that technological improvements may have on reducing carbon emissions in the supply chain. Technology improvements, for the purposes of this paper, correspond to improvements in fuel efficiency for transportation vehicles. These tests are motivated by a recent announcement from the US Department of Energy to fund nine projects (for a total of \$187 million) that propose improvements in the fuel efficiency of heavy duty trucks and passenger vehicles (US Department of Energy, 2010).

We define Technology 1 to be the base case scenario (i.e., business as usual). Due to improvements in fuel efficiency for Technologies 2, 3, and 4, carbon emissions are reduced by 10%, 20%, and 30%, respectively, as compared to Technology 1. Improving the fuel efficiency of transportation vehicles doubtlessly does not come free and will require investments. However, identifying these costs is not easy and not relevant to this paper, so we do not apply an arbitrary cost. Thus, our sensitivity analyses (and cost savings estimated) identify the maximum investments in these technologies in order to break even.

We solved all associated mixed integer programming models using the ILOG/ CPLEX commercial solver.

7.1. Carbon cap

Fig. 3(a) illustrates the relationship between costs and emissions under a carbon cap mechanism. We consider an annual carbon cap which varies from 2850 tons to 10,000 tons. We did not investigate smaller cap values because these led to infeasible problem instances for model (P_CC).

Five curves appear in Fig. 3(a). The straight line at the bottom shows the total costs if no carbon cap exists. The total emissions in this case equal 7145 tons. The top curve (Technology 1) represents the cost-carbon relationship when the supplier replenishes inventories using existing transportation vehicles with a relatively low fuel efficiency. The remaining curves correspond to the technological improvements in vehicle fuel efficiency as described above.

Fig. 3(a) indicates a decrease in total system costs as the carbon cap increases. The decrease in cost is steeper when the carbon cap is tighter. As the carbon cap increases, the curves become flatter and converge to the no-cap solution. At low levels of the carbon cap, the cost of maintaining operations (in order to satisfy demand) is higher compared to high levels of the carbon cap. The difference in costs between these technologies increases as the carbon cap decreases. This indicates that the benefits from technology improvements become more evident as the carbon cap gets tighter.

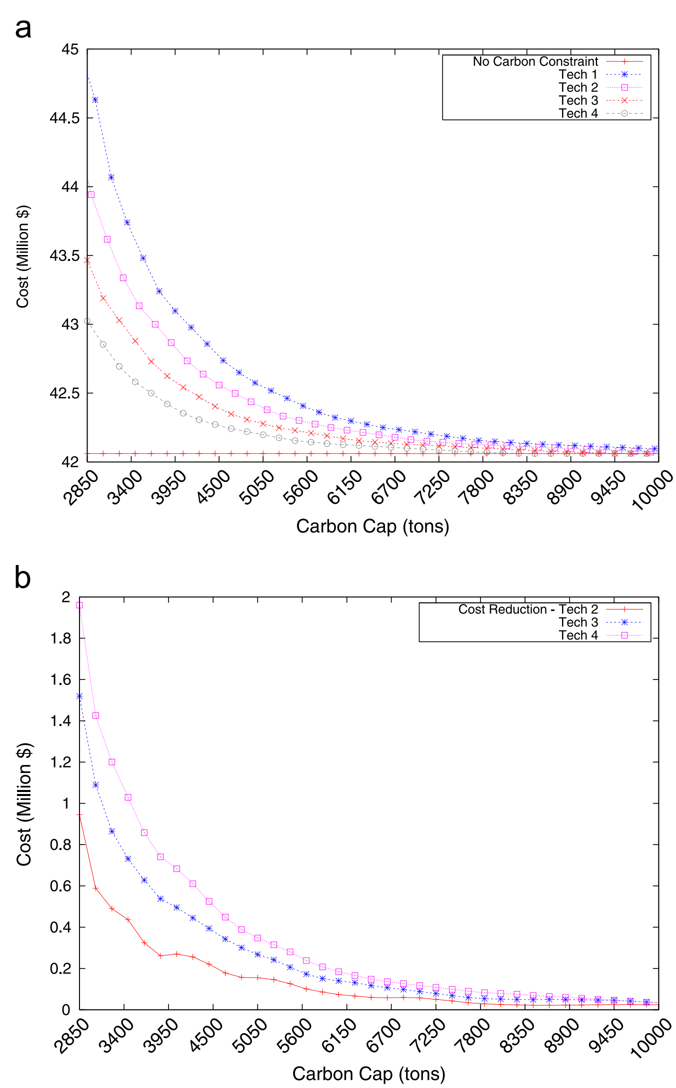

Fig. 3. Carbon cap mechanism—total costs. (a) Total costs, (b) savings compared to Tech 1.

Fig. 3(b) displays the amount of cost savings achieved by using better technologies instead of the base-case technology. This graph provides insights about the value that each technology generates for the facility, at different levels of the carbon cap. One can use these cost savings to identify when (under what cap) it becomes worth investing in any technology improvements. Note that the optimization models used find a minimum cost solution. Such a solution identifies changes in the operational decisions, such as supplier and transportation mode selection. Thus, the cost savings presented in these graphs result from the deployment of new technologies as well as due to operational changes.

Fig. 4 shows that, under a carbon cap mechanism, the amount of carbon emitted closely follows the carbon cap. As the carbon cap increases, the curves become flatter. The reason for the linear increase in emissions for tight caps is that there is no motivation for a facility to use less carbon than what is allowed by the cap. Technology improvements allow the facility to perform the same operations at a lower level of emissions. However, the facility can further reduce costs by exploring a larger pool of suppliers who are not necessarily located nearby (see Fig. 5). Therefore, total emissions remain the same, and total supply chain costs decrease with technology improvements.

A carbon cap mechanism impacts transportation mode selection decisions. Fig. 6 shows the percentage use of each transportation mode under each technology. Intuitively, selection of truck transportation is not anticipated at low levels of the carbon cap because trucks have higher emissions per mile and per ton compared to rail and barge. However, Fig. 6(a) indicates that when the carbon cap is small, inventories are primarily replenished using truck shipments from local suppliers. A company minimizes emissions by minimizing traveled distance. As the carbon cap increases, other modes of transportation are explored (see Fig. 6(b) and (c)). The volume shipped using rail transportation increases at a faster rate than the volume shipped by barge because only a small number of suppliers have access to barge.

We highlight a few additional observations from comparing the graphs in Fig. 6. First, technology improvements clearly impact transportation mode selection decisions and related costs. As the technology improves, the volume shipped using cost efficient transportation modes increases for tight carbon caps. For example, under Technology 1, at a carbon cap of 3350 tons, the volume shipped using road is 41%, rail 54%, and barge 5% of the total. At the same level of carbon cap, under Technology 3, the volume shipped by road decreases to 15%, rail increases to 75% and barge increases to 10% of the total. These modal shifts result in lower transportation costs.

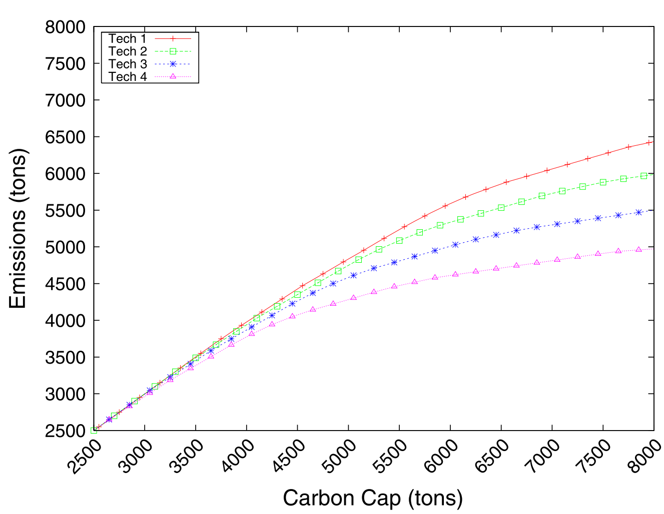

Fig. 4. Carbon cap mechanism—total emissions.

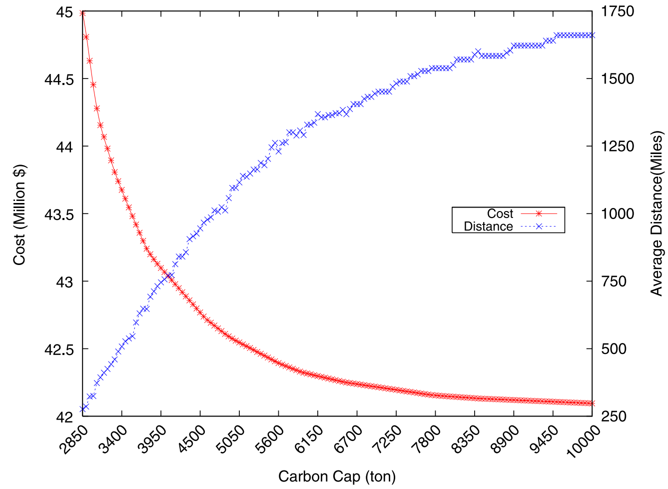

Fig. 5. Carbon cap mechanism—Tech 1—costs and distances.

Second, all the curves in these figures are steeper at low levels of the carbon cap. These curves become flat and overlap when the cap is over 5000 tons. This behavior indicates that the system is very sensitive and reacts fast to changes in the carbon cap when the cap is tight. At high levels of the carbon cap, the system stabilizes where 90% of the total volume is shipped using rail, and 10% using barge transportation.

In summary, a carbon cap is an effective tool to reduce emissions from transportation activities in the supply chain. Improvements in fuel efficiency of transportation vehicles give companies room to make better transportation-related decisions. These improvements have an impact on operational costs, but do not necessarily lead to reductions in emissions (below what is required) under a carbon cap policy.

7.2. *Carbon tax*

Fig. 7(a) shows the relationship between costs and the carbon tax rate (in \$/ton). We use tax rate which vary from \$0 to \$6000 per ton of CO_2 emitted. The \$6000 per ton tax is a very high value, as related studies discuss tax rates which are not higher than \$70 per ton (Clarke et al., 2007). However, the goal here is to analyze the behavior of the systems and identify trends which in fact do become apparent at high levels of tax.

Fig. 7(a) shows that the relationship between tax and carbon cap is almost linear since we consider a fixed tax rate for every unit of carbon emitted. The gap between the lines which represent different technologies widens as the tax rate increases indicating that cost savings by using fuel efficient technologies increase with the tax rate. Fig. 7(b) presents cost savings achieved by switching from Technology 1 to fuel-efficient technologies.

Fig. 8 shows the relationship between total emissions and carbon tax rate. As the tax rate increases, we initially see a drastic decrease in total emissions. This reflects the fact that the company seeks operational changes to reduce emissions and consequently costs. However, the curve eventually flattens since, given the supply chain structure, there exist no more operational changes which impact emissions.

The results in Fig. 9 indicate that the average distance traveled decreases as the carbon tax increases. However, this change does not occur linearly with the increase in taxes. We observe that small tax rates will not force firms to change their behavior. Long travel distances and high emissions prevail for tax rates smaller than \$100. Fig. 10 illustrates the shifts in transportation mode selection decisions as the carbon tax increases, and as the fuel efficiency of transportation vehicles improves. When the carbon tax is relatively

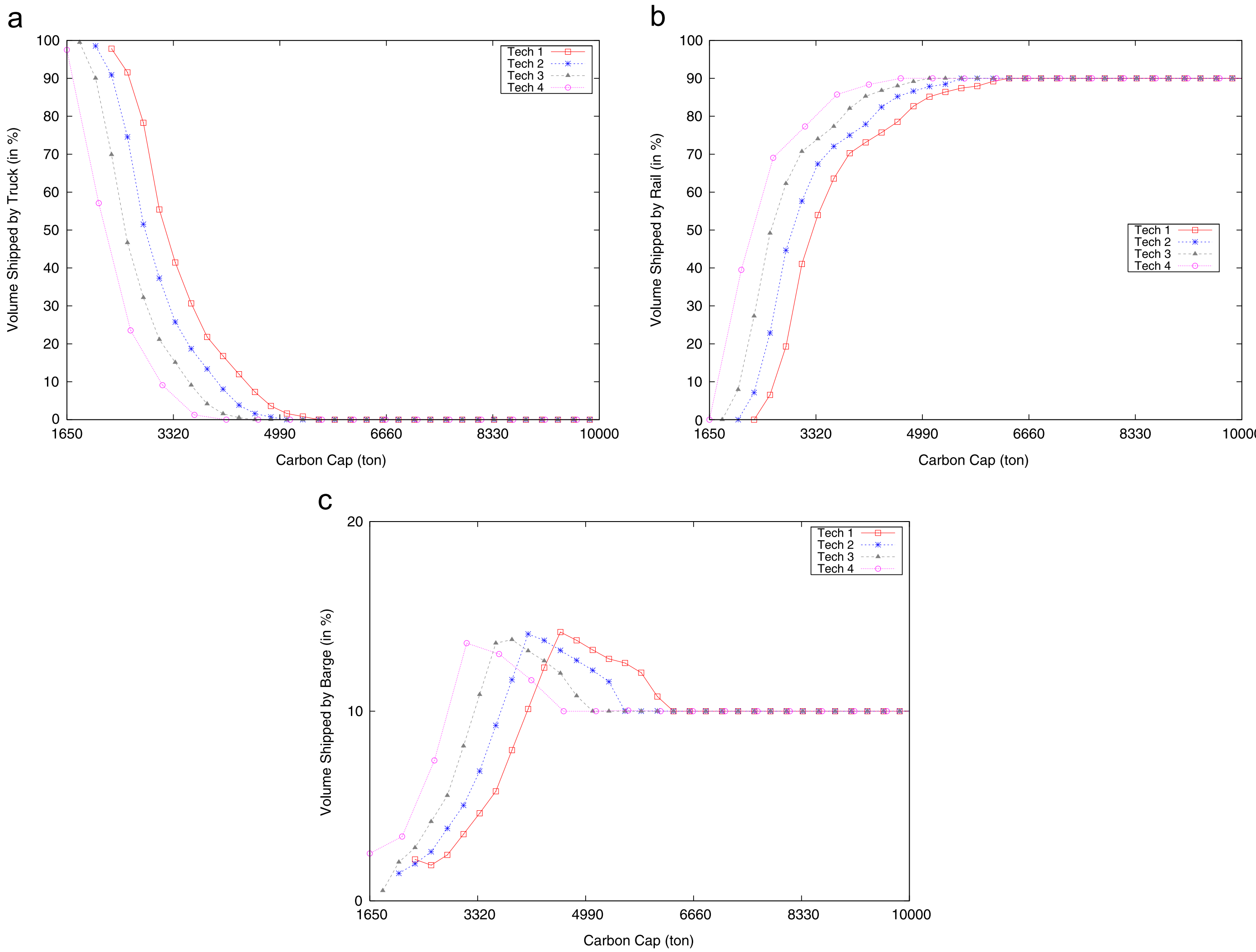

Fig. 6. Carbon cap mechanism—transportation mode percentages. (a) Road, (b) rail, (c) barge.

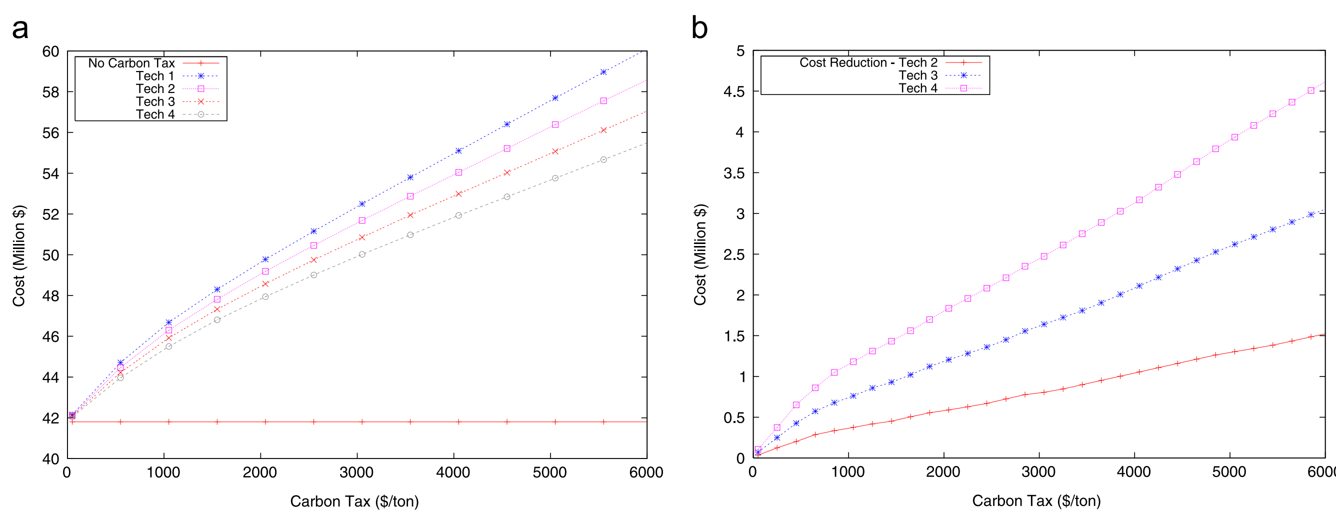

Fig. 7. Carbon tax mechanism—total costs. (a) Total costs, (b) savings compared to Tech 1.

small, rail and barge transportation are used to replenish inventories with suppliers located further away. As the tax increases, road shipments from local suppliers increase. The shape of the curves for different technologies is somewhat similar to the shapes in Fig. 6. However, the curves in Fig. 10 are step functions, which indicate that mode changes occur at discrete points in the tax rate. The graphs in Fig. 6, on the other hand, indicate a continuous reaction to changes in the carbon cap level. This continuous reaction is mainly due to the carbon cap constraint which forces the supply chain to identify operational changes (such as supplier selection) that result in lower emissions at each level of the cap.

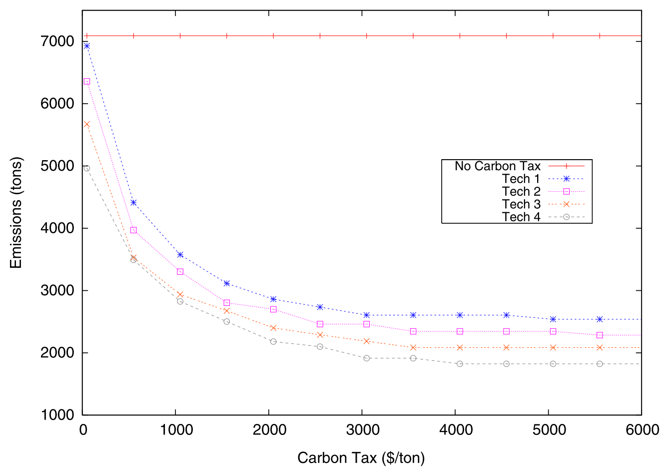

Fig. 8. Carbon tax mechanism—total emissions.

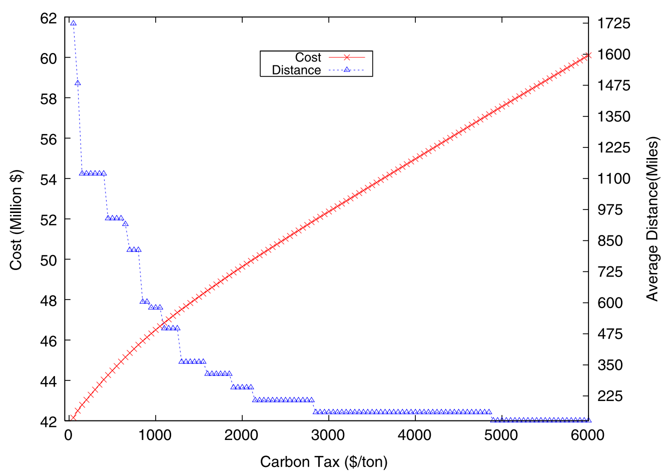

Fig. 9. Carbon tax mechanism—Tech 1—costs and distances.

7.3. Carbon cap and trade

In this section we present results from experimenting with the carbon cap and trade mechanism. We assume that the company trades emission credits at the market price we determine, and there is no limit on the amount of carbon traded at any of the market prices.

Fig. 11 shows the effect that a carbon cap and trade mechanism has on total costs at different values of the carbon credit market price. As the market price of carbon increases, the curves become steeper, indicating that changes in the carbon price have a greater impact on total system costs.

Comparing the results in Figs. 4 and 12 shows the relationship between the emissions and carbon cap levels in two different systems. Under a carbon cap mechanism, emissions initially increase linearly with the carbon cap. Emissions do not further increase beyond a certain level of the carbon cap. However, under a carbon cap and trade mechanism, the emissions level is constant, in spite of changes in the carbon cap level. This is because, as the carbon cap increases, the facility can make a profit by selling carbon credits to the market. The existence of a carbon market provides motivation for the firm to improve emissions performance. Obviously, the goal is to minimize the costs of replenishment and emissions. Therefore, the facility makes supplier selection decisions by looking at the tradeoffs between emission-related costs/benefits and transportation costs.

The market price of carbon affects emission levels. The straight lines in Fig. 12 indicate that emissions are smaller at higher levels of the carbon market price. Increasing market prices provides strong motivation for the facility to reduce emission levels, and as a result, reduces system costs either by selling unused carbon credits or by reducing the amount of carbon purchased in order to maintain operations. Fig. 13 shows the amount of carbon purchased and sold at different levels of carbon cap. Fig. 13(a) shows this relationship when the market price is $40 per ton, while Fig. 13(b) does it for a market price of $100 per ton.

At a higher market price, the firm will sell more and purchase less carbon to satisfy customer demand. We assume that the firm is able to emit less carbon by changing its operations decisions (e.g., by using local suppliers). At a higher carbon price, increased replenishment costs are offset by the benefit of selling carbon credits saved to the market. The slope of the line corresponding to the carbon credits sold is different under the two different market prices. The line is steeper when market price is $40 per ton, indicating that changes in the carbon cap will have a greater impact on the amount of carbon credits purchased when the market price is lower. At higher market prices, the line that represents carbon sales is steeper, indicating that a small change in the carbon cap will have a greater impact on the amount of carbon sold. Note that above a certain carbon cap level (3800 tons for carbon price of $40) the facility purchases carbon in certain periods and sells carbon in other periods in order to balance its operations while minimizing system-wide costs.

Under a carbon cap and trade mechanism, transportation mode selection is only determined by the carbon price (Fig. 14). For a fixed carbon price, the percent of volume shipped using each transportation mode is not affected by the level of the carbon cap. For example, between $20 and $40 per ton, 90% of the volume is received by rail, and 10% by barge. As the market price becomes more than $50 per ton, the volume shipped by barge increases to 20%.

7.4. Carbon offset

Fig. 15 displays the relationship between the carbon cap and the total system cost at different levels of the market offset price. The carbon offset amount and the corresponding prices impact total system costs. At low levels of carbon cap, the facility offsets the excess carbon used in order to maintain operations. As the offset price increases, the facility faces higher carbon offset costs. The curves belonging to different offset prices approach one another as the carbon cap increases and eventually (when the cap is loose) converges to the same total system cost (which corresponds to the total cost when there is no carbon cap). These lines are also steeper for smaller carbon cap levels indicating that system costs are more sensitive to changes in the offset price at smaller levels of carbon cap.

It is interesting to compare the curves in Figs. 4, 12, and 16. The shape of the emissions curves differs according to the carbon regulatory mechanisms. At a low carbon offset price (such as $20–$40), the level of emissions under the carbon offset mechanism is constant. This is similar to the behavior of the supply chain in a carbon cap and trade mechanism. However, as the carbon offset price increases, the level of emissions decreases, especially when the carbon cap is tight. For example, when the offset price is between $50 and $90 per ton, emissions are constant up to a carbon cap level of 4650 tons (similar to Fig. 12). As the carbon cap increases, emissions also increase. Since the facility cannot sell unused carbon credits, there is no motivation to reduce carbon emission below the requirements set by the cap. Therefore, emission amounts gradually climb to the levels with no carbon

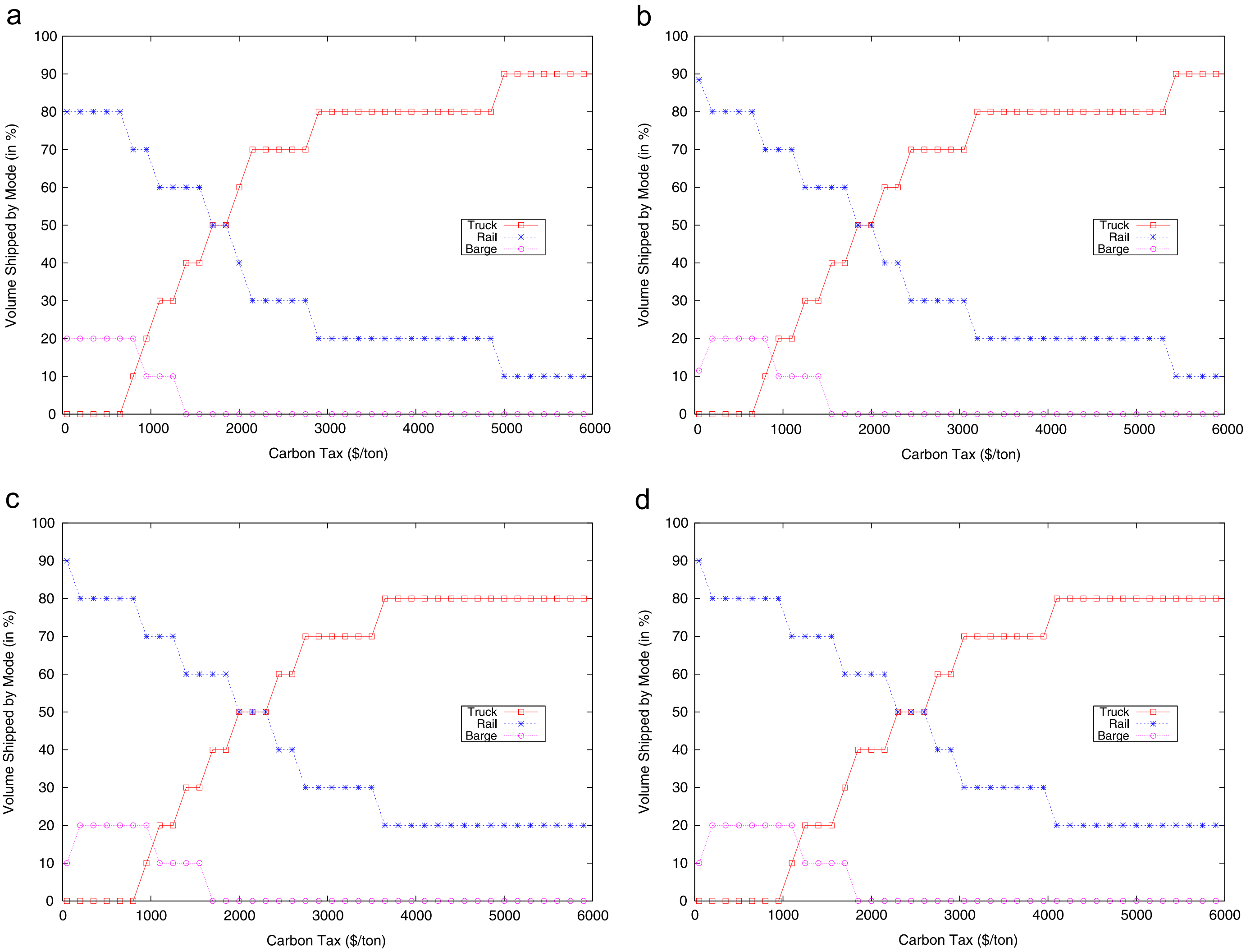

Fig. 10. Carbon tax mechanism—transportation mode percentages. (a) Tech 1, (b) Tech 2, (c) Tech 3, (d) Tech 4.

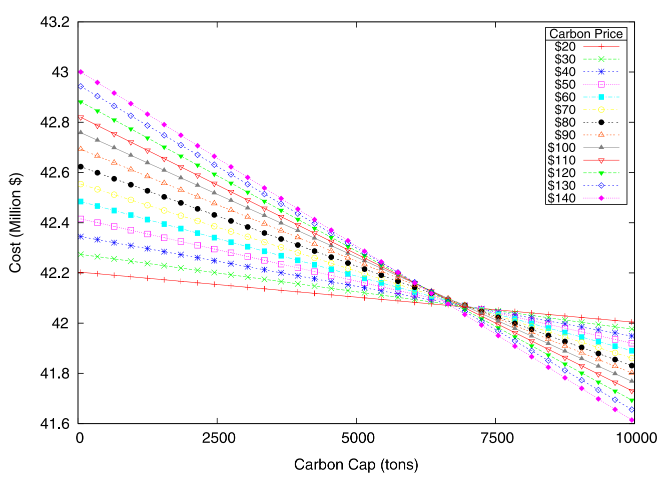

Fig. 11. Carbon cap and trade mechanism—total costs.

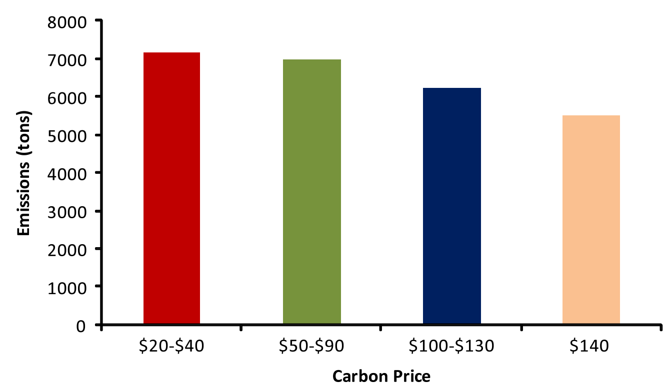

Fig. 12. Carbon cap and trade mechanism—total emissions.

cap. The graphs in Fig. 17 show the amount of carbon offset as the carbon cap increases at two different levels of offset prices.

Fig. 18 shows the volume shipped by each transportation mode as a function of the carbon cap, and for different levels of carbon offset price. When the offset price is between $20 and $40 per ton, rail ships 90%, and barge ships 10% of the total volume. Although the level of carbon cap increases, the volume shipped using each transportation mode does not change. This is similar to the carbon cap and trade mechanism. When the offset price is greater than $50 per ton, barge accounts for a constant 20% of the total volume shipped and rail accounts for 80% (for low carbon cap levels). When the cap becomes 4650 tons, the volume shipped by barge decreases to 10%, allowing the remaining shipments to be received by rail. This is a point in the system where the facility does not

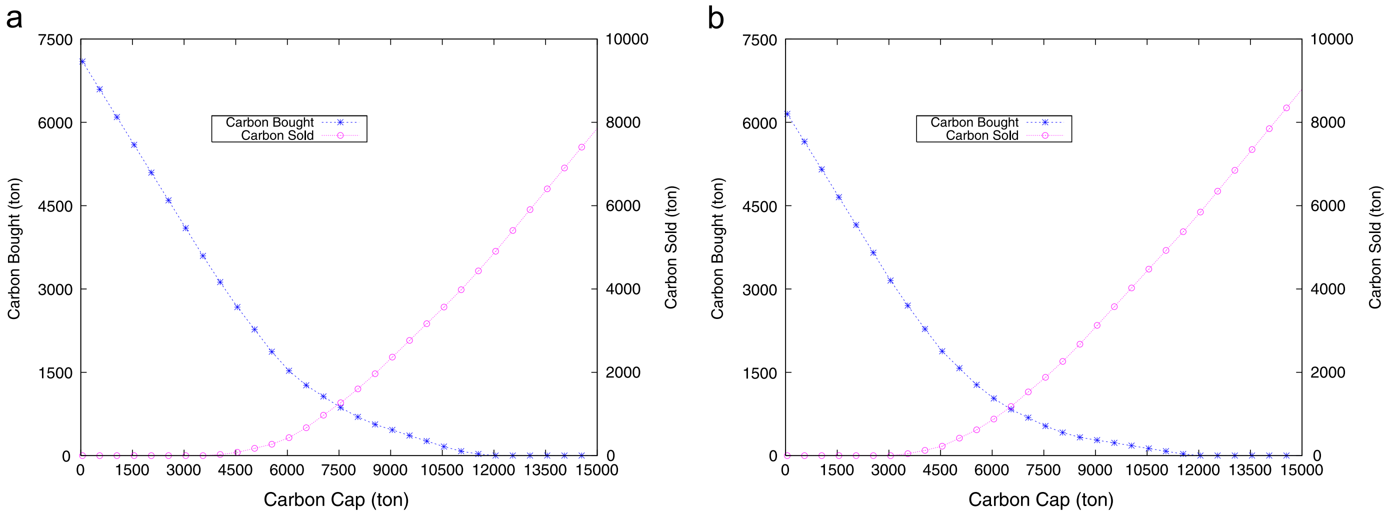

Fig. 13. Carbon cap and trade mechanism—average carbon bought and sold. (a) $40, (b) $100.

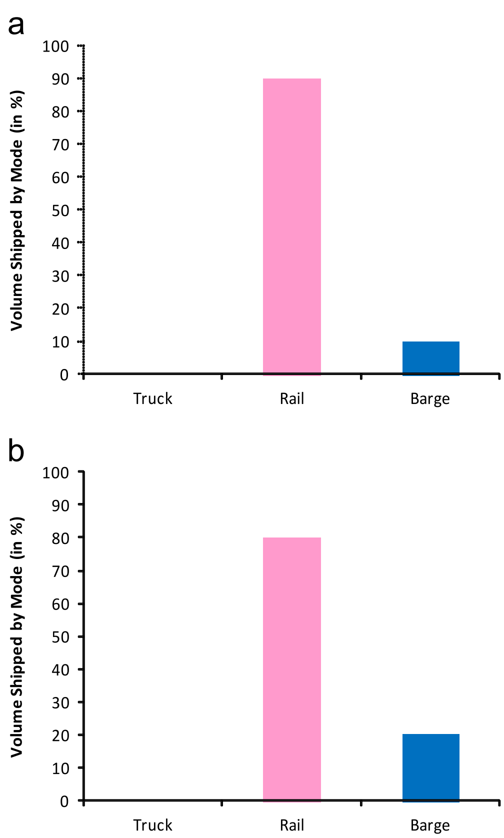

Fig. 14. Carbon cap and trade mechanism—transportation mode percentages wr/t carbon prices. (a) $20–$40, (b) $50–$140.

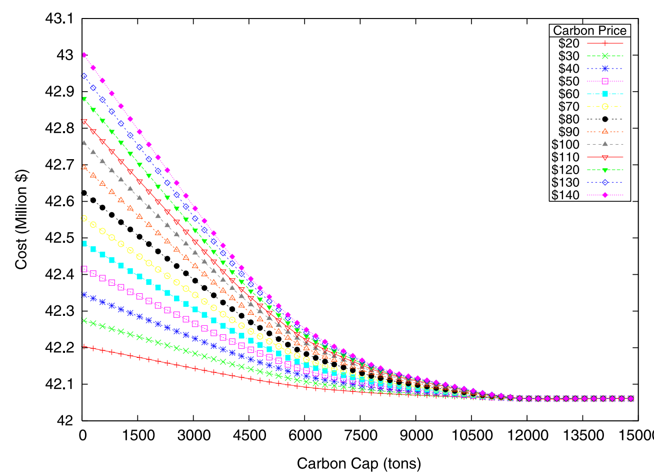

Fig. 15. Carbon offset mechanism—total costs.

have to make major operational changes to cope with the carbon cap. Since the facility cannot sell unused carbon credits in the market, there is no motivation to limit emissions. We observe that the distribution of volume shipped across different transportation modes (for high carbon caps) has the same pattern as in a carbon cap mechanism. In summary, for small carbon caps, this system behaves as it would under a carbon cap and trade mechanism; and for high carbon caps, the system behaves as it would under a carbon cap mechanism.

7.5. *Sensitivity analysis*

In this section, we present the results of a sensitivity analysis we conducted in order to evaluate the impact of problem parameters on costs and emissions in the supply chain. We perform a sensitivity analysis with respect to the variable replenishment costs. While the majority of the parameter settings in our experiments used distributions for data values that are representative of a wide range of practical problem instances, the settings for variable replenishment costs were somewhat narrow. In order to determine how system performance is affected by different assumptions on the distribution of variable replenishment costs, we considered different distribution forms and ranges.

Table 5 summarizes the problem parameters used in this analysis. Data set 1 refers to the original replenishment costs used to generate the results presented in the previous sections. In data sets 2–4, we modify these distributions by changing the type of distribution from uniform to normal, and by changing the corresponding parameters. For each problem we generate 10 problem instances and report on the averages.

Fig. 19 summarizes the results from the sensitivity analysis with respect to the variable replenishment costs. For the carbon cap and trade and carbon offset mechanisms (Fig. 19(c) and (d)) we assume a carbon market price of $50/ton.

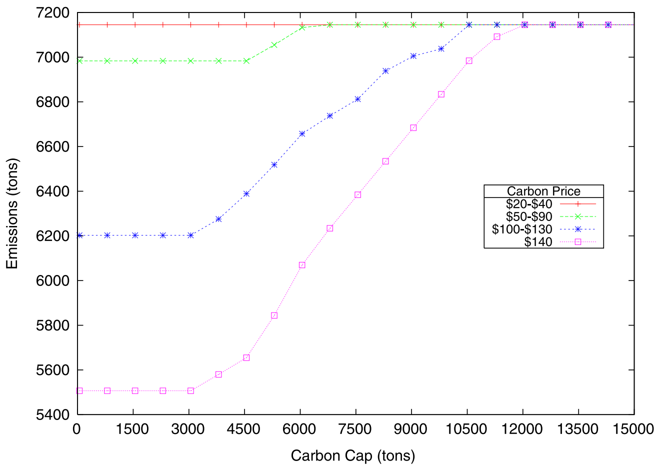

Fig. 16. Carbon offset mechanism—total emissions.

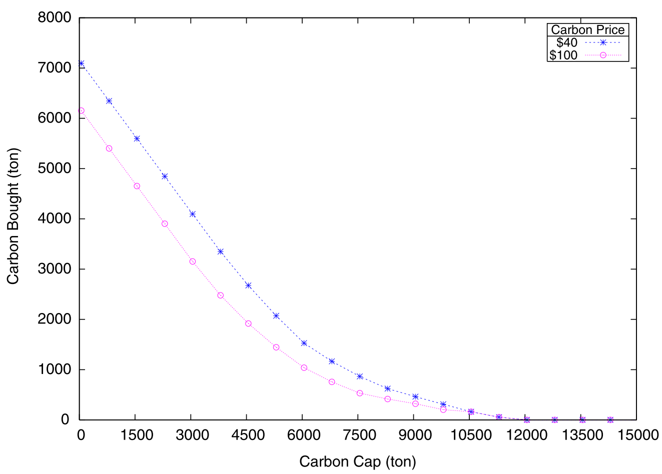

Fig. 17. Carbon offset mechanism—average carbon bought.

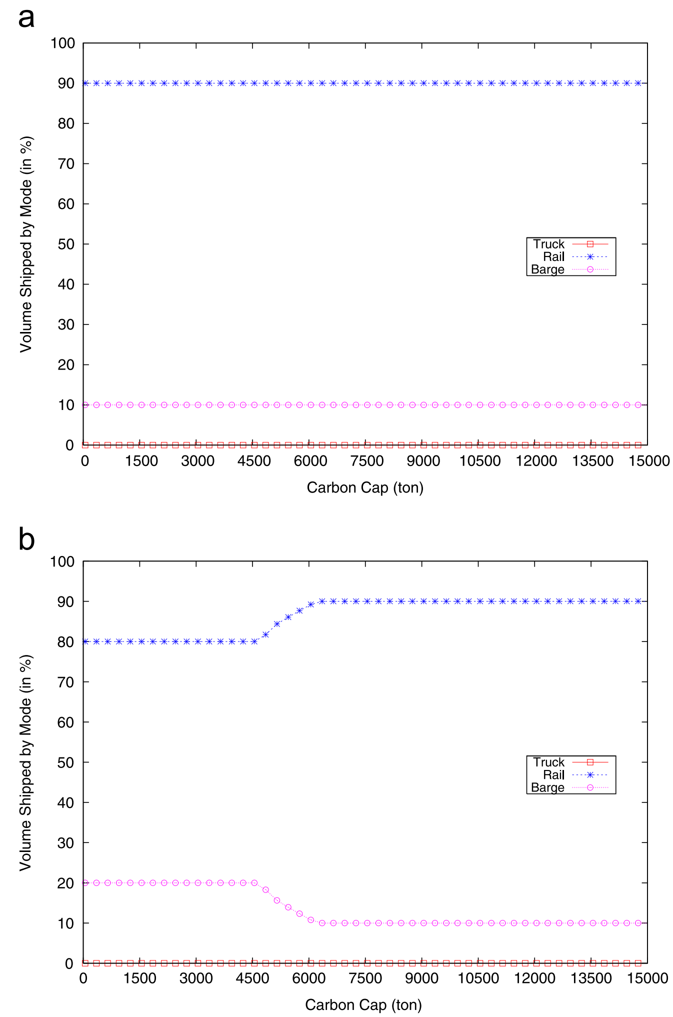

Fig. 18. Carbon offset mechanism—transportation mode percentages wr/t carbon prices. (a) \$20–\$40, (b) \$50–\$140.

For the carbon cap mechanism (Fig. 19(a)), it is possible to obtain low cost solutions that result in a higher emission levels as the carbon cap increases. For the carbon tax mechanism (Fig. 19(b)), total emissions can be very high while total costs are low due to the small carbon taxes. We observe a steep increase in the total costs with higher carbon taxes which reduces the total emissions significantly for all data sets. For the carbon cap and trade mechanism (Fig. 19(c)), we observe that total costs decrease while total emissions are at a fixed level for each data set. This is due to the increase in the carbon cap levels and the fact that the excess carbon credits can be sold in the market. For the carbon offset mechanism (Fig. 19(d)), total emissions stay constant until a certain carbon cap level. After that, the emissions start increasing since the carbon caps become very large and there is no incentive to sell the remaining carbon credits in the market.

Sensitivity analysis shows that trends between costs and emissions are maintained for the different data sets under different regulatory mechanisms. Differences in the total costs and emissions depend on the distribution forms and ranges used to generate variable replenishment costs.

8. Conclusion

This paper proposes models that capture the impact of carbon regulatory mechanisms such as carbon cap, carbon tax, carbon cap-and-trade, and carbon offset, on inventory replenishment decisions in a biomass supply chain. In particular, we investigate the impact of these mechanisms on supplier selection and transportation mode selection decisions. The models proposed are extensions of the classical economic lot sizing model. We modified the classical model to allow for multiple suppliers and transportation modes for replenishing inventories. The model selects the suppliers and transportation modes based on costs and emissions levels. Through our experimental results, we observed how existing carbon regulatory mechanisms affect the system's behavior. Below we summarize our key observations:

Observation 1: Carbon regulatory mechanisms have an impact on supplier and transportation mode selection decisions. As the carbon cap decreases, the carbon tax increases, or the market price of carbon increases, the firm tends to use local suppliers to minimize emissions related costs. Local suppliers in such cases rely on truck transportation.

Observation 2: Under a carbon cap mechanism, we can achieve a significant decrease in emissions through supply chain operations changes that come at a low cost. Note the shape of the curves in Fig. 3(a) for caps between 6000 tons and 10,000 tons. These curves are almost flat, indicating that changes in the carbon cap level have a small impact on costs.

Observation 3: Supply chain operations are less responsive to an increase in tax versus an increase in the carbon cap (see Figs. 6 and 10). The smoothness of the lines in Fig. 6 indicates a higher level of responsiveness to changes in the carbon cap level.

Observation 4: A carbon cap and trade mechanism is more efficient than a carbon offset mechanism. The supply chain behaves similarly under the two mechanisms when the carbon cap is tight. However, the supply chain behaves differently under the two mechanisms when the cap is loose. Under loose carbon caps, with a cap and trade mechanism, the unused carbon units can be sold in the market at a profit. This is not the case under a carbon offset mechanism, which punishes companies for going over the cap, but does not reward them for emissions below the cap. The shapes of the graphs in Figs. 12 and 16 support this observation. The existence of a carbon market has made the carbon cap and trade mechanism attractive to many countries. The European Union's Emissions Trading System (ETS), being the largest carbon cap and trade mechanism to date, provides a carbon market to the EU member states (Center for Climate and Energy Solutions, 2012). In 2012, California initiated its own cap and trade program. California is also collaborating with the member states of the Western Climate Initiative (WCI) to develop more comprehensive carbon cap and trade programs (California Air Resources Board, 2014).

Observation 5: Improvements in the fuel efficiency of transportation vehicles impact emissions levels. Therefore, investments in improving fuel efficiency are important in reducing both supply chain costs and emissions. The US DOE supports environmentally friendly highway transportation technologies, such as advanced combustion engines and hybrid vehicles, and biofuels (US Department of Energy, 2014). The impacts of these improvements on emissions and total supply chain costs are more obvious when the carbon caps are tight (Fig. 3), and/or the carbon tax is high (Fig. 7). However, these improvements should be accompanied by changes in supply chain operations. Otherwise, the increased demand for transportation will outweigh the positive effects of technological improvements.

Table 5
Problem parameters used in sensitivity analysis.

Distance (in miles)	Purchasing costs (in $/ton)			
	Set 1	Set 2	Set 3	Set 4
U[5–25]	U[40–42]	N(41,1)	U[40–45]	N(42.5,2.5)
U[25–100]	U[38–40]	N(39,1)	U[38–42]	N(40,2)
U[100–500]	U[36–38]	N(37,1)	U[36–40]	N(38,2)
U[500–1000]	U[34–36]	N(35,1)	U[34–38]	N(36,2)
U[1000–1500]	U[30–35]	N(32.5,2.5)	U[30–36]	N(33,3)

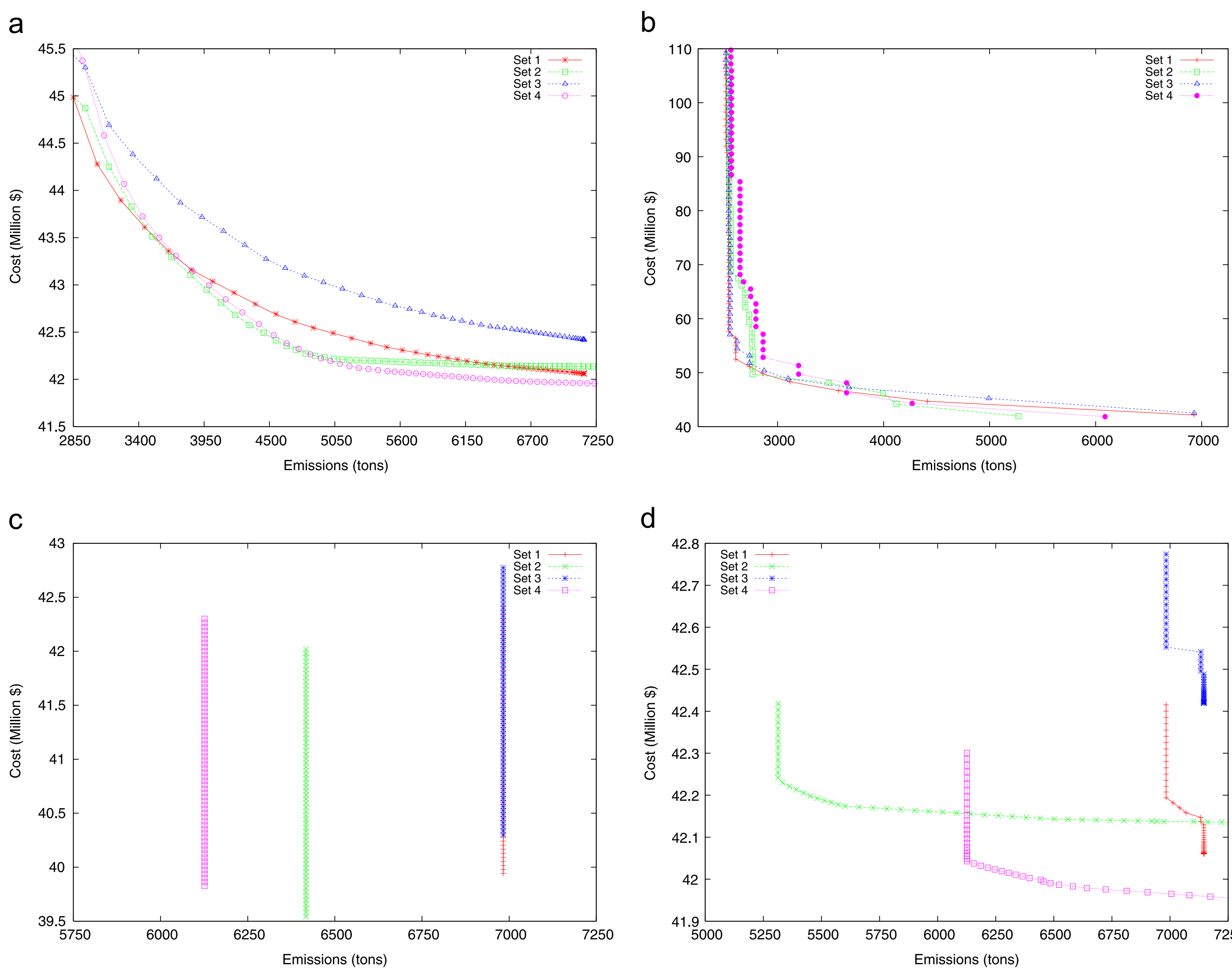

Fig. 19. Sensitivity analysis wr/t variable replenishment costs. (a) Carbon cap, (b) carbon tax, (c) carbon cap and trade, (d) carbon offset.

Appendix A

Proposition A.1. *There exists an optimal solution to* (P) *such that*:

$$q^*_{it}q^*_{lt}=0,\quad \text{for } i,l=1,\dots,I,\ i\neq l \text{ and } t=1,2,\dots,T$$
$$q^*_{it}H^*_{t-1}=0,\quad \text{for } i=1,\dots,I,\ t=1,\dots,T$$

Proof. Problem (P) minimizes a concave (fixed charge) cost function over a polyhedron. Therefore, optimizing (P) results in an extreme point solution. The extreme points of problem (P), which is an uncapacitated network flow model, correspond to tree solutions in the network model described above (Fig. 2). The tree structure of an optimal solution implies that demand is satisfied either by using existing inventories or receiving a shipment (*Zero Inventory Property*), but not both. The tree structure of the optimal solution also implies that inventories are replenished using a single supplier and a single transportation mode (*Single Source Property*). □

Theorem A.1. *There exists a dynamic programming algorithm that solves problem (P) in* $O(IT^2)$.

Proof. By the *Zero Inventory Property* of (P), an optimal replenishment schedule exists such that if period t is a replenishment period, the corresponding replenishment quantity equals $\sum_{\tau=t}^{t'-1}d_\tau$ for some $t\le t'\le T+1$ (where t' is the next replenishment period after period t, and we use the dummy period $T+1$ as a final replenishment period in any solution by convention). By the *Single Source Property* of (P), the minimum cost associated with periods t through $t'-1$ equals

$$g_{t,t'}=\left\{\min_{i=1,\dots,I}(f_{it}+c_{it}d_{t,t'-1})\right\}+\sum_{\tau=t}^{t'-1}h_\tau d_{\tau+1,t'-1},\tag{11}$$

where $d_{k,j}=\sum_{\tau=k}^{j}d_\tau$ and $k=1,\dots,T$ and $0<k\le j\le T$. Because any solution contains a sequence of setup periods, we can solve problem (P) by solving a shortest path problem in an acyclic network. That is, we create a graph G, where the total number of nodes in G is $T+1$, with one node per time period plus a dummy node $(T+1)$. Traversing arc $(t,t')\in G$ represents the choice of satisfying demand for periods $t,\dots,t'-1$ using a replenishment in period t. The cost of arc (t,t') is $g_{t,t'}$, and the supplier used for replenishment in period t is the one that gives the minimum in (11). The goal is to find the shortest path from node 1 to $T+1$ in G.

For any given supplier, we can determine all arc costs associated with the supplier in $O(T^2)$ time. Thus, computing all arc costs for every supplier takes a total of $O(IT^2)$ time. Then, for each of the $O(T^2)$ arcs, we can determine the minimum cost supplier associated with the arc in $O(I)$ time for a total of $O(IT^2)$ time. Finally, we can solve the shortest path problem in $O(T^2)$. The total worst-case complexity is therefore $O(IT^2+IT^2+T^2)$ which implies a worst-case complexity of $O(IT^2)$. □

Theorem A.2. *Problem (P_CC) is NP-hard.*

Proof. Consider the problem

$$\begin{aligned}
\text{minimize}\quad & \sum_{t=1}^{T}\{f_ty_t+c_tq_t+h_tH_t\}\\
\text{subject to}\quad & q_t+H_{t-1}-d_t=H_t,\quad t=1,\dots,T\\
& H_0=0\\
& q_t\le d_{t,T}y_{it},\quad t=1,\dots,T\\
& \sum_{t=1}^{T}(\hat f_ty_t+\hat c_tq_t+\hat h_tH_t)\le C\\
& y_t\in\{0,1\},\quad t=1,\dots,T\\
& q_t,H_t\ge 0,\quad t=1,\dots,T
\end{aligned}$$

We begin with an instance of the knapsack problem (KP) in which we have n items, where item j has value r_j and weight w_j for $j=1,\dots,n$ (assume without loss of generality that all r_j and w_j are positive). The knapsack problem determines a subset of items $S\subset N=\{1,\dots,n\}$ such that $\sum_{j\in S}w_j\le C$ (for some positive real number C) with a maximum value of $\sum_{j\in S}r_j$.

Given an instance of KP we create an instance of (P) that equivalently solves KP. We create the instance of (P) as follows.

1. For each item j, create two periods $t_j=2j-1$ and $t_{j+1}=2j$ (thus $T=2n$).
2. For $j=1,\dots,n$ set $d_{t_j}=0$ and $d_{t_{j+1}}=1$ so we have alternating demands of 0 and 1 in each pair of periods.
3. For $j=1,\dots,n$ set $f_{t_j}=r_j+K$ for some positive constant K and let $f_{t_{j+1}}=K$ (note that $f_{t_{j+1}}=f_{t_j}-r_j$).
4. For $j=1,\dots,n$ set $h_{t_j}=0$ and $h_{t_{j+1}}=M$ for some large positive number M.
5. For $j=1,\dots,n$ set $\hat f_{t_j}=0$ and $\hat f_{t_{j+1}}=w_j$.
6. For $t=1,\dots,2n$ set $c_t=\hat c_t=\hat h_t=0$.

Items 2–4 above imply that an optimal solution will never set both y_{t_j} and $y_{t_{j+1}}$ both equal to one, and the requirement that we meet all demands in problem (P) thus implies that for any j we must have $y_{t_j}+y_{t_{j+1}}=1$ in an optimal solution. Our assumptions on cost and demands imply that for each j we must therefore produce the demand in period t_{j+1} in either period t_j or t_{j+1} in an optimal solution. We can write our objective function value as

$$\begin{aligned}\sum_{j=1}^{n}\{f_{t_j}y_{t_j}+f_{t_{j+1}}y_{t_{j+1}}\}&=\sum_{j=1}^{n}\{f_{t_j}y_{t_j}+(f_{t_j}-r_j)y_{t_{j+1}}\}.\\
&=\sum_{j=1}^{n}\{f_{t_j}(y_{t_j}+y_{t_{j+1}})-r_jy_{t_{j+1}}\}=\sum_{j=1}^{n}f_{t_j}-\sum_{j=1}^{n}r_jy_{t_{j+1}}.\end{aligned}$$

Thus, this special case of (P) is equivalent to

$$\begin{aligned}
\text{maximize}\quad & \sum_{j=1}^{n}r_jy_{t_{j+1}}\\
\text{subject to}\quad & \sum_{j=1}^{n}\hat f_{t_{j+1}}y_{t_{j+1}}\le C\\
& y_{t_{j+1}}\in\{0,1\},\quad j=1,\dots,n
\end{aligned}$$

Because $\hat f_{t_{j+1}}=w_j$ for $j=1,\dots,n$, the above is equivalent to our knapsack problem. □

Proposition A.2. *One can identify whether problem* (*P_CC*) *has a feasible solution or not in* $O(IT^2)$.

Proof. If carbon emissions were minimized instead of costs, the model would reduce to problem (P) and the optimal solution would thus be a tree solution. This is because the emissions function E_{it} for supply mode i in period t (defined below) is concave, and the sum of concave functions ($\sum_{i=1}^{I}\sum_{t=1}^{T}E_{it}$) is concave.

$$E_{it}(q_{it},H_t)=\begin{cases}\hat f_i+\hat c_{it}q_{it}+\hat h_tH_t & \text{if supplier } i \text{ is used in period } t\\ 0 & \text{otherwise}\end{cases}$$

As is the case with problem (P), an optimal solution to this problem will satisfy the Zero Inventory and Single Source properties. This problem can be solved to optimality using the dynamic programming algorithm described in the Appendix in $O(IT^2)$. Therefore, identifying whether problem (P_CC) has a feasible solution takes $O(IT^2)$. In this case, one would solve the variation of problem (P) which minimizes emissions rather than costs. If the corresponding minimum function value is less than the cap C, the problem at hand has a feasible solution. □

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