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Robust Design of a Closed-loop Supply Chain Network for Uncertain Carbon Regulations and Random Product Flows

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Abstract

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Keywords

closed-loop supply chain, network design, carbon emission, stochastic programming, robust optimization

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Keywords Closed-loop supply chain · Network design · Carbon emission · Stochastic programming · Robust optimization

1 Introduction

Environmental and economic factors have motivated firms to plan their supply chain structures to handle both forward and reverse flows of products. Activities in the reverse supply chain occur due to commercial and consumer returns, or to capture the potential profits derived from remanufacturing and resale. For example, the annual costs of commercial returns in the US exceed \$100 billion [3]. Usually, these items are shipped back to the manufacturer from the retailer. The reverse flows are also compelled by various regulations [4]. Many state-operated programs in the

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US require the manufacturer to collect and recycle electronic waste (e-waste) [33]. This leads to the idea of closed-loop supply chain (CLSC) management. According to Guide and Wassenhove [53], CLSC management focuses on "the design, control, and operation of a system to maximize value creation over the entire life cycle of a product with dynamic recovery of value from different types and volumes of returns over time" (p.10). One of the most important strategic decisions in a firm's CLSC management is its network design. As the CLSC network is expected to be in use for a considerable amount of time, the firm should consider all the possible factors that will affect the design decisions.

CLSC network design is typically driven by factors such as cost, time and service quality, with little consideration for environmental impact [29]. In recent decades, concerns over global climate change are increasingly focusing attention on both the fuel costs and the carbon emissions that result from transporting goods. Although subject to political vagaries, regulation of carbon emissions is becoming inevitable. Compared to a more rigid command-and-control policy, market-based environmental mechanisms that put a price on greenhouse gas emissions are usually favored because they provide incentives for emission reduction. The market-based approach has been proven effective in controlling sulphur dioxide in the US and, elsewhere, to reduce carbon emissions. For example, in 2005 the European Union instituted a carbon emission trading scheme (EU ETS) for the energy-intensive industries with the aim of reducing greenhouse gas emissions by at least 20% below 1990 levels [16]. Also, the New Zealand Emissions Trading Scheme (NZ ETS) was introduced in 2009 [37]. In 2012, Australia introduced a carbon tax of $23 AUD per tonne of emitted CO2 on selected fossil fuels consumption [42]. Likewise, Japan introduced a carbon tax scheme in October 2012, aiming to reduce its greenhouse gas emission by 80% by 2020 [39]. Such regulations aim to eventually reduce emissions in all economic sectors, among which transportation is a main source of emissions. This is due to the fact that the transportation and handling of goods is inherently carbon-intensive, as logistics is almost completely powered by non-renewable energy sources. According to the U.S. Energy Information Administration (EIA), 33.2% of carbon emission are from the transportation sector [27]. Therefore, it is not surprising that several world regions including California and Canada are discussing cap-and-trade systems that would include the transportation sector [32]. These developments motivate industry to utilize integrated logistic solutions to reduce carbon footprint in critical areas such as network design, facilities and building use, and transportation [49].

This paper is motivated by the effect that carbon emission regulations will have on a firm's CLSC network design [30]. A firm that wishes to proactively design a CLSC in anticipation of market mechanisms to control carbon emissions faces multiple forms of uncertainty. The first question is the type of policy (carbon tax or cap-and-trade system) that may be administered. In major carbon emitting nations such as the United States and China, there are extensive debates over which regulatory policy will be favored. The network design under carbon tax may not be optimal if the regulator favors the trade scheme. Even if the firm could know which policy will be applied, it still faces considerable uncertainty about the magnitudes of incentives or penalties and the stringency of constraints. Carbon emission permit prices elsewhere have exhibited considerable volatility. In the EU ETS, the permit price increased from around 7 euros in January, 2005 to above 30 euros in April, 2006, before crashing to below 10 euros within 3 days. It then rose again and stabilized above 15 euros for about 4 months before decreasing to nearly zero by mid-2007 [10]. Such behavior implies that estimation of credible probability distributions for carbon prices based on historical data might be very difficult. Second, forecasting consumer demand is a perennial challenge even with the aid of historical or market research information to inform the construction of a probability distribution, and forecasting return flows is even harder.

Designing a CLSC network involves long-term decisions to invest in fixed facilities such as manufacturing or remanufacturing plants, warehouses, and collection facilities. The goal of this paper is to provide a unified CLSC network design model, and solve it to obtain a facility configuration that is robust to variations in possible carbon emission regulations while enabling responsiveness to the random variations in retailer demands and returns.

We propose a two-stage, multi-period stochastic programming model in which the demands for new products and returns of those products are discrete random variables. Then we extend this formulation to incorporate two carbon regulation policies: tax or cap and trade. By analyzing the similarity in the effects of the two regulation policies, we propose a hybrid model that could account for them both. The carbon prices or tax rates are characterized as uncertain parameters that fall within specified sets, and a robust optimization method based on Ben-Tal and Nemirovski [7, 8] is adopted to handle such uncertainty. Based on the possible primary scenarios the decision maker has, tractable forms of a robust counterpart under box and ellipsoidal uncertainty sets are developed. A case study shows how the optimal network configuration balances the trade-offs among investment costs, transportation costs and carbon emission costs. The network configurations obtained under the "carbon-aware" model are different from those obtained under a "carbon-oblivious" model. More facilities will be opened to reduce the distance traveled, and transportation modes with lower carbon emission rates will be favored as the uncertainty in either carbon emission regulation policy increases (in terms of carbon permit price or carbon tax). The total expected carbon emissions and total cost will also increase as the product flow variability increases. Simpler formulations under deterministic demands and returns as well as nominal carbon prices or tax rates are also derived. Numerical experiments show how, if the ellipsoidal uncertainty set is adopted, the decision maker can balance the trade-off between robustness and cost by changing the size of the ellipsoidal set. Also, compared to the nominal carbon prices or tax rates model, the robust model yields solutions that provide protection under the worst-case scenario without being overly conservative. This paper contributes to the literature by formulating the network design problem with multiple types of uncertainty. To the best of our knowledge, this is the first paper that solves the CLSC network design problem with the combination of robust optimization and stochastic programming to address the effects of uncertain environmental regulations.

The rest of the paper is organized as follows. In the next section, we review the literature related to our work. In Section 3, we provide the two-stage, multi-period stochastic programming model without consideration of carbon emissions, then extend it to include the possible carbon emission regulations. A hybrid model of both possible regulation policies is provided in Section 4, where we also propose the tractable robust counterparts under box and ellipsoidal uncertainty sets. We present case studies and computational results in Section 5 and finish the paper with concluding remarks in Section 6.

2 Literature Review

Supply chain network design problems have been relatively well-studied both for forward-only supply chain and for CLSCs (see [41], [1] and [51] for reviews). Mixed-integer programming (MIP) models are commonly used. These models range from simple uncapacitated facility location models to complex capacitated multi-stage or multi-commodity models. Their common objective is to determine the least cost system design, which usually involves making tradeoffs among fixed opening costs of facilities and variable transportation costs. Various solution methods have been developed to solve the network design problem but only a few studies have considered the uncertain nature of various input parameters in a strategic planning horizon through scenario-based stochastic programming [50, 40]. For example, Chouinard and Daoud [21] proposed a stochastic programming model for designing networks that integrate reverse logistics. They focused on

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evaluating impacts of randomness related to recovery, processing and demand volumes on the design decisions. A heuristic method was used to solve the model. Easwaran and Üster [26] studied a multi-product closed-loop logistics network design problem with hybrid manufacturing/remanufacturing facilities. Their model also had finite-capacity hybrid distribution/collection centers to serve a set of retail locations. They provided a solution method based on Benders' decomposition, and showed the effectiveness of the algorithm. Those papers used probabilistic optimization methods which take advantage of known or estimated probability distributions for the data. But these scenario-based optimization methods encounter difficulty if a discrete probability distribution of the uncertain parameters is largely unknown [13].

To overcome this shortcoming, a robust optimization methodology was first developed by Soyster [52] and then further developed by Mulvey *et al.* [45], El-Ghaoui and Lebret [28], and Ben-Tal and Nemirovski [7, 8]. This approach has also been applied to network design problems. For the robust network flow problem, Mudchanatonguk *et al.* [44] developed a method to solve a network flow problem under transportation cost and demand uncertainty. They defined an affine function for the arc flows in terms of the uncertain demand and then transformed the model into a MIP problem. Atamtürk and Zhang [2] described a two-stage robust optimization approach for solving network flow and design problems with uncertain demand, including both capacity allocation and routing decisions. That work focused on the network flow problems and did not involve the selection of locations for the facilities. Pishvaee *et al.* [47] proposed a robust optimization model for handling the inherent uncertainty of customer demands and transportation costs in a CLSC network design problem. Their model was a single stage robust optimization problem with box uncertainty, which could be converted to an equivalent mixed-integer linear program. Baron *et al.* [5] applied robust optimization to the problem of locating facilities in a network facing uncertain demand over multiple periods. They used box and ellipsoidal uncertainty sets to characterize the demand uncertainty. The latter two papers considered only uncertainties in the demand and/or cost data, and the effects of carbon emission regulations were not considered.

This paper is also related to operational and strategic impacts of supply chain decisions on carbon emissions. Benjaafar *et al.* [9] presented an extension of the lot sizing model that accounts for carbon emissions under various regulatory policies. Also, with the increase of environmental consciousness, those environmental parameters have also been taken into account when designing the supply chain network [20, 24, 48] and optimizing logistics [22]. Several authors [20, 24, 48] have used deterministic models to study the network design problem when different regulations are taken into account. But because they focused on the impact of subcontracting and production activities with a predetermined supply chain network, the effect of carbon regulations on the network configuration was not addressed. More recent studies have started to more explicitly incorporate carbon emissions into network design and transportation mode selection. Hoen *et al.* [35] examined the effect of two regulation mechanisms on the transport mode selection decision when a single mode must be selected for all transport of a single item. In their simplified setting, they found that introducing an emission cost for freight transport via either a direct emission tax or a market mechanism such as cap and trade was not likely to result in significant changes in transport modes and hence would not reduce emissions much. Fahimnia *et al.* [30] built a closed-loop supply chain cost minimization model with emissions expressed in terms of carbon cost and applied it to a case study in Australia. Krikke [38] developed a decision framework for optimizing the combined disposition and location transport decision in a closed loop network configurations and applied it to study the carbon footprint of a copier (closed-loop) supply chain. Chaabane *et al.* [19] built a multiperiod MIP model for sustainable supply chain design under emission trading scheme. Diabat *et al.* [23] introduced a multiechelon multiproduct facility location problem considering emission trading scheme and studied the impact of carbon prices on cost and configuration of supply chain network.

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This paper differs from previous research in several ways. First, we explicitly address the effects of uncertain carbon emission regulations on the CLSC network configuration by incorporating two such policies into a hybrid model. Second, this paper models the CLSC network design problem with the combination of both robust optimization and stochastic programming methodologies. The carbon regulation parameters characterized by prices or tax rates are modeled with uncertainty sets while the demands and returns are represented by discrete probabilistic scenarios.

3 A Two-stage Multi-period Stochastic Programming Model for CLSC Network Design

In this paper, we consider the design of a CLSC network for a single product. The primary decisions regard the investment in fixed facilities in anticipation of forward and reverse flows between facilities over multiple periods. The firm must decide the locations of factories for manufacturing new and recovering returned products. It will open separate warehouse and collection facilities for distributing new products and collecting returned products, respectively. In each period, the warehouses will satisfy the retailer demands, and returns will occur due to buyer remorse, product malfunction and other reasons. The returned products are first shipped by the retailers to the collection center, and then transported to the factories for inspection and recovery. Several transportation modes allow the firm to accommodate the flows between facilities. Each mode has different cost and emission implications. The network topology is illustrated in Figure 1.

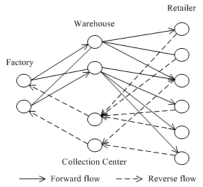

Fig. 1 Closed-loop supply chain network structure

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This problem has a two-stage, multi-period structure. It has a two-stage structure because the first-stage facility investment decisions must be made before the realization of demand and return scenarios. It is multi-period because transportation flows can vary in response to changing demand and return quantities (and in the robust extension, to changing carbon regulation parameters). After this basic model is set up, we will extend it to incorporate the uncertainty from carbon emission regulations. In the extended model, investment decisions also must be made within the first-stage prior knowing which type of regulation will be used. The product flow decisions for each subsequent period constitute the second stage, after all uncertainties are realized. The following notation will be used throughout this paper.

Sets and Indices

$\mathscr{P}$ set of potential factories for manufacturing new and recovering returned products, $p \in \mathscr{P}$
$\mathscr{W}$ set of potential warehouses for distributing new products, $w \in \mathscr{W}$
$\mathscr{L}$ set of potential collection centers for returned products, $l \in \mathscr{L}$
$\mathscr{K}$ set of retailer locations, $k \in \mathscr{K}$
$\mathscr{M}$ set of transportation modes, $m \in \mathscr{M}$
$\mathscr{T}$ set of time periods, $t \in \mathscr{T}$
$\mathscr{S}$ set of alternative scenarios of retailer demands and returns, $s \in \mathscr{S}$
$\mathscr{A}$ set of all the arcs in the network $\mathscr{A} \equiv \{ij : i \in \mathscr{P}, j \in \mathscr{W}\} \cup \{ij : i \in \mathscr{W}, j \in \mathscr{K}\} \cup \{ij : i \in \mathscr{K}, j \in \mathscr{L}\} \cup \{ij : i \in \mathscr{L}, j \in \mathscr{P}\}$
$\mathscr{F}$ set of potential facilities, $\mathscr{F} = \mathscr{P} \cup \mathscr{W} \cup \mathscr{L}$
$\mathscr{N}$ set of all potential nodes in the network, $\mathscr{N} = \mathscr{F} \cup \mathscr{K}$

Parameters

ω_t^s probability of scenario s in period t, $s \in \mathscr{S}$, $t \in \mathscr{T}$
d_{kt}^s new product demand of retailer k under scenario s in period t, $k \in \mathscr{K}$, $s \in \mathscr{S}$, $t \in \mathscr{T}$
μ_t^s return rate in period t under scenario s, $s \in \mathscr{S}$, $t \in \mathscr{T}$
r_{kt}^s returns from retailer k under scenario s in period t, $r_{kt}^s = \mu_t^s d_{kt}^s$. $k \in \mathscr{K}$, $s \in \mathscr{S}$, $t \in \mathscr{T}$.
c_{ijmt} present value of unit transportation cost from node i to node j using transportation mode m in period t, $ij \in \mathscr{A}, m \in \mathscr{M}, t \in \mathscr{T}$
f_i the investment cost for building facility, $i \in \mathscr{F}$
Λ_{it} maximum capacity of facility i in period t, $i \in \mathscr{F}$, $t \in \mathscr{T}$
β_{ij} distance (km) from node i to node j, $i, j \in \mathscr{A}$
τ_m carbon emission factor (g/ton-km) for transportation mode m, $m \in \mathscr{M}$
w unit weight of product (ton)
α_t present value of carbon tax rate in period t (dollar per ton), $t \in \mathscr{T}$
ϕ_t present value of average spot price of emission allowance in period t (dollar), $t \in \mathscr{T}$
κ_t number of carbon permits firm received from allocation in period t, $t \in \mathscr{T}$

Decision Variables

x_{ijmt}^s the amount of product transported from node i to node j using transportation mode m under scenario s in period t, $ij \in \mathscr{A}, m \in \mathscr{M}$, $s \in \mathscr{S}$, $t \in \mathscr{T}$
$y_i = 1$ if facility i is opened, 0 otherwise, $i \in \mathscr{F}$
e_t^{s+} , e_t^{s-} the number of carbon permits the firm purchases and sells in period t under scenario s, $s \in \mathscr{S}$, $t \in \mathscr{T}$

The model is based on the following assumptions.

Assumption 1 *In each period, the inventory is carried by retailers. Warehouse and collection center,which act as a break-bulk centers, do not accumulate stocks.*

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Assumption 2 *The firm owns the transportation vehicles. Each transportation mode has unlimited capacity.*

In this paper, we do not consider the possibility of third-party logistics. To avoid the complication of routing and other operational decisions, we also assume that each transportation mode has unlimited capacity.

Assumption 3 *Under the carbon cap-and-trade system, carbon permits can be either purchased or sold at the same price in a given period.*

Speculative trading; i.e., the buying and selling of carbon permits to benefit from the price difference, would involve formulation of the firm's carbon permit trading strategy, which is beyond the scope of this paper. Similar assumptions are also made in [9, 36].

Assumption 4 *Under the carbon cap-and-trade system, there is no banking or investment in financial derivatives of carbon allowances.*

This assumption permits a focus on the network design decision.

Assumption 5 *The returns in each period depend only on the sales volumes in that period; i.e., the random demands, $\tilde{d}_{kt}$, for retailer k in period t. The return rate $\tilde{\mu}_t$ is also a random variable. We further assume that for each retailer k, $\tilde{d}_{1t}, ..., \tilde{d}_{kt}$ are mutually independent and independent of $\tilde{\mu}_t$. For each period t, $\{\tilde{d}_{k1}, ..., \tilde{d}_{kt}\}$ and $\{\tilde{\mu}_1, ..., \tilde{\mu}_t\}$ are also mutually independent.*

The retailer demands for new products and the return amounts in each period are the first source of uncertainty. The realizations of random variables $\tilde{d}_{kt}$ and $\tilde{\mu}_t$ can be characterized by discrete scenarios. For each time period t, there are $|\mathscr{S}|$ discrete scenarios and ω_t^s is the probability of scenario s in period t. Thus, for each (k, t), $\tilde{d}_{kt} = d_{kt}^s$ and $\tilde{\mu}_t = \mu_t^s$ with probability $w_t^s, s \in \mathscr{S}$. Once the y_i are fixed, we are actually solving $|\mathscr{S}| \times |\mathscr{T}|$ subproblems to determine the flows between different facilities. The extensive form of the two-stage multi-period stochastic programming model without carbon emission regulations (called the *baseline problem*) can be then formulated as follows:

$$\min \sum_{i\in\mathscr{F}} f_i y_i + \sum_{s\in\mathscr{S}} \sum_{t\in\mathscr{T}} \sum_{m\in\mathscr{M}} \sum_{ij\in\mathscr{A}} \omega_t^s c_{ijmt} x_{ijmt}^s \tag{1}$$

$$\text{s.t.} \sum_{w\in\mathscr{W}} \sum_{m\in\mathscr{M}} x_{wkmt}^s = d_{kt}^s, \forall k \in \mathscr{K}, s \in \mathscr{S}, t \in \mathscr{T} \tag{2}$$

$$\sum_{l\in\mathscr{L}} \sum_{m\in\mathscr{M}} x_{klmt}^s = r_{kt}^s, \forall k \in \mathscr{K}, s \in \mathscr{S}, t \in \mathscr{T} \tag{3}$$

$$\sum_{i\in\mathscr{N}} \sum_{m\in\mathscr{M}} x_{ijmt}^s - \sum_{i\in\mathscr{N}} \sum_{m\in\mathscr{M}} x_{jimt}^s = 0, \forall j \in \mathscr{W} \cup \mathscr{L}, s \in \mathscr{S}, t \in \mathscr{T} \tag{4}$$

$$\sum_{j\in\mathscr{N}} \sum_{m\in\mathscr{M}} x_{ijmt}^s - \Lambda_{it} y_i \leq 0, \forall i \in \mathscr{F}, s \in \mathscr{S}, t \in \mathscr{T} \tag{5}$$

$$\sum_{l\in\mathscr{L}} \sum_{m\in\mathscr{M}} x_{lpmt}^s - \Lambda_{pt} y_p \leq 0, \forall p \in \mathscr{P}, s \in \mathscr{S}, t \in \mathscr{T} \tag{6}$$

$$y \in \{0, 1\}^{|\mathscr{F}|}, x \in \mathbb{R}_+^{|\mathscr{A}|\times|\mathscr{M}|\times|\mathscr{T}|\times|\mathscr{S}|} \tag{7}$$

The objective is to minimize the total present value of investment and expected operating costs. Constraints (2) and (3) ensure that retailer demands are met and returned products are collected. Constraints (4) ensure that the warehouse and collection facilities will not accumulate stocks. Constraints (5) and (6) enforce capacity constraints of the processing nodes. If facility i is not built ($y_i = 0$) they, along with (4), will force all flows into and out of the facility to zero.

3.1 Incorporating the Carbon Emission Regulation

When evaluating the firm's carbon emission intensity, we neglect those emissions resulting from the construction and maintenance of the facilities to focus our analysis on the logistics activities. The total carbon emissions Γ_t^s (tons per period) from transportation under scenario s in period t can be computed as:

$$\Gamma_t^s = w \sum_{ij \in \mathscr{A}} \beta_{ij} \sum_{m \in \mathscr{M}} \tau_m x_{ijmt}^s, \forall t \in \mathscr{T}, s \in \mathscr{S} \tag{8}$$

We consider two possible regulatory policies. Under a linear carbon tax scheme, the regulatory party penalizes the units of carbon emitted in each period. For carbon tax rate α_t, the problem can be restated as:

$$\min \sum_{i \in \mathscr{F}} f_i y_i + \sum_{t \in \mathscr{T}} \sum_{s \in \mathscr{S}} \sum_{m \in \mathscr{M}} \sum_{ij \in \mathscr{A}} \omega_t^s c_{ijmt} x_{ijmt}^s + \sum_{t \in \mathscr{T}} \sum_{s \in \mathscr{S}} \alpha_t \omega_t^s \Gamma_t^s \tag{9}$$

subject to constraints (2) – (8). Here, the term $\sum_{t \in \mathscr{T}} \sum_{s \in \mathscr{S}} \alpha_t \omega_t^s \Gamma_t^s$ is the expected future cost of the carbon tax.

Under a cap-and-trade system, the firm will receive an allocation of carbon permits κ_t in each period (i.e., the "cap"). Every permit allows the firm to emit one ton of carbon. It may emit more than its cap if it buys additional permits from the market, and it can also sell excess permits. Under this setting, the problem can be reformulated as follows:

$$\min \sum_{i \in \mathscr{F}} f_i y_i + \sum_{t \in \mathscr{T}} \sum_{s \in \mathscr{S}} \sum_{m \in \mathscr{M}} \sum_{ij \in \mathscr{A}} \omega_t^s c_{ijmt} x_{ijmt}^s + \sum_{t \in \mathscr{T}} \sum_{s \in \mathscr{S}} \phi_t \omega_t^s (e_t^{s+} - e_t^{s-}) \tag{10}$$

$$\text{s.t. } \Gamma_t^s - e_t^{s+} + e_t^{s-} \leq \kappa_t, \forall s \in \mathscr{S}, t \in \mathscr{T} \tag{11}$$

$$e_t^{s+}, e_t^{s-} \geq 0 \tag{12}$$

in addition to constraints (2) – (8). Here, the last term in the objective function is the expected future cost or profit from the carbon trading market. Note that, although carbon emission permits are nondivisible, introducing discrete carbon emission permits will impose another layer of complexity to the model [12]. For simplicity, we assume they can be traded in any continuous quantity.

There are some similarities between the regulation policies. In the cap-and-trade version of the model, which replaces (1) with (10) and includes constraints (11) and (12), for any $\phi_t \geq 0$ the net number of permits purchased, $e_t^{s+} - e_t^{s-}$, will be as small as possible at optimality. Therefore, constraint (11) will bind at optimality, so that $e_t^{s+} - e_t^{s-} = \Gamma_t^s - \kappa_t$ will hold for every scenario and every period. Thus, $\sum_{t \in \mathscr{T}} \sum_{s \in \mathscr{S}} \phi_t \omega_t^s (e_t^{s+} - e_t^{s-}) = \sum_{t \in \mathscr{T}} \sum_{s \in \mathscr{S}} \phi_t \omega_t^s (\Gamma_t^s - \kappa_t)$, where $\sum_{t \in \mathscr{T}} \sum_{s \in \mathscr{S}} \phi_t \omega_t^s \kappa_t = \sum_{t \in \mathscr{T}} \phi_t \kappa_t$. Because the term $\sum_{t \in \mathscr{T}} \phi_t \kappa_t$ will affect only the objective value but not the optimal solution, it can be dropped from the objective function without loss of optimality. Then, the objective has the same form as that for the carbon tax (9). The two policies thus can be represented in a single model as follows:

$$\min \sum_{i \in \mathscr{F}} f_i y_i + \sum_{t \in \mathscr{T}} \sum_{m \in \mathscr{M}} \sum_{ij \in \mathscr{A}} c_{ijmt} \bar{x}_{ijtm} + \sum_{t \in \mathscr{T}} (\alpha_t \bar{\Gamma}_t) \tag{13}$$

$$\text{s.t. } \Gamma_t^s - e_t^{s+} + e_t^{s-} = \kappa_t, \forall s \in \mathscr{S}, t \in \mathscr{T} \tag{14}$$

$$e_t^{s+}, e_t^{s-} \geq 0 \tag{15}$$

along with constraints (2) – (8). Here, $\bar{\Gamma}_t \equiv \sum_{s\in\mathscr{S}} \omega_t^s \Gamma_t^s$ and $\bar{x}_{ijtm} \equiv \sum_{s\in\mathscr{S}} \omega_t^s x_{ijmt}^s$ represent the expected amount of carbon emissions and the expected flows, respectively, in period t. A tax policy is represented by setting κ_t to a large enough value that it does not affect the optimization and setting α_t to the unit tax, while a cap-and-trade policy is represented by setting κ_t to a restrictive level and letting α_t represent the market price of carbon permits. In this paper, we consider the α_t and κ_t to be uncertain data, which vary within an uncertainty set ($\mathscr{U}$). The distributions of $\{\alpha_t\}$ and $\{\kappa_t\}$ are not known but the decision maker has the nominal data $\hat{\alpha}_t$ and $\hat{\kappa}_t$, which are estimates of α_t and κ_t.

Compared with MIP or stochastic programming models, which have been well studied, robust optimization models require more sophisticated formulations. Therefore, several "easy" approximations for this problem could be formulated. The implications of different approximations are explored in the numerical study. One is to replace the uncertain α_t with the nominal values but still retain the stochastic demands and returns in the formulation. This results in a *nominal stochastic* model.

$$\text{(Problem NS)}: \ \min \sum_{i\in\mathscr{F}} f_i y_i + \sum_{t\in\mathscr{T}} \sum_{m\in\mathscr{M}} \sum_{ij\in\mathscr{A}} c_{ijmt}\bar{x}_{ijtm} + \sum_{s\in\mathscr{S}} \sum_{t\in\mathscr{T}} \hat{\alpha}_t \bar{\Gamma}_t \tag{16}$$

along with constraints (2) -(8) and (14) -(15). Another approximation of the problem is to replace the stochastic demands and returns in each period with their expected values. Under this approximation, the decision variables will be y_i and x_{ijmt}, as the second stage consists of a single scenario. The emission in each period Γ_t can be computed as $\Gamma_t = w \sum_{ij\in\mathscr{A}} \beta_{ij} \sum_{m\in\mathscr{M}} \tau_m x_{ijmt}, \forall t \in \mathscr{T}$. If we replace the carbon permit price or tax rate in (41) with the estimated nominal values, we obtain the *nominal deterministic* problem.

$$\text{(Problem ND)}: \quad \min \sum_{i\in\mathscr{F}} f_i y_i + \sum_{t\in\mathscr{T}} \sum_{m\in\mathscr{M}} \sum_{ij\in\mathscr{A}} c_{ijmt} x_{ijt}^m + \sum_{t\in\mathscr{T}} \hat{\alpha}_t \Gamma_t \tag{17}$$

$$\text{s.t.} \ \Gamma_t - e_t^+ + e_t^- = \hat{\kappa}_t, \forall t \in \mathscr{T} \tag{18}$$

$$\sum_{w\in\mathscr{W}} \sum_{m\in\mathscr{M}} x_{wkmt} = \bar{d}_{kt}, \forall k \in \mathscr{K}, \forall t \in \mathscr{T} \tag{19}$$

$$\sum_{l\in\mathscr{L}} \sum_{m\in\mathscr{M}} x_{klmt} = \bar{r}_{kt}, \forall k \in \mathscr{K}, \forall t \in \mathscr{T} \tag{20}$$

$$\sum_{i\in\mathscr{N}} \sum_{m\in\mathscr{M}} x_{ijmt} - \sum_{j\in\mathscr{N}} \sum_{m\in\mathscr{M}} x_{jimt} = 0, \forall j \in \mathscr{W} \cup \mathscr{L}, \forall t \in \mathscr{T} \tag{21}$$

$$\sum_{j\in\mathscr{N}} \sum_{m\in\mathscr{M}} x_{ijmt} - \Lambda_{it} y_i \le 0, \forall i \in \mathscr{F}, \forall t \in \mathscr{T} \tag{22}$$

$$\sum_{l\in\mathscr{L}} \sum_{m\in\mathscr{M}} x_{lpmt}^s - \Lambda_{pt} y_p \le 0, \forall p \in \mathscr{P}, t \in \mathscr{T} \tag{23}$$

$$y \in \{0,1\}^{|\mathscr{F}|}, x \in \mathbb{R}_+^{|\mathscr{A}|\times|\mathscr{M}|\times|\mathscr{T}|}, e_t^+, e_t^- \ge 0, \alpha_t, \kappa_t \in \mathscr{U} \tag{24}$$

where $\bar{d}_{kt}$ is the expected demand for the new products and $\bar{d}_{kt} = \sum_{s\in\mathscr{S}} \omega_t^s d_{kt}^s, t = 1,..,T$. Similarly, $\bar{r}_{kt}$ is the expected amount of the returned products and $\bar{r}_{kt} = \sum_{s\in\mathscr{S}} \omega_t^s r_{kt}^s, t = 1,..,T$.

4 Hybrid model for CLSC network design

4.1 Robust Optimization Methodology

The goal of robust optimization is to make decisions that are robust to any realization of the uncertain data. To illustrate the robust optimization methodology we will use in this study,

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consider a linear optimization problem with an objective function $c^T x$ to minimize, subject to constraints $Ax \leq b$ where uncertain parameters c, A, b vary in a given uncertainty set U. The general uncertain linear optimization problem can be stated as follows:

$$\{\min_x c^T x \ s.t.\ Ax \leq b\}, (c, A, b) \in U \tag{25}$$

Here the decision variables are x and the uncertain parameters c, A, b belong to a closed, bounded and convex uncertainty set U. A solution x is robust feasible if it satisfies constraint $Ax \leq b$ for all realizations of A, b within U. Each robust feasible solution x is associated with a robust objective value $\hat{c}(x) = \sup_{c \in U}[c^T x]$. The purpose of robust optimization is to find a optimal solution x^* among robust feasible solutions x which will return the best robust objective value. Such x^*, called a robust optimal solution, is obtained by solving the following Robust Counterpart (RC) problem [6]:

$$\min_x \{\hat{c}(x) = \sup_{c \in U}[c^T x] : \ Ax \leq b, \forall (A, b) \in U\} \tag{26}$$

Ben-Tal and Nemirovski [7, 8] show that the RC of a linear optimization problem is tractable for most uncertainty sets. For the case of ellipsoidal uncertainty set, the RC is equivalent to a second-order cone program (SOCP). If U is polyhedral, the robust counterpart is equivalent to a linear optimization problem [11].

4.2 Hybrid Model

The robust optimization approach is adopted here to address the policy uncertainty; i.e., we formulate an uncertainty set ($\mathscr{U}$) for the combination of α_t and κ_t, and then seek a solution to the robust counterpart of this problem. At the same time, we retain the stochastic demands and returns in the constraints. We introduce a scalar variable z to represent the value of the objective function (13). The compact matrix form of this hybrid model can be stated as follows, and we denote this *robust stochastic* formulation as problem RS.

$$\text{(Problem RS)}: \min_{z,y,x,e^+,e^-,\Gamma} z \tag{27}$$

$$\text{s.t.} \quad \forall (\alpha, \kappa) \in \mathscr{U} \begin{cases} \alpha^T \bar{\Gamma} \leq z - f^T y - c^T \bar{x} \\ \Gamma - e^+ + e^- = K \end{cases} \tag{28}$$

$$Bx = \tilde{v} \tag{29}$$

$$-Fy + Gx \leq 0 \tag{30}$$

$$-wH^T x + \Gamma = 0 \tag{31}$$

$$y \in \{0,1\}^{|\mathscr{F}|}; x \in \mathbb{R}_+^{|\mathscr{A}| \times |\mathscr{M}| \times |\mathscr{T}| \times |\mathscr{S}|}; e^+, e^-, \Gamma \in \mathbb{R}_+^{|\mathscr{T}| \times |\mathscr{S}|} \tag{32}$$

The vectors α, f and κ correspond to carbon prices or tax rates, fixed opening costs and emission caps, respectively. Matrix c contains transportation costs among different nodes and K is a matrix of $| \mathscr{S} |$ columns, each consisting of $(\kappa_1, \ldots, \kappa_{|\mathscr{T}|})^T$. The matrix B contains coefficients for the flow-conservation constraints (19)-(21), while $\tilde{v}$ contains the right-hand-sides $\tilde{d}_{kt}, \tilde{r}_{kt}$ and zero. F and G contain coefficients of the constraints (5). For the emissions, H is a matrix with dimension conformable to x and $\tilde{v}$ whose element $h_{ijmts} = \beta_{ij}\tau_m, \forall t, s$. All binary decision variables are included in the vector y, flow variables under different scenarios are included in the matrix x and the expected flows constitute matrix $\bar{x}$. The objective function (27) is to minimize the total costs. Constraints (28) will ensure the cost objectives be considered and the carbon cap in each period will be met. Constrains (29) and (30) ensure the flow and capacity in the network while constraint (31) is the compact form for calculating the total carbon emissions. To obtain a tractable form of problem RS, let us first consider the following two generic LPs:

$$\text{(P1)}: \min_{u,s} \quad c^T u \tag{33}$$

$$\text{s.t.} \quad \forall (D,e) \in \mathscr{U} \begin{cases} Du \leq b \\ Hx + s = e \end{cases} \tag{34}$$

$$u \geq 0, s \text{ free} \tag{35}$$

and

$$\text{(P2)}: \min_{u} \quad c^T u \tag{36}$$

$$\text{s.t.} \quad Du \leq b, \forall D \in \mathscr{U}_D \tag{37}$$

$$u \geq 0 \tag{38}$$

where c is an $n \times 1$ vector, b is an $m \times 1$ vector and D is an $m \times n$ matrix for the coefficients. The set $\mathscr{U}_D$ is the projection of $\mathscr{U}$ on the space of the data for constraint (37). Note that (P1) has a form similar to Problem RS omitting (29)-(31) and the binary restrictions on some variables. To solve P1, we can apply the following:

Theorem 1 *If u^* is an optimal solution of P2 with objective value v, then $(u^*, e - Hu^*)$ is an optimal solution of P1 with the same objective value v.*

Proof By contradiction. Suppose u_2^* is an optimal solution for $P2$ but there is no optimal (u_1, s_1) for $P1$ with $u_1 = u_2^*$. This means we can find a solution u_1^* that satisfies $Du_1^* \leq b$, $Hu_1^* + s = e$ and $c^T u_1^* < c^T u_2^*$. Let Ω_1 and Ω_2 denote the feasible regions of P1 and P2, respectively, where $\Omega_1 = \{(u,s) : Du \leq b, Hu + s = e, \forall (D,e) \in \mathscr{U}, u \geq 0\}$ and $\Omega_2 = \{u : Du \leq b, \forall A \in \mathscr{U}_D, u \geq 0\}$. We can see that $\Omega_1 \subseteq \Omega_2$, which implies $c^T u_1^* \geq c^T u_2^*$. This contradicts the supposition and concludes the proof.

Based on Theorem 1, we can discard constraints $(\Gamma - e^+ + e^- = \kappa)$ from (28) and construct the following problem (RS') instead:

$$\text{(Problem } RS') : \min_{z,y,x} z \tag{39}$$

$$\text{s.t.} \quad \alpha^T \bar{\Gamma} \leq z - f^T y - c^T \bar{x}, \forall \alpha \in \mathscr{U}_\alpha \tag{40}$$

along with constraints (29)-(32). The set $\mathscr{U}_\alpha$ is the projection of set $\mathscr{U}$ on the space of the data for constraint (40), which describes only uncertainty in α.

Corollary 1 *If z^*, y^*, x^* are an optimal solution to RS', and Γ^* is the corresponding total carbon emissions, then $z^*, y^*, x^*, e^{+*} = \max(\Gamma^* - \kappa, 0)$ and $e^{-*} = \max(\kappa - \Gamma^*, 0)$ is an optimal solution to problem RS.*

Proof Theorem 1 remains valid after introducing binary variables y where $u = (x, y, z)$. Here the slack variable is $e^- - e^+$. If no speculative trading or banking is considered, it is expected that the firm participates in buying or selling carbon permits only to handle the difference between their cap and their emissions.

A special case of the hybrid model is formulated with a single scenario for consumer demands and returns equal to their expected values. Similar to the way we formulate problem NS and ND, we can define the *robust deterministic* problem as follows:

$$\text{(Problem RD)}: \ \min \sum_{i\in\mathscr{F}} f_i y_i + \sum_{t\in\mathscr{T}} \sum_{m\in\mathscr{M}} \sum_{ij\in\mathscr{A}} (c_{ijmt} x_{ijmt}) + \sum_{t\in\mathscr{T}} (\alpha_t \Gamma_t) \tag{41}$$

$$\text{s.t. } \bar{\Gamma}_t - e_t^+ + e_t^- = \kappa_t, \forall t \in \mathscr{T} \tag{42}$$

along with constraints (19) - (24). It can be solved in the same way as problem RS. We will numerically study the implications or ignoring demand and return uncertainty as well.

From the decision maker's point of view, how should the uncertainty set $\mathscr{U}_\alpha$ be constructed? When carbon permit prices or tax rates are considered, some primary scenarios might be gained based on the experience of EU ETS. We could then construct the uncertainty set based on the available data and decision maker's attitude towards risk. Assume the actual carbon permit prices or tax rates, α_t, are unknown but bounded by a symmetric interval around an estimated nominal value. That is, $\alpha_t \in \Delta_t = [\hat{\alpha}_t - \delta_t, \hat{\alpha}_t + \delta_t]$, where $\hat{\alpha}_t$ is the nominal value and $\delta_t < \hat{\alpha}_t$ are the possible deviations in each period. We will then present two possible uncertainty sets, box and ellipsoidal that the decision maker could use.

4.2.1 Hybrid Model under Box Uncertainty Set

A box uncertainty set may be represented by $\mathscr{U}_{box} = \{\alpha \in \mathbb{R}^n : |\alpha_t - \hat{\alpha}_t| \leq \delta_t\}$, where $n = |\mathscr{T}|$. Define $W_t = \hat{\alpha}_t + \delta_t$, which is the worst case scenario of carbon prices or tax rates in each period. The problem RS' under box uncertainty can be represented as follows:

$$\min_{z,y,x} z \tag{43}$$

$$\text{s.t.} \quad \max_{\alpha\in\mathscr{U}_\alpha} \{\alpha^T \bar{\Gamma}\} \leq z - f^T y - c^T \bar{x} \tag{44}$$

along with constraints (29)-(32), and the problem RS' under the box uncertainty set is further equivalent to the following *worst-case stochastic* problem:

$$\text{(Problem WS:)} \min_{z,y,x,\lambda} z \tag{45}$$

$$\text{s.t.} \quad W^T \bar{\Gamma} \leq z - f^T y - c^T \bar{x} \tag{46}$$

along with constraints (29)-(32), where W is the vector of $\{W_t\}$. Considering that $\bar{\Gamma} \geq 0$, it is straightforward that $\max\{\alpha^T \bar{\Gamma}\} = W^T \bar{\Gamma}$. This is the same approach proposed by Soyster [52]. The robust optimal solution would be obtained by solving the problem assuming the carbon permit price or tax rate in period t is W_t. Although the resulting problem WS is a MILP which could be solved efficiently, choosing such an uncertainty set is very conservative.

4.2.2 Hybrid Model under Ellipsoidal Uncertainty Set

For the network design problem, the decision maker might be interested in a set of problem RS' solutions $(x, y, z) \in \Psi(\epsilon)$ such that (x, y, z) will violate the constraint (40) with probability at most ϵ. The set $\Psi(\epsilon)$ can be represented by following chance constraint [43]:

$$\Psi(\epsilon) = \{(x, y, z) : Pr(\alpha^T \bar{\Gamma} > z - f^T y - c^T \bar{x}) < \epsilon\} \tag{47}$$

where $\bar{\Gamma} = \omega^T \Gamma$. We want to design an uncertainty set such that the probability statement is guaranteed and the robust solution is feasible without being overly conservative. One way to design such an uncertainty set is to use an ellipsoidal set:

$$\mathscr{U}_{ellips} = \{\alpha \in \mathbb{R}^n : \sum_{t=1}^{n} \delta_t^{-2}(\alpha_t - \hat{\alpha}_t)^2 \le \rho^2\} \tag{48}$$

Using P to denote the diagonal matrix with entries δ_t, an equivalent representation is $\mathscr{U}_{ellips} = \{\hat{\alpha} + Pu : \|u\|_2 \le \rho\}$. The problem RS' under the ellipsoidal uncertainty set can be represented as follows:

$$(\text{Problem} RS'_{ellips}) : \quad \min_{z,y,x} z \tag{49}$$

$$\text{s.t.} \quad \max_{\|u\|_2 \le \rho} \{(\hat{\alpha}^T + (Pu)^T)\bar{\Gamma}\} \le z - f^T y - c^T \bar{x} \tag{50}$$

along with constraints (29)-(32).

Theorem 2 *The problem RS'_{ellips} is equivalent to the following problem:*

$$\min_{z,y,x,\lambda} z \tag{51}$$

$$s.t. \quad \hat{\alpha}^T \bar{\Gamma} + \rho \|P\bar{\Gamma}\|_2 \le z - f^T y - c^T \bar{x} \tag{52}$$

along with constraints (29)-(32).

Proof The left-hand side in constraint (50) equals $\hat{\alpha}^T \bar{\Gamma} + \max_{\|u\|_2 \le \rho} (Pu)^T \bar{\Gamma}$, where $\max_{\|u\|_2 \le \rho} (Pu)^T \bar{\Gamma} = \max_{\|u\|_2 \le \rho} \sqrt{((Pu)^T \bar{\Gamma})^2}$. According to the Cauchy–Schwarz inequality, $((Pu)^T \bar{\Gamma})^2 \le (\|u\|_2)^2 (\|P\bar{\Gamma}\|)^2 \le \rho^2 (\|P\bar{\Gamma}\|)^2$. Thus, $\max_{\|u\|_2 \le \rho} (Pu)^T \bar{\Gamma} \le \rho \|P^T \bar{\Gamma}\|_2$, which concludes the proof.

We can get different sets by varying the value of the uncertainty budget ρ. For $\rho = 0$, $\mathscr{U}_{ellips}$ shrinks to the nominal data $\hat{\alpha}_t$. For $\rho = 1$, $\mathscr{U}_{ellips}$ is the largest ellipsoid contained in $\mathscr{U}_{box}$. For $\rho = \sqrt{n}$, which is the worst case uncertainty budget, $\mathscr{U}_{ellips}$ is the smallest volume ellipsoid containing the $\mathscr{U}_{box}$. Ben-Tal and Nemirovski [8] proved that the feasible solutions will violate constraint (40) with probability at most $\exp(-\rho^2/2)$. For example, $\rho = 3.0349$ will guarantee at least 0.99 feasibility. But for problems with a small number of uncertain data values, this bound is not particularly attractive, and we can obtain a tighter bound based on Dufour and Hallin's work [25].

Theorem 3 *If the uncertainty intervals are given by $\Delta_t = [\hat{\alpha}_t - \delta_t, \hat{\alpha}_t + \delta_t]$ and (x, y, z) is a feasible solution, then $Pr\{\alpha^T \bar{\Gamma} > z - f^T y - c^T \bar{x}\} < B(\rho, t)$ as tabulated in Table 3 of [25].*

Proof Dufour and Hallin derive the probability bound for $|\sum_{t=1}^{n} a_i Y_i| \ge y$ where $\sum_{t=1}^{n} a_i^2 = 1$ and random variables $|Y_i| \le 1, \forall i = 1, ..., n$. The uncertainty in carbon permit price in each period t can be represented by $\tilde{\alpha}_t = \hat{\alpha}_t + \eta_t \delta_t$, where the random variable η_t obeys an unknown but symmetric distribution on $[-1, 1]$. Then $Pr\{\alpha^T \bar{\Gamma} > z - f^T y - c^T \bar{x}\} = Pr\{\sum_{t=1}^{n} (\tilde{\alpha}_t + \eta_t \delta_t) \bar{\Gamma}_t > z - f^T y - c^T \bar{x}\}$, and $z - f^T y - c^T \bar{x} \ge \sum_{t=1}^{n} \tilde{\alpha}_t \bar{\Gamma}_t + \rho \sqrt{\sum_{t=1}^{n} (\delta_t \bar{\Gamma}_t)^2}$ from constraint (52). So we have

$$Pr\left\{\alpha^T \bar{\Gamma} > z - f^T y - c^T \bar{x}\right\} < Pr\left\{\sum_{t=1}^{n} \eta_t \delta_t \bar{\Gamma}_t > \rho \sqrt{\sum_{t=1}^{n} (\delta_t \bar{\Gamma}_t)^2}\right\} < Pr\left\{\sum_{t=1}^{n} \eta_t \delta_t \bar{\Gamma}_t \ge \rho \sqrt{\sum_{t=1}^{n} (\delta_t \bar{\Gamma}_t)^2}\right\}.$$

Let $p_t = \delta_t \bar{\Gamma}_t / \sqrt{\sum_{t=1}^{n} (\delta_t \bar{\Gamma}_t)^2}$, and $\sum_{t=1}^{n} p_t^2 = 1$. Then we have

$$Pr\left\{\alpha^T \bar{\Gamma} > z - f^T y - c^T \bar{x}\right\} < Pr\left\{\sum_{t=1}^{n} \eta_t p_t \geq \rho\right\} \leq Pr\left\{|\sum_{t=1}^{n} \eta_t p_t| \geq \rho\right\}.$$

This probability bound can be derived based on the Proposition 1 of [25].

We should note that bound in [25] is tighter than $\exp(-\rho^2/2)$. For example, based on Dufour and Hallin's calculation, 0.99 feasibility will be guaranteed at $\rho = 2.686$. Thus, the decision maker can easily balance the trade-off between robustness and performance by changing the size of ellipsoidal set. In addition, even though the problem RS'_{ellips} is a mixed-integer second order cone program (MISOCP), it can be solved efficiently by some commercial solvers, e.g., the ILOG CPLEX Optimizer.

5 Computational Experiments

In this section, we describe numerical experiments to understand the impact of uncertainties on the CLSC network configuration. Specifically, we investigate the impacts of carbon emission regulation uncertainty and product flow variability on the number of facilities opened, transportation mode selection, total carbon emissions and total cost. Before presenting the results, we first describe the detailed method to generate the parameters.

5.1 Parameter Generation

All the parameters are randomly generated according to uniform distributions. The candidate facility locations are randomly generated in a $[0, 5000] \times [0, 5000]$ square. The fixed cost f_i (\$M) of opening a factory, warehouse, or collection center are randomly generated according to uniform distributions on $[5, 8]$, $[0.5, 1.5]$, and $[0.125, 0.5]$, respectively. Capacities of the factory, warehouse and collection center in each period Λ_{it} are randomly generated according to uniform distributions on $[2.5, 4]$, $[0.25, 0.75]$, $[0.062, 0.25]$ (million units), respectively. We assume that only the road transport options are available and do not consider rail, water and air transport. For the transportation modes, the calculations of carbon emission factors are based on data from Pirog *et al.*[46]. The cost per km per ton is calculated based on the data from Byrne *et al.* [18], which is calculated based on fuel costs, capital costs, operation and maintenance cost over the fleet's life cycle and adjusted by incorporating the weight consideration. The distance between any two locations is considered to be the Euclidean distance (with kilometer as distance unit). We further assume that the weight of $1,000$ units is one ton; i.e., w=1000g.

In each period, three scenarios for new product demand are considered, namely low (L), medium (M) and High (H). The following steps are used to generate demands and returns of each retailer in each period:

1. For $t = 1$ to T :

2. The probability ω_t^L is randomly generated between $[0.3, 0.35]$, ω_t^M is randomly generated between $[0.3, 0.35]$ and $\omega_t^H = 1 - (\omega_t^1 + \omega_t^2)$.

3. For $k = 1$ to K :

4. Low, medium and high demand scenarios d_{kt}^L, d_{kt}^M and d_{kt}^H are randomly generated in $[800, 2000]$, $[3000, 6000]$, and $[8000, 10000]$, respectively. The return rates under the low, medium

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and high demand scenarios, μ_t^L, μ_t^M, and μ_t^H are randomly generated in $[0.05, 0.08]$, $[0.07, 0.1]$ and $[0.08, 0.12]$, respectively.

5. Next k

6. Next t.

Table 1 Characteristics of road transport options

Transport Mode	Fuel Type	CO_2 Emissions Factor (g/ton-km)	Cost ($/ton-km)
1.Heavy–duty Truck	Diesel	62	0.47
2.Mid–size Truck	Diesel	122	0.32
3.Light Truck	Gasoline	459	0.19

In the computational experiments, the estimated carbon price $\hat{\alpha}_t$ is randomly generated in $[5, 30]$ while the δ_t is randomly generated in $[4, 10]$ to satisfy $\hat{\alpha}_t - \delta_t \geq 0$. The randomly generated $\hat{\alpha}_t$ and δ_t will be discarded if $\delta_t > \alpha_t$. Only ellipsoidal uncertainty sets are considered in this experiment so we abbreviate RS'_{ellips} as RS. The proposed problems RS and RD are implemented in GAMS and solved by CPLEX 11.0 MIQCP solver. The baseline problem and problem NS are solved by CPLEX 11.0 MIP solver. The data are manipulated by GDXMRW utilities with Matlab [31]. All computations are carried out on an Intel Core(TM)2 Quad CPU 3.00 GHz, 3.25 GB RAM computer. The largest instance has 3,762 rows and 54,107 columns. It took up to 21 MB of memory and 262387 iterations to solve it in a matter of minutes.

5.2 Network Configuration under Different Problem Formulations

To investigate how the optimal network configurations are affected by different model formulations, we first generate a test problem with 10 potential factories, 15 potential warehouse locations, 10 potential collection centers and 30 retailers with $n = 6$ planning periods and uncertainty budget $\rho = 2.45$. The locations for retailers and potential facilities are shown in Figure 2. We then solve the baseline case, problem ND, problem RS, problem NS and problem RD. Figure 3 shows the network configurations under different demands and returns scenarios from the baseline problem. The arcs represent the product flows between different nodes, where an arc between two nodes is displayed if a flow occurs of any period between the two nodes. Different line widths are used to represent different amounts (average over time periods) of product flow between two nodes. For the forward flow between the factory and warehouse, the thickest line represents the product flows greater than 1 million units and the medium thick line represent product flows greater than 0.5 million units. Between the warehouse and retailers, the line thicknesses represent product flows greater than $100,000$ units and $50,000$ units, respectively. The reverse flows are shown by dashed lines. The line thickness between the retailer and the collection center represent product flows greater than $10,000$ units and 5000 units, respectively. Similarly, the line thickness from the collection center to the factory represent product flow greater than $100,000$ units and $50,000$ units, respectively.

The main issue is to determine an appropriate network design that simultaneously optimizes both forward and reverse network flows on average. The optimal solution for the baseline problem reflects the trade–offs between the facility investment costs, transportation costs and satisfaction of the capacity constraints. Generally speaking, a higher fixed cost will result in fewer facilities while a higher transportation cost will favor more facilities. Under the baseline case, 1 factory, 3

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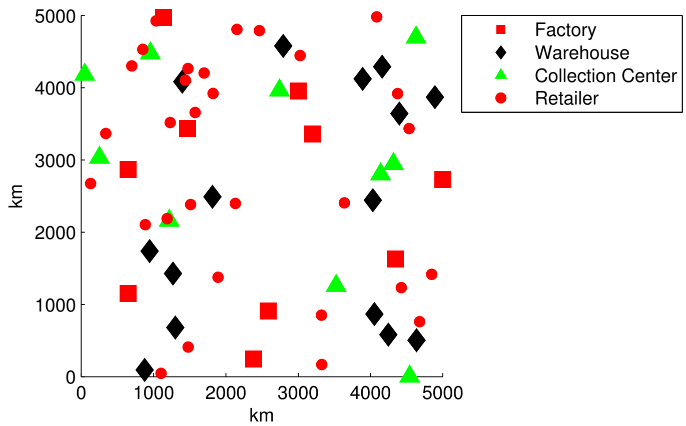

Fig. 2 Customer locations and potential locations for facilities

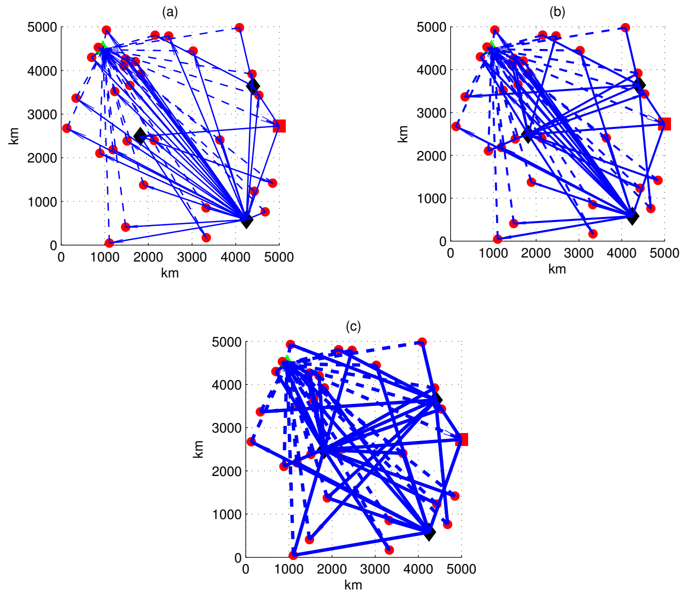

Fig. 3 Optimal network configuration for baseline problem under different scenarios (a) Low; (b) Medium; (c) High

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warehouses and 1 collection center will be opened. As there are no costs other than for investment and transportation in the baseline formulation, it is not surprising that a relatively "centralized" network configuration is obtained where a few facilities serve different markets and each facility serves a large subregion. As the capacities of different transportation modes are unlimited, the light truck is favored exclusively because it has the lowest unit transportation cost.

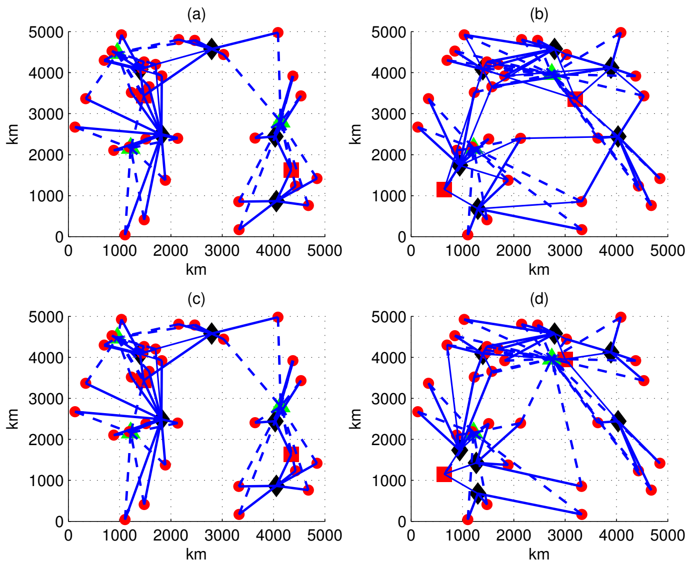

Fig. 4 Optimal network configuration and expected flows for different formulations (a) ND; (b) NS ; (c) RD; (d) RS

The network configurations obtained when carbon regulation is considered show quite different characteristics compared to the baseline case. If the carbon regulations are incorporated, the variable costs include both transportation and carbon emission costs. As the carbon emission cost is proportion to the distance traveled, more facilities will be opened to mitigate the carbon cost and we will get a relatively "decentralized network" for problems RS, NS and RD. For problems ND and RD, 2 factories, 5 warehouse and 3 collection centers will be opened. For problem NS, 2 factories, 6 warehouse and 2 collection centers will be used. For problems RS, 2 factories, 7 warehouse and 2 collection centers will be opened. Comparing to the baseline solution, facilities are located closer to markets.

We use degree centrality to indicate the denseness of the CLSC network. Degree centrality is calculated by counting the number of edges incident to a given node [17]. We focus on the warehouse and collection centers because they act as the hubs between the factories and retailers. For the warehouses, we calculate the average outdegree; i.e., the average of number of links from the warehouses to the retailers. For the collection centers, we calculate the average indegree; i.e., the average number of links from the retailers to the collection centers. The results are shown in the left-hand columns of Table 2. The baseline model results in a more centralized network than the other four models. This suggests that if there is no carbon emission regulation, it is optimal to build a few main hubs for distributing the new products and collecting the used ones. When carbon emissions are considered in a nominal way (ND and NS), the network is less centralized than in the baseline case. When uncertainty in carbon emissions is also considered (RD and RS),

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the forward chain becomes even less centralized but the reverse chain is more centralized than in the nominal models. In these numerical instances, the reverse chain can afford more centralization as the transported volumes are relatively small compared with those in the forward chain.

Table 2 Centrality and shares of transportation by mode comparision

	Warehouse-Outdegree	Collection Center-Indegree	MR_1	MR_2	MR_3
Baseline	10	30	0	0	100%
ND	6	10	0	100 %	0
NS	6	10	0	100 %	0
RD	5	15	52.88%	46.85%	0.27%
RS	4.3	15	49.08%	48.61%	2.31%

To study the usage of transportation modes, we also calculate the shares of different transportation modes over all scenarios (see Table 2) for the five different formulations. The portions of total flows carried by heavy-duty truck, mid-size truck and light truck are denoted as MR_1, MR_2 and MR_3. The MR_m is computed as follows:

$$MR_m = \frac{|\sum_{s\in\mathscr{S}}\sum_{t\in\mathscr{T}}\sum_{ij\in\mathscr{A}} x^s_{ijmt} > 0|}{|\sum_{s\in\mathscr{S}}\sum_{t\in\mathscr{T}}\sum_{m\in\mathscr{M}}\sum_{ij\in\mathscr{A}} x^s_{ijmt} > 0|} \times 100\% \tag{53}$$

Transportation modes balance the trade-offs between transportation and carbon costs. The heavy-duty truck has a lower emission factor but higher unit cost while the light truck will lead to higher carbon cost but lower unit transportation costs. For problems RS and RD, transportation mode 1 and 2 will be favored as they have lower emissions, while for problem NS and ND, transportation mode 2 will be favored exclusively as the mid-size truck has the medium transportation cost and carbon emission rate.

Figure 4 shows the difference in network configurations between the deterministic and the stochastic problems. The network configurations under deterministic demands and returns are relatively “centralized” while the stochastic versions are more “decentralized”. This is because the total transportation cost is lower under the deterministic settings compared to the stochastic settings. Thus, under the deterministic settings, fewer facilities will be utilized. Also, from Figure 4 (a) and (c) we can observe that problems ND and RD have the same selection of facilities. This is because the optimal network configuration is obtained by balancing the trade-off between fixed cost, transportation cost and carbon cost. If the carbon cost under problems ND and RD lacks much impact on the total cost, then we will get a rather similar configuration. Otherwise, the network configurations will be different between ND and RD. For comparison purposes, we reduce the transportation cost to $0.047, 0.032, 0.019$ for the corresponding transportation modes. The results from resolving all the five problems are shown in figures 5 and 6. Under this new settings, the transportation cost will be reduced, and problem RD have more facilities than problem ND. This means more facilities will be opened under problem RD to further reduce the carbon costs. Problem NS and RS have different configurations under both settings. This means if the decision maker solves problem NS rather than problem RS, the optimal network configurations will be quite different. This is because under the stochastic settings, the problem will have a higher expected carbon cost, which might have more impact on the total cost. In the next section, we will show that problems NS and RS have different cost implications. Generally speaking, the optimal configuration obtained under problem NS will result in a higher cost than problem RS under the worst case scenario.

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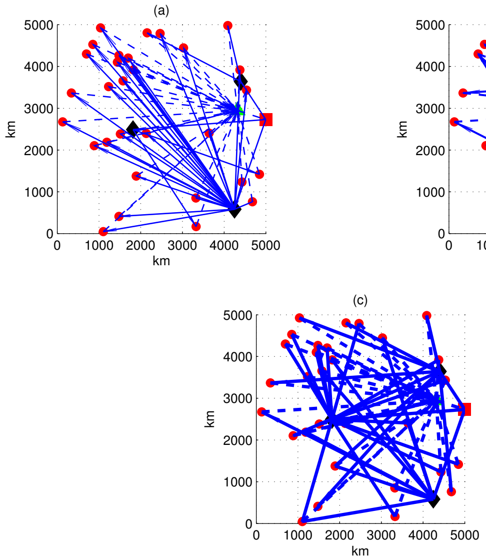

Fig. 5 Optimal network configuration for low transportation cost baseline problem under different scenarios (a) Low; (b) Medium; (c) High

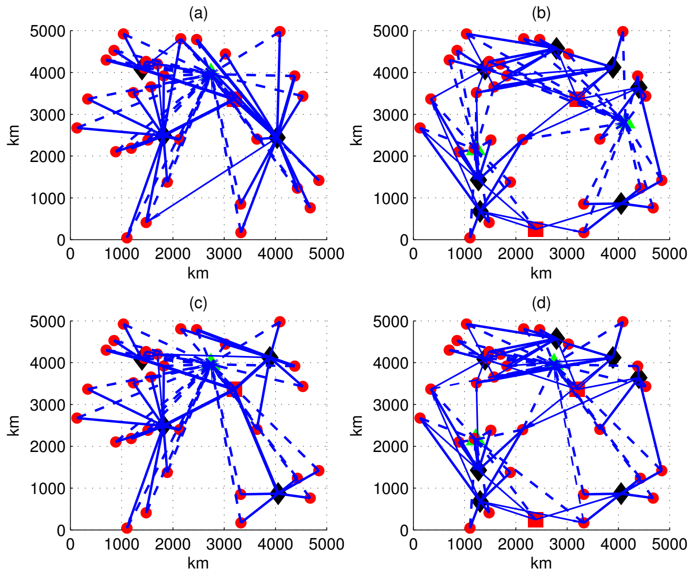

Fig. 6 Optimal network configuration and expected flows for different formulations under low transportation cost (a) ND; (b) NS ; (c) RD; (d) RS

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5.3 Impact of Carbon Emission Regulation Uncertainty

To study the impact of carbon emission regulation uncertainty on CLSC network, we perform a computational experiment by varying the uncertainty budget. A larger ρ will result in the carbon prices or tax rates varying within a larger ellipsoidal uncertainty set and, thus, the degree of uncertainty faced by the decision maker. Thus, by purposely changing the value of ρ, we can change the volatility of the emission regulation uncertainty. We then design 6 levels of uncertainty from $\rho = 0$ to $\rho = 20$. For each level of uncertainty, we randomly generate 10 instances. We then compute the average number of eacg facility type, expected total emission and total cost. We also compute the share of transportation by each mode following equation (53). We use N_F, N_W, N_C to denote the average number of factory, warehouse and collection center that are used. Finally, we use TE and TC to denote the total expected carbon emission and total expected cost for all periods. The complete results of the experiment are shown in Table 3.

Table 3 Impact of carbon emission regulation uncertainty

Uncertainty Level	N_F	N_W	N_C	MR_1 (%)	MR_2 (%)	MR_3 (%)	TE (M ton)	TC (M $)
0	3	7.1	5	34.14	52.69	13.17	1.52	111.29
4	3.5	7.3	5.7	58.61	29.50	11.89	1.08	127.97
8	3.6	7.6	6.1	70.97	19.91	9.13	0.93	140.88
12	3.9	7.4	5.9	89.14	7.78	3.09	0.89	152.82
16	4	7.6	6.4	94.71	3.72	1.58	0.87	164.68
20	4.2	7.7	6.3	100	0	0	0.86	176.43

Observe that more facilities will be opened as the uncertainty level increases. As the policy uncertainty increases, it is possible that the permit will end up with a relatively high price. To counter the emissions from transportation, more facilities will be opened to lower the distance traveled. Second, total expected emissions will decrease as the uncertainty level increases while the total expected cost will increase as the regulation uncertainty level increases. Again, the total expected emissions will decrease because of the possible high permit price as the policy uncertainty level increases. The total expected cost will increase due to the construction of more facilities and the employment of transportation mode 1. Third, the share of transportation mode 1, with the lowest emission rate, will increase as the uncertainty level increases.

5.4 Impact of Random Product Flow Variability

We considered three different levels of the variability, with the scenario distributions generated above considered as medium. Under the low variability level, the probabilities of high and low demand in each period are generated in $[0.05, 0.1]$, while under the high variability level, the probabilities of high and low demand in each period are generated in $[0.4, 0.45]$. We generated 20 instances for each variability level. The complete results of the experiment are shown in Table 4. We observe that the product flow variability has rather limited impact on the number of facilities opened and transportation mode selection, but the total expected emission and total cost will increase as the variability level increases.

Table 4 Impact of random product flow variablity

Variability Level	Average SD (M)	N_F	N_W	N_C	MR_1 (%)	MR_2 (%)	MR_3 (%)	TE (M ton)	TC (M \$)
Low	0.064	2.8	6.3	4.8	47.34	36.99	15.67	1.19	112.43
Medium	0.117	2.9	6.8	5.2	48.83	38.37	12.80	1.30	121.33
High	0.151	3.2	7.4	4.9	47.52	37.26	15.23	1.32	125.23

6 Performance of the Robust Optimization Solution

Because the benefits of results solved by stochastic demands and returns have been discussed in [15, 34], we will focus our discussion on the case of stochastic demands and returns. To study the performance of the robust optimization solution, we first solve problems NS, WS, and RS. Then, we compute the following values:

Z_R The optimal value of problem RS
Z_N The optimal value of problem NS
Z_W The optimal value of problem WS
Z_{NW} The objective value of NS solution under the worst case scenario
Z_{RW} The objective value of RS solution under the worst case scenario

Z_{NW} and Z_{RW} are obtained by evaluating the optimal solutions of problem NS and RS under the problem WS objective function, respectively. To see the relative gap between those values, we also compute $R_{WR} = \frac{Z_W - Z_R}{Z_R}$, $R_{NR} = \frac{Z_{RS} - Z_{NS}}{Z_{NS}}$ and $R_{NRW} = \frac{Z_{NW} - Z_{RW}}{Z_{RW}}$. The quantity R_{NR} is the relative loss of optimality of the robust solution compared results from the nominal data of carbon prices or tax rates. The ratio R_{WR} is the relative improvement of the robust solution on the results with the worst case of carbon prices or tax rates. The quantity R_{NRW} is the relative improvement of the robust solution compared with the results from the nominal data of carbon prices or tax rates if the worst case carbon prices or tax rates were to occur.

For the experiment, we considered four different protection levels and generated 30 random instances for network configuration with 6 potential plant locations and 10 potential locations for warehouse, 7 potential locations for collection center and 20 retailer locations, respectively. Those random instances are solved with different ρ. The length of the horizon is set to be 12. The other parameters are generated according the aforementioned method. The computation time for problems NS and WS are less than 1 minutes while the solver took 10-15 minutes to solve problem RS. We report the mean and standard deviation for the results in Table 5.

As we observe from Table 5, $Z_W \geq Z_R \geq Z_N$ and $Z_{NW} \geq Z_{RW} \geq Z_W$. R_{WR} decreases, R_{NR} increases and NRW increases as the protection level increases. Problem NS provides an unrealistically optimistic approximation to the true problem while problem WS offers a conservative strategy to solve the true problem. The optimal solution under proposed problem RS lies between the "best solution" obtained by solving problem NS and the "worst solution" obtained by solving problem WS. Formulating the problem as WS might be too conservative to be of real interest. Formulating the problem as NS seems promising considering the cost savings between the solutions of problem NS and RS. But problem NS can only account for an "average" situation of the carbon prices or tax rates, not the variability in carbon prices or tax rates. Problem RS, on the other hand, allows the decision maker to choose between robustness and performance. For example, setting $\rho = 1.575$, the problem RS does not immunize much

Table 5 Results under different protection level (Mean ± standard deviation) $| \mathscr{T} |= 12$

Protection level	ρ	Z_N (M \$)	Z_R (M \$)	Z_W (M \$)	Z_{NW} (M \$)	Z_{RW} (M \$)	R_{NR} (%)	R_{WR} (%)	R_{NRW} (%)
80%	1.575	163.29 ± 19.06	172.9 ± 20.17	181.59 ± 21.41	183.73 ± 21.71	182.27 ± 21.33	5.89 ± 0.75	5.01 ± 0.71	0.79 ± 0.4
90%	1.901	163.29 ± 19.06	174.73 ± 20.39	181.59 ± 21.41	183.73 ± 21.71	182.11 ± 21.36	7.02 ± 0.88	3.91 ± 0.6	0.88 ± 0.42
95%	2.174	163.29 ± 19.06	176.23 ± 20.53	181.59 ± 21.41	183.73 ± 21.71	182.04 ± 21.33	7.94 ± 1	3.02 ± 0.48	0.92 ± 0.49
99.9%	2.686	163.29 ± 19.06	178.85 ± 20.96	181.59 ± 21.41	183.73 ± 21.71	181.93 ± 21.42	9.53 ± 1.19	1.52 ± 0.35	0.99 ± 0.48

against uncertainty, but the solutions perform close to the problem NS. Setting $\rho = 2.686$, the performance of problem RS decreases as the model provides higher protection against the uncertainties in carbon prices or tax rates. In addition, under the worst case scenario, solutions of problem RS always provide a lower cost than solutions of problem NS, the percentage of cost saving varying from $0.79\% - 0.99\%$. Moreover, as the protection level increases, the solution of problem RS will perform better than the solution of problem NS under the worst case scenario.

For this experiment, the number of uncertain coefficients of problem RS is only 12. To see that the attractiveness of formulating the problem as RS will increase as the number of uncertain data increases, we perform another experiment with the length of horizon $| \mathscr{T} |= 20$. As we can observe from Table 6, the gap between Z_R and Z_N decreases and the gap between Z_R and Z_W increases as the horizon increases for different level of protections. This result is similar to that of Bertsimas and Thiele [14].

Table 6 Results under different protection level (Mean ± standard deviation) $| \mathscr{T} |= 20$

Protection level	ρ	Z_N (M \$)	Z_R (M \$)	Z_W (M \$)	Z_{NW} (M \$)	Z_{RW} (M \$)	R_{NR} (%)	R_{WR} (%)	R_{NRW} (%)
80%	1.580	240.16 ± 40.13	252.63 ±42.32	268.87 ±45.51	272.65 ±45.88	270.97 ±45.88	5.18 ±0.54	6.41 ±0.92	0.64 ±0.59
90%	1.911	240.16 ± 40.13	255.33 ± 42.94	268.87 ± 45.51	272.65 ± 45.88	270.82 ± 46.03	6.3 ± 0.67	5.29 ± 0.75	0.7 ± 0.59
95%	2.194	240.16 ± 40.13	257.28 ± 43.36	268.87 ± 45.51	272.65 ± 45.88	270.7 ± 46.01	7.1 ± 0.78	4.5 ± 0.68	0.74 ± 0.63
99.9%	2.736	240.16 ± 40.13	261 ± 43.97	268.87 ± 45.51	272.65 ± 45.88	270.46 ± 45.82	8.66 ± 0.86	3.01 ± 0.56	0.83 ± 0.52

7 Conclusions

In this paper, we consider a closed-loop supply chain network design problem where the demands and returns of products are stochastic variables. To cope with the uncertainty in carbon emission regulations, two regulatory policies are considered and a robust extension of a stochastic program is proposed. Further, tractable robust counterparts of the proposed hybrid model are developed to find the robust solutions for box and ellipsoidal uncertainty sets. A case study illustrates how optimal network configuration balances the trade-offs between investment, transportation and carbon emission costs if the carbon regulation is incorporated. More facilities will be opened and the total expected cost will increase as the uncertainty level increases. Moreover, the share of transportation by the low-emitting modes will also increase as the regulation policy uncertainty level increases. The problem formulation with nominal carbon prices or tax rates provides an unrealistically optimistic estimation of the real problem while the worst case scenario problem provides a conservative solution. The problem formulation with ellipsoidal uncertainty set allows the decision maker to balance the trade-off between robustness and performance. In addition, the proposed model can provide certain protection under the worst case scenario.

This paper has several limitations. First, this paper addresses only the cost minimization objective while neglecting strategic issues such as product/consumer segment. Although including other strategic variables such as price would greatly complicate the model, it will provide the decision maker with a more strategic view of the network design problem. Secondly, limits on the transportation capacity could be incorporated to provide a more realistic model and investigate trade-offs between location and transportation decisions. Thirdly, a multi-stage formulation would better represent the ability of decisions in future periods to adapt to realized values of the uncertain parameters as they become known. Lastly, relaxing the assumption on the continuity of the carbon emission permits would result in a more challenging but more realistic model under a cap-and-trade system.

The methodology presented in this paper can be applied to the planning of other systems as well. The integration of discrete optimization with robust methods that address policy uncertainty and stochastic formulations that use available probabilistic information will enable the decision maker to reduce different types of risk and derive better managerial insights. Many possible extensions could be made on this topic. For example, addressing the problem in a multi-product setting, considering operational issues such as inventory management or routing, of combining logistics outsourcing decisions together with the network design problem would be interesting topics for future research. It would also be interesting to study how the impact of policy uncertainty would affect firm's participation in CLSC activities. Other extensions could be made to relax the assumptions on speculative trading and banking, and to study how the CLSC network design will be affected when firm's carbon permit trading strategy is taken into consideration.

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