ROBUST OPTIMIZATION FOR CLOSED-LOOP SUPPLY CHAIN NETWORK
DESIGN CONSIDERING CARBON POLICIES UNDER UNCERTAINTY

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Climate change attributed by greenhouse gas emissions have triggered some countries to implement various carbon regulatory mechanisms to curb and regulate industrial carbon emissions. To be effective, the industry environmental footprint needs to address holistically via closed-loop supply chains (CLSC). This research proposes an optimization approach to address CLSC design problem with carbon footprint considerations. It integrates the carbon emission policies into supply chain’s strategic, tactical and operational selection decisions. A robust counterpart of the proposed model is developed based on three alternative uncertainty sets. The model extends further to investigate the impact of the three commonly practiced carbon regulatory policies including carbon cap, carbon tax, and carbon cap-and-trade on the supply chain strategic and operational decisions. Numerical results indicate that carbon cap-and-trade policy is the most flexible and efficient policy as compared to carbon cap and carbon tax policies. This study provides insightful observations with respect to robust optimization, CLSC network decisions, and carbon emissions. The proposed robust optimization models could be useful to decision-makers to achieve a robust supply chain network which can withstand any possible uncertainty in a given uncertainty set.

Keywords: closed-loop supply chain; supply chain network design; robust optimization; uncertainty; carbon policies; mathematical modeling

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1. INTRODUCTION

Increasing environmental concerns, energy crisis, global warming, and increased carbon regulations have driven firms to redesign their supply chains in order to reduce carbon emissions. Since supply chain activities are significant sources greenhouse gases (GHG) such as carbon dioxide, methane, etc. Government agencies across the globe strive to mitigate GHG emissions by passing legislation and pay attention to develop market-based environmental strategies like carbon regulatory policies which put a price on GHG emissions. These strategies not only provide economic benefits to the firm but also help in emission reduction. Such types of strategies are the “Kyoto Protocol” was in 1997, the “European Union Emission Trading System” was in 2009, “New Zealand Emissions Trading Scheme” was in 2009, and “Japan carbon tax scheme” was in 2012, etc., (Gao and Ryan 2014). “Kyoto Protocol” was introduced and 181 countries all over the world are as part of the “United Nations Framework Convention on Climate Change” by 2008 to control GHG emissions. The Protocol introduced three flexibility mechanisms through which countries all over the world can cooperate to meet their emission reduction targets and decrease costs (Ramudhin et al., 2010). First, Emissions Trading or Carbon Market allows countries that pollute more than their target to buy emission credits from those who have excess credits. Second, Clean development mechanism allows countries to gain carbon emissions credits who invest in emission reduction projects in developing countries. Third, countries can also earn emissions credits through joint implementation. This mechanism allows a country to benefit by carrying out emission reduction projects in another industrialized country committed to its emission reductions (Abdullah et al., 2012). The most common carbon emission reduction policies are the strict carbon cap policy, carbon tax policy, and carbon cap-and-trade policy which have been implemented in some developing as well as in developed counties. Most of the GHG emission reduction initiatives on the firm level are concerned with acquiring energy efficient equipment and facilities, using low pollution energy sources and implementing energy saving projects. However, there has been limited study covering strategic and operational activities in the supply chain. For instance, the frequency of logistical activities, facility location, and selection of transportation modes will influence GHG emission, which in turn influence carbon emissions of the final product (Choudhary et al., 2015, He et al., 2016, Mohammed et al., 2017).
Due to resource scarcity and environmental concerns, there has been growing need for remanufacturing and recycling activities. This requires firms to coordinate the forward and reverse material flows in their supply chains which motivates the design of a closed-loop supply chain (CLSC) network. The issue of recycling their end-of-life products and reusing products residue and scrap would not only minimize environmental impact but also improve their business market status globally. A large volume of the literature is available on CLSC network design (Jayaraman et al., 1999; Ko and Evan 2007; Easwaran and Üstör 2010; Vahdati et al., 2012; Ramezani et al., 2013; Amin and Zhang 2013; Zevallos et al., 2014; Govindan et al., 2015; Kalaizidou et al., 2015; Gaur et al., 2017; Kumar et al., 2016; Kadambala et al., 2017; Yi et al., 2016; Tahirov et al., 2016). However, the existing supply chain models are either focusing on minimizing cost or maximizing profit. Recently few papers (Choudhary et al., 2015; Fareeduddin et al., 2015; Xu et al., 2017) reported studies that integrate environmental consideration under different carbon policies. This integration can help policymakers to understand better how different carbon policies would reduce the negative effects of GHG. In addition, the integrated models could be used to understand the effect of policy parameters on the total cost and carbon emissions of various supply chain activities of the firm.

Consideration of uncertainties in the model parameters is a natural extension of a deterministic approach which leads to more realistic problems. Supply chain network design (SCND) is a strategic decision whose effect will last for several years, during which critical parameters such as raw material supply and demand of customers will change, i.e., quite uncertain (Pishvae et al., 2009). Especially reverse logistics where activities are complex and tend to a high degree of uncertainty. Such as collection rate, a variety of returns, quality and quantity of returned products are highly uncertain in even in a short period of time. Thus, designing and planning of CLSC configuration under uncertainty are highly necessary to cope with uncertain parameters such that the impact of parameter fluctuations on network configuration will be less. To deal with uncertainty, different mathematical programming techniques, such as dynamic programming, stochastic programming, robust optimization, and fuzzy programming have been used to solve SCND problems. Among all, the robust optimization methodology has attracted researchers’ attention (Pishvae et al., 2011; Kisomi et al., 2016). Robust optimization could be helpful to study real-world problems where there is not enough historical data to estimate the probability distribution of uncertain parameters and also due inherent uncertainty in input data. Robust optimization theory provides a framework to handle the uncertainty of parameters in optimization problems that could immunize the optimal solution for any realization of the uncertainty in a given bounded uncertainty set (Ben-Tal and Nemirovski 1999).

This paper proposes an optimization model to address a multi-period, multi-product CLSC network design problem. A mixed integer linear programming (MILP) is used for model formulation. A robust counterpart of the proposed model is developed to cope with uncertainty in product demand, returns, variable costs, and transportation costs. Three uncertainty sets are considered that are based on set-based robust optimization methodology: Box, Polyhedral, and Interval+Polyhedral uncertainty set. To make the model realistic, several supply chain requirements are taken into accounts, such as multiple planning periods, selection of technologies at the production facilities, transportation mode selection, as well as capacity limits on production, distribution, and storage. The proposed model is further extended by integrating carbon emissions consideration and correspondingly various emission related regulatory policies such as carbon emission cap, carbon emission tax, and carbon cap-and-trade policies to investigate the impact of these policies on supply chain strategy as well as operational decisions.

The rest of the paper is organized as follows: Section 2 reviews relevant literature. Section 3 provides the model description, assumptions, and model formulation of the base model. The robust optimization framework is explained in Section 4. Model formulation for various carbon emission policies is presented in Section 5. Computational results are presented in Section 6. Sensitivity analysis is discussed in Section 7. Finally, Section 8 concludes the paper.

2. LITERATURE REVIEW

The literature review focuses on three main areas: (i) CLSC network design, (ii) uncertainty in the CLSC network, and (iii) carbon emission and regulations in supply chain strategic and operational decisions.

2.1 CLSC Network Design

The configuration of SCND is one of the crucial strategic decisions in the SC strategic and planning activities that has been received the attention from the academia and practitioners since recent decades. Many attempts have been made to develop and optimize SCND models, ranged from simple deterministic problems to complex stochastic problems (Ramezani et al., 2013). Due to growing environmental concerns and governmental legislation, attention has been paid to reverse logistics, which addresses the number, location, and capacities of the collection, recycling, recovery, and disposal centers needed running inventories and logistics activities among the facilities. Several works have been published to propose the SCND problems in the context of reverse logistic (Jayaraman et al., 1999, Sabri and Beamon 2000, Listeş and Dekker 2005, Salema
et al., 2007). Integration of forwarding SC and reverse SC activities is called CLSC. There are five main reasons that motivate manufacturers towards focusing on CLSC issues; customer awareness, social responsibilities, environmental concerns, governmental legislation, waste management. In the past, CLSC used to be an undesirable constraint but now it is an acceptable necessity, and remarkably, it will be the only remedy to sustain in the future. Many papers used MILP formulation for designing CLSC networks and various solution methods have been developed to solve the network design problems (Jayaraman et al., 1999; Fleischmann et al., 2001; Min et al., 2006; Soleimani et al., 2013; Özceylan et al., 2014; Soleimani and Kannan 2015; Kalaitzidou et al., 2015; 2016; Kadambala et al., 2016). Very useful literature reviews are presented by Melo et al., 2009, Akçali et al., 2009; Souza 2013; Govindan et al., 2015.

2.2 Uncertainty in CLSC Network Design

In recent years, increasing concerns about internal and external sources of uncertainty has spurred researchers to develop CLSC networks under uncertainty because ignoring uncertainty can lead to sub-optimal or infeasible outcomes. To cope with uncertainty in models, some techniques have been used in the CLSC issue.

More and more researchers investigated uncertainty in CLSC configuration using stochastic programming approaches. Salema et al., (2007) proposed a MILP formulation to deals with stochastic scenario-based programming approach for designing a generic reverse logistics network where uncertainty on product demands and returns is considered. Francas and Minner (2009) studied two different network structures and two different markets under capacity expansion investment. They built models based on a two-stage stochastic programming approach to tackle the uncertainty of demand and return. Pishvaa et al., (2009) developed a scenario based stochastic programming model for integrated logistics network design under uncertainty. Ramezani et al., (2013) presented a multi-objective stochastic programming approach to design a forward/reverse supply chain with three performance measures: profit, customer responsiveness, and quality of suppliers (using Six Sigma concept). Vahdani et al., (2012) proposed a novel bi-objective MILP formulation for designing a reliable network of facilities in CLSC under uncertainties. Amin and Zhang (2013) proposed MILP formulation for designing CLSC network, then extended it to multi-objective facility location model by incorporating environmental factor as a performance measure. They investigated the impact of demand and returned uncertainties on the network by using a scenario-based approach. Cardosoa et al., (2013) developed MILP formulation for the design and planning of integrated reverse logistics network with forwarding SC under uncertain product demand. Uncertainty is modeled through a scenario-based approach. Zeballos et al., (2014) developed a multi-stage stochastic programming model for designing and planning of a generic multi-product multi-period CLSC under uncertain demand and return. The uncertainty of demand and return is modeled through multi-stage scenario-based approach. The model also accounts environmental impact, mainly carbon emissions from different transportation options.

Several papers considered the uncertain nature of various input parameters in CLSC design using fuzzy methods. Pishvaae and Torabi (2010) implemented a possibilistic MILP model with two functions for minimizing the total cost and responsiveness. They combined some of the effective approaches in the literature and designed an interactive fuzzy method. Vahdani et al., (2012) proposed a novel bi-objective mathematical programming formulation for designing a reliable network of facilities in CLSC under uncertainties. They developed a mixed non-linear programming model in which fuzzy numbers were used to express uncertain factors. Mohajeri and Fallah (2015) developed an optimization model for a CLSC network design under uncertainty of product demand and returned rate. Uncertainty was described as fuzzy numbers. Carbon emission constraints are used in the model to limit the carbon emission per unit of product supplied with different transportation modes.

Few researchers paid attention to uncertainty issues of CLSC network design using robust optimization methodology. Pishvaae et al., (2011) proposed a robust optimization model for handling the inherent uncertainty of input data in a CLSC network design problem using box uncertainty set, whose solutions are compared to those generated by the deterministic model in a number of realizations under different test problems. Gao et al., (2014) addressed multi-products, multi-periods, multi-echelon CLSC network design problem subject to the uncertainty of the demands and returns as well as potential carbon emission regulations due to transportation. They proposed a two-stage stochastic programming model in which the demands for new products and returns of those products are discrete random variables. Keyvanshokooh et al., (2016) proposed multi-period CLSC network design model under to different types of uncertainties simultaneously including stochastic scenarios for transportation costs and polyhedral uncertainty sets for demands and returns, and handle via a novel hybrid robust-stochastic programming approach. In the above literature, researchers are considered one type or at most two types of methodologies to deal with uncertainty in SCND problems. However, Li et al., (2011) studied set-induced robust counterpart optimization techniques for both linear optimization and MILP problems. They proposed several novel uncertainty sets such as adjustable box; pure polyhedral; combined interval and polyhedral set, and more. Uncertainty set offers flexibility not only to decision makers for designing a set size that leads to desired robustness in their decision but also to overcome the worst
possible combination of values (box uncertainty proposed by Ben-Tal et al., 1999). This type of approach for handling uncertainty is very rarely used in SCND problems.

### 2.3 Carbon Emissions and Regulations

Recently, few papers proposed optimization models for supply chains to minimize the carbon footprint by changing supply chain operations. Benjaafar et al., (2013) proposed optimization models for supply chain operational decision making under various carbon policies such as carbon cap, carbon tax rate, carbon cap-and-trade, and carbon offset policies. Palak et al., (2014) analyzed the impact of potential carbon regulatory mechanisms on supplier and transportation mode selection in a biofuel supply chain. However, these studies are limited to inventory management decisions, such as economic lot size and economic order quantity. Diabat et al., (2013) studied the issues of facility location problem in CLSC with the trading of carbon emission and cost of procurement. Fahimnia et al. (2013) developed a unified MILP model for a CLSC in which carbon footprint is evaluated based on the influence of forward and reverse supply chain where carbon emissions are expressed in terms of dollar carbon cost. The main limitation of the above works is that all parameters are assumed to be known and fixed, and they considered only carbon tax policy. Marufuzzaman et al., (2014) proposed a two-stage stochastic programming model for designing and managing biodiesel supply chains under uncertainty. Various carbon regulatory mechanisms are used to study the impact of carbon emissions on supply chain related activities. Jin et al., (2014) proposed optimization models for major retailers and investigated the impact of three carbon policies on supply chain strategy and transportation mode selection decisions. Fareeduddin et al., (2015) extended the work of Jin et al., (2014) by incorporating reverse logistics to their traditional forward supply chain and investigated multi-product multi-period CLSC network design and carbon emissions issues under various carbon policies. However, their study is limited to the deterministic approach.

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A more detailed classification of some of the recently published literature on SCND and carbon emission reduction policies are presented in Table 1. This classification is based on the following distinguishing factors; supply chain network structure, modeling features, parameter uncertainty, carbon regulatory policies, modeling methodologies, and solution methods. As evident from Table 1, most of the researches in CLSC network design have focused on deterministic conditions. Only a few studies reported on uncertain conditions and using a stochastic approach. Few researchers have considered fuzzy and robust optimization.

Moreover, very few have integrated SCND with carbon emission policies under deterministic conditions. This paper addresses several gaps in the literature. First, proposing a more realistic model by considering multi-products, multiple planning periods, selection of technologies at the production facilities and transportation mode selection between the facilities. Second, considering parameters uncertainty and solving with robust optimization approach based on three common uncertainty sets box, polyhedral and interval + polyhedral. Third, integrating carbon emission regulations along with CLSC network design and operational decisions.

3. PROBLEM DESCRIPTION AND MODEL FORMULATION

3.1 Problem Description

A generalized CLSC network under investigation is shown in Figure 1. It consists of three layers in the forward direction includes production centers (PCs), distribution centers (DCs), and customer zones and three layers in reverse direction which includes collection centers (CCs), recycling centers (RCs), and disposals.

![Figure 1. A generalized CLSC network](image)

In the forward chain, raw material and component requirements of the PCs are satisfied by both suppliers and RCs \( r \in R \). Multiple product types \( l \in L \) are produced in different PCs \( p \in P \) using a set of technologies \( h \in H \). A PC has its own production cost and carbon emission rate for processing one unit of product. Production cost and emission rate depend on the type of potential technologies to use. Because each technology differs in terms of acquisition and operation costs as well as carbon emission rate. Finished products are shipped to customer zones or markets \( c \in C \) through a set of DCs \( q \in Q \). Different transportation modes \( m \in M \) are available to use for shipping products between the facilities with different prices and fuel efficiency rates.

In the reverse network, returned products are collected by CCs \( k \in K \) and shipped to RCs \( r \in R \). At RCs, after inspection and sorting operation, products are disassembled into components (recyclable and non-recyclable) \( n \in N \). Non-recyclable components are shipped WCs \( w \in W \) for land-filling. The recyclable components are gone through further processing after recycling has done, it shipped to PCs. Point to be noted here that all recycled components are assumed as good as new (satisfy minimum quality requirements). Logistic activities carried out using different transportation modes \( m \in M \) varies in unit transportation cost and emission rate.

3.2 Model Assumptions

The model assumptions are as follows:

1. The number, capacity and potential location of PCs, DCs, CCs, RCs, and disposals are known.
2. The number and location of customer zones are known.
3. Product demand, returns, variable costs, and transportation costs are considered as uncertain.
4. Flows are permitted between two consecutive stages however there are no flows between facilities at the same stage. This assumption will make the model simple, but it is also realistic. For example, the transportation cost between the PCs and DCs (stages) is less than the transportation cost between two DCs (transshipment) of the same stage.
5. Emissions due to processing products at facilities and emissions for shipping products from PCs to end users are known and determined. These are based on the type of technology used at PCs and type of transportation mode used in logistic activities (Fahimnia et al., 2013).
6. Cost of emission for holding/storing products at facilities is assumed to be negligible when compared to the overall supply chain emission.

3.3 Base Model Formulation

The CLSC network design problem under uncertainty is formulated as a multi-period multi-products MILP model. First, we consider the case in which carbon emission is ignored. In other words, the base model (D1), in which strategic and tactical/operational decisions are solely based on economic performance.

The definition of sets, input parameters, and decision variables that will be used throughout the paper is presented in Appendix.

Figure 2 shows the summary of investigated models in this research. First, we formulated the MILP model for a multi-period, multi-product CLSC network design problem under the deterministic condition and without considering carbon emissions (called based model, D1). Then we incorporated robust optimization methodology to deal with uncertainty and developed robust counterpart of proposed MILP model under three uncertainty sets: Box (R1), Polyhedral (R2), and Interval+Polyhedral (R3). To investigate the effect of carbon emissions on CLSC network design and operational decisions, three alternative carbon emission policies such as carbon cap (D1.1, R1.1, R2.1, R3.1), carbon tax (D1.2, R1.2, R2.2, R3.2), and carbon trade (D1.3, R1.3, R2.3, R3.3) policies are considered in this research. Model formulation of each policy under both deterministic and robust conditions is presented in Section 5.

### 3.3.1 The objective function

The total cost of the CLSC is derived from the opening of facilities, production, inventory, collection, recycling, disposal, and transportation.

Total fixed cost (TFC).

\[
TFC = \sum_{p \in P} \sum_{h \in H} Z_{ph} + \sum_{q \in Q} cf_{q} Z_{Qq} + \sum_{k \in K} cf_{k} Z_{Kk} + \sum_{r \in R} cf_{r} Z_{Rr} + \sum_{w \in W} cf_{w} Z_{Ww}
\]
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Total procurement and production costs (TPRC).

\[ TPRC = \sum_{n \in N} \sum_{p \in P} \sum_{t \in T} c_{po}^{t} \cdot Q_{np}^{t} + \sum_{p \in P} \sum_{h \in H} \sum_{l \in L} \sum_{t \in T} c_{mpl}^{t} \cdot Q_{phl}^{t} \]

Total collection cost (TCC).

\[ TCC = \sum_{c \in C} \sum_{k \in K} \sum_{l \in L} \sum_{t \in T} c_{cc}^{t} \cdot Q_{ckl}^{t} \cdot Q_{c\text{clm}} \]

Total recycling cost (TRC).

\[ TRC = \sum_{r \in R} \sum_{e \in E} \sum_{n \in N} \sum_{t \in T} c_{cr}^{t} \cdot Q_{rpn}^{t} \cdot Q_{r\text{pnm}} \]

Total disposal cost (TDC).

\[ TDC = \sum_{r \in R} \sum_{w \in W} \sum_{n \in N} \sum_{m \in M} \sum_{t \in T} c_{cw}^{t} \cdot Q_{rw}^{t} \cdot Q_{rwnm} \]

Shortage cost (TSC).

\[ TSC = \sum_{c \in C} \sum_{l \in L} \sum_{t \in T} \pi_{c}^{t} \cdot \delta_{c}^{t} \]

Total transportation cost (TTC)

\[ TTC = \sum_{p \in P} \sum_{q \in Q} \sum_{m \in M} \sum_{e \in E} \sum_{l \in L} \sum_{t \in T} t_{pq}^{t} \cdot Q_{pq}^{t} \cdot Q_{p\text{qlm}} + \sum_{q \in Q} \sum_{c \in C} \sum_{l \in L} \sum_{t \in T} t_{qc}^{t} \cdot Q_{qc}^{t} \cdot Q_{qc\text{clm}} + \sum_{c \in C} \sum_{k \in K} \sum_{l \in L} \sum_{t \in T} t_{ck}^{t} \cdot Q_{ck}^{t} \cdot Q_{ck\text{klm}} + \sum_{k \in K} \sum_{r \in R} \sum_{m \in M} \sum_{l \in L} \sum_{t \in T} t_{rk}^{t} \cdot Q_{rk}^{t} \cdot Q_{rk\text{rklm}} + \sum_{r \in R} \sum_{w \in W} \sum_{n \in N} \sum_{m \in M} \sum_{t \in T} t_{rw}^{t} \cdot Q_{rw}^{t} \cdot Q_{rwnm} \]

The objective function to be minimized is thus given by:

\[ Z_{\text{base}} = TFC + TPRC + TCC + TRC + TDC + TTC \] (1)

3.3.2 The constraints

This section provides the constraints of the proposed model: Constraints (2) – (9) are called balance constraints. Constraint (2) states that sum of the exiting flow of each recycled raw material at RC equals the production quantity of finished products at the PC in each time period.

\[ \sum_{r \in R} \sum_{m \in M} Q_{rpn}^{t} + Q_{Enp}^{t} + I_{pn}^{t-1} = \sum_{l \in L} \sum_{h \in H} \varphi_{hl}^{t} \cdot Q_{phl}^{t} + I_{phn}^{t} \cdot I_{pn}^{0} \text{ for } 0, p \in P, n \in N, t \in T \] (2)

Constraint (3) ensures that at each PC sum of the exiting flow of finished products equals the production quantity in each time period.
\[
\sum_{p \in P} Q^t_{p,l,h} = \sum_{q \in Q} \sum_{m \in M} QPQ^{t}_{p,q,l,m} \quad \text{for } p \in P, l \in L, t \in T
\] (3)

Constraint (4) guarantees that, for each product in each time period, the sum of the flow entering each DC from all PCs and its residual inventory from the previous periods is equal to the sum of the flow exiting from each DC and residual inventory of the existing period.

\[
IQ^{t-1}_{q,l} + \sum_{p \in P} \sum_{m \in M} QPQ^{t}_{p,q,l,m} = IQ^{t}_{q,l} + \sum_{c \in C} \sum_{m \in M} QQ_{c,q,l,m}^{t}, IQ^{0}_{q,l} = 0 \quad \text{for } q \in Q, l \in L, t \in T
\] (4)

The following constraint ensures that the demand for each market is satisfied through shipments from the distribution centers for each time period.

\[
\sum_{q \in Q} \sum_{m \in M} QQ_{c,q,l,m}^{t} = D^{t}_{c,l} \quad \text{for } c \in C, l \in L, t \in T
\] (5)

The constraint below shows that for each time period, the EOL returns of each product equals the shipments of these returns to the collection centers.

\[
\sum_{k \in K} \sum_{m \in M} QCK_{c,k,l,m}^{t} = R^{t}_{c,l}, c \in C, l \in L, t \in T
\] (6)

Constraint (7) gives the inventory balance equation of returned products at each CC at each time period.

\[
\sum_{c \in C} \sum_{m \in M} QCK_{c,k,l,m}^{t} = \sum_{r \in R} \sum_{m \in M} KKR_{c,r,k,l,m}^{t}, k \in K, l \in L, t \in T
\] (7)

Constraint (8) shows the inventory balance equation of recycled components at each RC in time period \( t \).

\[
\sum_{p \in P} \sum_{m \in M} QRP_{p,n,l,m}^{t} = \sum_{k \in K} \sum_{l \in L} \sum_{m \in M} \alpha_n \gamma_{l,n} QKR_{c,r,k,l,m}^{t}, r \in R, n \in N, t \in T
\] (8)

Constraint (9) shows the inventory balance equation of disposable components at each RC in time period \( t \).

\[
\sum_{w \in W} \sum_{m \in M} QRW_{w,n,l,m}^{t} = \sum_{k \in K} \sum_{l \in L} \sum_{m \in M} (1 - \alpha_n) \gamma_{l,n} QKR_{c,r,k,l,m}^{t}, r \in R, n \in N, t \in T
\] (9)

Constraints (10) – (14) are called capacity constraints of the facilities. Constraint (10) ensures that at each PC with available technology, the sum of entering flow of recycled products and inventory of finished products does not exceed the maximum capacity of the PC.

\[
\sum_{l \in L} t\lambda_{l,h} Q_{p,l,h}^{t} \leq SP_{p}, ZP_{p,h}, \quad p \in P, h \in H, t \in T
\] (10)

Constraint (11) states that the sum of residual inventory at DC does not exceed the relevant capacity.

\[
\sum_{l \in L} \nu_{l} IQ_{q,l}^{t-1} + \sum_{p \in P} \sum_{l \in L} \sum_{m \in M} \nu_{l} QPQ_{p,q,l,m}^{t} \leq SQ_{q}, ZQ_{q}, \quad IQ_{q,l}^{0} = 0, \quad q \in Q, t \in T
\] (11)

Constraint (12) guarantees that the sum of residual inventory at collection/inspection center does not exceed its capacity.
\[
\sum_{c \in C} \sum_{l \in L} \sum_{m \in M} vl_t QCK^t_{c\text{K}lm} \leq SK_K ZK_k, \quad k \in K, t \in T
\]  
(12)

Constraint (13) ensures that the sum of entering flow of recyclable products at CC does not exceed its predefined capacity.

\[
\sum_{k \in K} \sum_{l \in L} \sum_{n \in N} \sum_{m \in M} trn_n \varphi_{ln} QKR^t_{k\text{R}lm} \leq SR_r ZR_r, \quad r \in R, t \in T
\]  
(13)

Constraint (14) states that the sum of the entering flow of scrapped products at disposal center does not exceed its predefined capacity.

\[
\sum_{k \in K} \sum_{n \in N} \sum_{m \in M} \sum_{t \in T} trn_n QRW^t_{r\text{W}nm} \leq SW_w ZW_w, \quad w \in W, t \in T
\]  
(14)

Constraint (15) ensures that at each potential location of PC, at most one technology type can be established.

\[
\sum_{t \in T} \sum_{h \in H} ZP^t_{p h} \leq 1, p \in P
\]  
(15)

The following constraints (16) – (29) allow the existence of entering and exiting flows of products to a given facility only if the facility is a part of the network.

\[
\sum_{q \in Q} \sum_{l \in L} \sum_{m \in M} \sum_{t \in T} QPQ^t_{pqlm} \leq M \sum_{h \in H} ZP_{ph}, \quad p \in P
\]  
(16)

\[
\sum_{n \in N} QE^t_{np} \leq M \sum_{h \in H} ZP_{ph}, \quad p \in P
\]  
(17)

\[
\sum_{h \in H} \sum_{l \in L} \sum_{t \in T} QP^t_{phl} \leq M \sum_{h \in H} ZP_{ph}, \quad p \in P
\]  
(18)

\[
\sum_{n \in N} \sum_{t \in T} IP^t_{pn} \leq M \sum_{h \in H} ZP_{ph}, \quad p \in P
\]  
(19)

\[
\sum_{t \in T} IQ^t_{q} \leq M ZQ_q, \quad q \in Q
\]  
(20)

\[
\sum_{c \in C} \sum_{l \in L} \sum_{m \in M} \sum_{t \in T} QCK^t_{c\text{K}lm} \leq M ZK_k, \quad k \in K
\]  
(21)

\[
\sum_{r \in R} \sum_{n \in N} \sum_{m \in M} \sum_{t \in T} QRP^t_{r\text{P}nm} \leq M \sum_{h \in H} ZP_{ph}, \quad p \in P
\]  
(22)

\[
\sum_{p \in P} \sum_{l \in L} \sum_{m \in M} \sum_{t \in T} QPQ^t_{pqlm} \leq M ZQ_q, \quad q \in Q
\]  
(23)

\[
\sum_{c \in C} \sum_{l \in L} \sum_{m \in M} \sum_{t \in T} QQC^t_{c\text{Q}lm} \leq M ZQ_q, \quad q \in Q
\]  
(24)
\[
\sum_{\ell \in L} \sum_{m \in M} \sum_{t \in T} QK_{krm}^t \leq M Z_K, \quad k \in K
\]  
(25)

\[
\sum_{k \in K} \sum_{\ell \in L} \sum_{m \in M} \sum_{t \in T} QK_{krm}^t \leq M Z_R, \quad r \in R
\]  
(26)

\[
\sum_{p \in P} \sum_{n \in N} \sum_{m \in M} \sum_{t \in T} QR_{pnm}^t \leq M Z_R, \quad r \in R
\]  
(27)

\[
\sum_{\omega \in W} \sum_{n \in N} \sum_{m \in M} \sum_{t \in T} QR_{\omega mn}^t \leq M Z_W, \quad w \in W
\]  
(29)

Constraints (30) – (39) permit the existence of entering and exiting the transportation mode moves if a given facility is a part of the network in a particular time period.

\[
\begin{align*}
YP_{pqm}^t & \leq \sum_{k \in K} ZP_{ph}, \quad \text{for } p \in P, q \in Q, m \in M, t \in T \\
YP_{rpm}^t & \leq \sum_{k \in K} ZP_{ph}, \quad \text{for } r \in R, p \in P, m \in M, t \in T \\
YP_{qpm}^t & \leq ZQ_q, \quad p \in P, q \in Q, m \in M, t \in T \\
YQ_{qcm}^t & \leq ZQ_q, \quad q \in Q, c \in C, m \in M, t \in T \\
YCK_{ckm}^t & \leq ZK_c, \quad c \in C, k \in K, m \in M, t \in T \\
YKR_{krm}^t & \leq ZK_r, \quad k \in K, r \in R, m \in M, t \in T \\
YKR_{krm}^t & \leq ZR_r, \quad k \in K, r \in R, m \in M, t \in T \\
YRP_{rpm}^t & \leq ZR_r, \quad r \in R, p \in P, m \in M, t \in T \\
YRW_{rwm}^t & \leq ZR_r, \quad r \in R, w \in W, m \in M, t \in T \\
YRW_{rwm}^t & \leq ZW_w, \quad r \in R, w \in W, m \in M, t \in T
\end{align*}
\]

Constraints (40) – (51) ensures that if a specific transportation mode is used, then the shipment must be between the minimum and maximum capacity of this mode.

\[
\begin{align*}
\sum_{\ell \in L} QP_{pqm}^t & \geq tpq_{pqm} YP_{pqm}^t, \quad \text{for } p \in P, q \in Q, m \in M, t \in T \\
\sum_{\ell \in L} QP_{pqm}^t & \leq Tpq_{pqm} YP_{pqm}^t, \quad \text{for } p \in P, q \in Q, m \in M, t \in T \\
\sum_{\ell \in L} QQ_{qcm}^t & \geq tqc_{qcm} YQ_{qcm}^t, \quad \text{for } q \in Q, c \in C, m \in M, t \in T \\
\sum_{\ell \in L} QQ_{qcm}^t & \leq Tqc_{qcm} YQ_{qcm}^t, \quad \text{for } q \in Q, c \in C, m \in M, t \in T
\end{align*}
\]
4. ROBUST OPTIMIZATION METHOD

The robust optimization specifies a suitable uncertainty set for imprecise input data and gives a solution that ensures feasibility in all amounts of uncertain parameters within the uncertainty set (Ben-Tal and Nemirovski 1999). To illustrate this method, take the following linear optimization model into account:

\[
\text{Minimize} \sum_j \hat{c}_j x_j \quad (52)
\]

\[
\text{subject to} \sum_j \hat{a}_{ij} x \leq \hat{b}_i, \quad \forall i \in I
\]

In the model, \(\hat{a}_{ij}, \hat{b}_i\) and \(\hat{c}_j\) represent the model parameter, which are exposed to uncertainty. Without loss of generality of the problem, the objective function and right hand side uncertainty can be transformed into left hand side uncertainty as follow:

Minimize \(W\)

subject to

\[
\sum_j \hat{c}_j x_j \leq W \quad (53)
\]
\[ -\hat{b}_i + \sum_j \hat{a}_{ij} x_j \leq 0, \quad \forall i \in I \]  

Uncertain parameters are defined as follows:

\[ \hat{a}_{ij} = a_{ij} + \rho_{ij} \bar{a}_{ij} \quad \forall j \in J \]  

\[ \hat{b}_i = b_i + \rho_i \bar{b}_i \quad \forall i \in I \]  

\[ \hat{c}_j = c_j + \rho_{j0} \bar{c}_j \quad \forall j \in J \]  

For determination of the true values, parameters \( a_{ij}, b_i \) and \( c_j \) are defined as nominal values; \( \bar{a}_{ij}, \bar{b}_i, \) and \( \bar{c}_j \) are used as the scale of uncertainty; \( \rho_{ij}, \rho_i, \) and \( \rho_{j0} \) represent the set of variables subject to uncertainty. A known uncertainty set \( U \) is defined, using Ben-Tal and Nemirovski (1999), for any \( \rho \) to minimize the model against infeasibility:

Minimize \( W \)

subject to:

\[ \sum_j c_j x_j + \left[ \max_{\rho \in U} \left( \sum_j \rho_{j0} \tilde{c}_j x_j \right) \right] \leq W \]  

\[ -b_i + \sum_j a_{ij} x_j + \left[ \max_{\rho \in U} \left( -\rho_i \bar{b}_i + \sum_j \rho_{ij} \bar{a}_{ij} x_j \right) \right] \leq 0, \quad \forall i \in I \]  

4.1 Uncertainty Set

Li et al., (2011) described the mentioned uncertainty sets with \( \infty \)-norm, 1-norm and \( 1 \cap \infty \)-norm, respectively.

\[ U_{\text{box}} = \{ \rho | \rho_\infty \leq \varphi \} = \{ \rho | |\rho_j| \leq \varphi, \forall j \in J \} \]  

\[ U_{\text{polyhedra}} = \{ \rho | \rho_1 \leq \Gamma \} = \left\{ \rho | \sum_{j \in I} |\rho_j| \leq \Gamma \right\} \]  

\[ U_{\text{box+polyhedra}} = \left\{ \rho | \sum_{j \in I} |\rho_j| \leq \Gamma, |\rho_j| \leq \varphi, \forall j \in J \right\} \]  

Where \( \varphi \) and \( \Gamma \) are the adjustable parameters for the size of the sets. Note that the box uncertainty set has a special case known as interval uncertainty set and it is when \( \varphi=1 \).

4.2 Robust Counterpart Optimization Formulation

In robust optimization, each nominal problem with uncertain parameters has a model known as a robust counterpart that is a worst-case formulation of the main problem. According to Ben–Tal and Nemirovski (1999), the robust counterpart of the proposed model with the uncertainty set is as follows:

Minimize \( \sum_j c_j x_j \)
subject to: \( \sum_{j} a_{ij}x_j \leq b_i, \forall i \in I \) where \((a, b, c \in U)\)

If uncertainty is given in box, polyhedral, and interval+polyhedral form, then the robust counterpart model is equivalent to as shown in Table 2.

<table>
<thead>
<tr>
<th>Box uncertainty set (Model R1)</th>
</tr>
</thead>
</table>

Minimize \( W^{RB} \) (62)

Subject to:

\( W^D + W^N \leq W^{RB} \) (63)

\[ \sum_{q \in Q} \sum_{m \in M} Q_{QC_{i}^{l}}^{t} + \delta_{cl}^{t} \geq D_{cl}^{t} + \varphi^{D} D_{cl}^{t}, \quad \forall \ c \in C, l \in L, t \in T \] (64)

\[ \sum_{k \in K} \sum_{m \in M} QC_{cl}^{t} \geq R_{cl}^{t} + \varphi^{B} R_{cl}^{t}, \quad \forall \ c \in C, l \in L, t \in T \] (65)

\[ \sum_{k \in K} \sum_{m \in M} QC_{cl}^{t} \geq R_{cl}^{t} - \varphi^{B} R_{cl}^{t}, \quad \forall \ c \in C, l \in L, t \in T \] (66)

\[ W^D = \sum_{p \in P} \sum_{h \in H} ZP_{ph} + \sum_{q \in Q} cf_{q}Z_{Qq} + \sum_{k \in K} cf_{k}Z_{Kk} + \sum_{r \in R} cf_{r}Z_{Rr} + \sum_{w \in W} cf_{w}Z_{Ww} + \sum_{c \in C} \sum_{l \in L} \sum_{t \in T} \pi_{cl}^{t} \delta_{cl}^{t} \] (67)
\[ W^N = \phi^{cpo} \sum_{\text{nen p nert}} cpq_{np} Qe_{np}^{t} + \phi^{cmp} \sum_{\text{pep nern elt tetr}} cmp_{phi} Qp_{phi}^{t} + \phi^{cco} \sum_{\text{cel kek lel melt tet}} ccc_{k l} Qck_{k l m}^{t} \]
\[ + \phi^{tec} \sum_{\text{rer epn nem me tett}} cre_{rn} QRP_{rp nm}^{t} + \phi^{tqc} \sum_{\text{rwr wwe wmen mem tet}} tqc_{qcm} Qqc_{qcm}^{t} \]
\[ + \phi^{trp} \sum_{\text{rer epn nem me tett}} trp_{rpmnm} QRP_{rpmnm}^{t} + \phi^{trw} \sum_{\text{rwr wwe wmen mem tet}} trw_{rwmnm} QRW_{rwmnm}^{t} \]
\[ \phi^{trw} \sum_{\text{rwr wwe wmen mem tet}} trw_{rwmnm} QRW_{rwmnm}^{t} \]

Polyhedral uncertainty set (Model R2)

\[ \text{Minimize } W^{RP} \]

Subject to:

\[ W^D + Z^N \leq W^{RP} \]

Where

\[ W^D = \sum_{\text{pep nep ner}} \sum_{\text{qeq qe}} cfrq Zq_{q} + \sum_{\text{kee kep kee leel tete}} cfr Zr_{r} + \sum_{\text{wew wwe we we mement et et}} cfq Zw_{w} + \sum_{\text{ceel lel dile mel tet}} \pi_{et} \delta_{et} \]
\[ + \sum_{\text{rer pep nem me tett}} cpq_{np} Qe_{np}^{t} + \sum_{\text{pep nep nel etl tet}} cmp_{phi} Qp_{phi}^{t} + \sum_{\text{rwr wwe wmen mem tet}} cdw_{wn} QRW_{rwmnm}^{t} \]
\[ + \sum_{\text{rwr wwe wmen mem tet}} tpc_{pct} QQP_{pqrt}^{t} + \sum_{\text{qee ceel lel mcm tet}} tqc_{qcm} Qqc_{qcm}^{t} \]
\[ + \sum_{\text{rwr wwe wmen mem tet}} tck_{ckt} QCK_{ckt}^{t} + \sum_{\text{rer kep nem me m tet}} trw_{rwmnm} QRW_{rwmnm}^{t} \]

\[ Z^N = \Gamma^{cpo} Z^{cpo} + \Gamma^{cmp} Z^{cmp} + \Gamma^{cco} Z^{cco} + \Gamma^{tec} Z^{tec} \]
\[ + \Gamma^{trp} Z^{trp} + \Gamma^{trw} Z^{trw} \]

(68)

(70)

(71)

(72)

(73)

(74)

(75)

(76)

(77)

(78)
\[ Z^{qcl} \geq \text{tpw}_{qclm} QQC_{qclm}, \quad \forall \ q \in Q, c \in C, l \in L, m \in M, t \in T \]  
(79)  
\[ Z^{ckl} \geq \text{tkcl}_{cklm} QCK^{t}_{cklm}, \quad \forall \ c \in C, k \in K, l \in L, m \in M, t \in T \]  
(80)  
\[ Z^{kr} \geq \text{tkr}_{krm} QKR^{t}_{krm}, \quad \forall \ k \in K, r \in R, l \in L, m \in M, t \in T \]  
(81)  
\[ Z^{trp} \geq \text{trrp}_{rpmn} QRP^{t}_{rpmn}, \quad \forall \ r \in R, p \in P, n \in N, m \in M, t \in T \]  
(82)  
\[ Z^{trw} \geq \text{trwr}_{wrmm} QRW^{t}_{wrmm}, \quad \forall \ r \in R, w \in W, n \in N, m \in M, t \in T \]  
(83)  
\[ \sum_{q \in Q} \sum_{m \in M} QQC^{t}_{qclm} + \delta^{t}_{cl} \geq D^{t}_{cl} + \Gamma^{t}_{cl} \quad \forall \ c \in C, l \in L, t \in T \]  
(84)  
\[ \sum_{k \in K} \sum_{m \in M} QCK^{t}_{cklm} \leq R^{t}_{cl} + \Gamma^{t}_{cl} \quad \forall \ c \in C, l \in L, t \in T \]  
(85)  
\[ \sum_{k \in K} \sum_{m \in M} QCK^{t}_{cklm} \geq R^{t}_{cl} - \Gamma^{t}_{cl} \quad \forall \ c \in C, l \in L, t \in T \]  
(86)  
\[ Z^{po}, Z^{cmp}, Z^{ccc}, Z^{cc}, Z^{cdw}, Z^{twp}, Z^{tqc}, Z^{tck}, Z^{tkr}, Z^{trp}, Z^{trw} \geq 0 \]  
(87)  

**Interval + Polyhedral** uncertainty set (Model R3)  

**Minimize** \( W^{RIP} \)  

**Subject to:**  
\[ W^{D} + P^{N} + Z^{N} \leq W^{RIP} \]  
(88)  
(89)  

Where  
\[ p^{p} = \sum_{k \in K} \sum_{p \in P} \sum_{t \in T} p^{t}_{cpp} + \sum_{k \in K} \sum_{p \in P} \sum_{t \in T} p^{t}_{cpp} \]  
(90)  
\[ Z^{N} = \Gamma^{po} Z^{po} + \Gamma^{cmp} Z^{cmp} + \Gamma^{ccc} Z^{ccc} + \Gamma^{cc} Z^{cc} + \Gamma^{cdw} Z^{cdw} + \Gamma^{twp} Z^{twp} + \Gamma^{tqc} Z^{tqc} + \Gamma^{tck} Z^{tck} + \Gamma^{tkr} Z^{tkr} + \Gamma^{trp} Z^{trp} + \Gamma^{trw} Z^{trw} \]  
(91)  
\[ Z^{po} + p^{t}_{cpp} \geq \text{cpp}_{np} QE^{t}_{np}, \quad \forall \ n \in N, p \in P, t \in T \]  
(92)  
\[ Z^{cmp} + p^{t}_{cpp} \geq \text{cpp}_{np} QE^{t}_{np}, \quad \forall \ p \in P, h \in H, l \in L, t \in T \]  
(93)  
\[ Z^{ccc} + p^{t}_{cpp} \geq \text{cpp}_{np} QE^{t}_{np}, \quad \forall \ c \in C, k \in K, l \in L, m \in M, t \in T \]  
(94)
\begin{align}
Z^{cr} + p_{crct} & \geq cr_{ct} QR_{R_{rwmn}}, \quad \forall r \in R, p \in P, n \in N, m \in M, t \in T \\
Z^{cw} + p_{cw} & \geq cw_{wn} QR_{R_{rwmn}}, \quad \forall r \in R, w \in W, n \in N, m \in M, t \in T \\
Z^{pq} + p_{pq} & \geq pq_{pqlm} QP_{P_{qlm}}, \quad \forall p \in P, q \in Q, l \in L, m \in M, t \in T \\
Z^{qc} + p_{qct} & \geq qct_{qctm} QQ_{Q_{qctm}}, \quad \forall q \in Q, c \in C, l \in L, m \in M, t \in T \\
Z^{ck} + p_{ck} & \geq ck_{cklm} QC_{cklm}, \quad \forall c \in C, k \in K, l \in L, m \in M, t \in T \\
Z^{kr} + p_{kr} & \geq krm_{krm} KR_{krm}, \quad \forall k \in K, r \in R, l \in L, m \in M, t \in T \\
Z^{tr} + p_{tr} & \geq tr_{rwmn} QR_{tr_{rwmn}}, \quad \forall r \in R, p \in P, n \in N, m \in M, t \in T \\
\sum_{q \in Q} \sum_{m \in M} QC^{t}_{qctm} + \delta^{t}_{cl} & \geq D^{t}_{cl} + \Gamma^{t}_{D_{cl}} \quad \forall c \in C, l \in L, t \in T \\
\sum_{k \in K} \sum_{m \in M} QC^{t}_{cklm} & \leq R^{t}_{cl} + \Gamma^{t}_{R_{cl}} \quad \forall c \in C, l \in L, t \in T \\
\sum_{k \in K} \sum_{m \in M} QC^{t}_{cklm} & \geq R^{t}_{cl} - \Gamma^{t}_{R_{cl}} \quad \forall c \in C, l \in L, t \in T \\
Z^{op}, Z^{mp}, Z^{cc}, Z^{cr}, Z^{cd}, Z^{tp}, Z^{qc}, Z^{ck}, Z^{kr}, Z^{tr}, Z^{tw} & \geq 0 \\
p_{cp} + p_{cm} + p_{cc} + p_{cr} + p_{cd} + p_{tp} + p_{qc} + p_{ck} + p_{kr} + p_{tr} + p_{tw} & \geq 0 \\
\end{align}

5. CLSC NETWORK MODEL WITH CARBON POLICIES

In this section, we present four extensions of the base model with carbon emission constraints and costs to study the impact of various carbon policies on the CLSC design and planning decisions. These policies include a carbon cap policy, carbon tax policy, and carbon cap-and-trade policy. Each policy has been described in details in below subsections. These extensions were prompted by recent works from Benjaafar et al., (2013) and Palak et al., (2014) on classical economic log-sizing problem, Jin et al., (2014) on supply chain design and mode choice for major retailers, Marufuzzaman et al., (2014) on design and management of the biodiesel supply chain, Fareeduddin et al., (2015) on CLSC design and planning decisions. These authors explore the impact of the above mentioned policies on lot-sizing decisions and supply chain design and planning decisions.

5.1 Model with Carbon Cap Policy

Under this policy, a firm is allowed to emit a limited amount of carbon emissions over the planning horizon. The carbon emissions included are those due to production, storage, and transportation activities. The imposed carbon allowance is referred to as the carbon cap, \( C_{max} \). Constraint (109) gives the sum of emissions within the facilities, and emissions due to logistic activities. The deterministic model (D1.1) to be solved in this case is given by:

\begin{align}
\text{Minimize } Z_{cap} = Z_{base} \\
\text{Subject to: Constraints (2) – (51) and}
\end{align}
Robust counterpart of proposed MILP model (base model, D1) is developed under various uncertainty sets based on carbon cap policy as shown in below Table 3.

Table 3. Robust counterpart of the proposed model under various uncertainty sets based on carbon cap policy

<table>
<thead>
<tr>
<th>Uncertainty set</th>
<th>Objective function</th>
<th>Constraints</th>
</tr>
</thead>
<tbody>
<tr>
<td>Box (R2.1)</td>
<td>$W^{RB}_{CAP}$</td>
<td>$W^D + W^N \leq W^{RB}_{CAP}$, (2) – (51), (64) – (68), and (109)</td>
</tr>
<tr>
<td>Polyhedral (R2.1)</td>
<td>$W^{RP}_{CAP}$</td>
<td>$W^D + Z^N \leq W^{RP}_{CAP}$, (2) – (51), (71) – (87), and (109)</td>
</tr>
<tr>
<td>Interval+polyhedral (R3.1)</td>
<td>$W^{RP}_{CAP}$</td>
<td>$W^D + P^N + Z^N \leq W^{RP}_{CAP}$, (2) – (51), (90) – (107), and (109)</td>
</tr>
</tbody>
</table>

5.2 Model with Carbon Tax Policy

This policy is an alternative to strict carbon cap policy. Under this policy, a financial penalty is incurred per unit of CO₂ emission in supply chain operations. The penalty assumes a linear relationship. The objective function, in this case, comprises the sum of economic costs given by equation (1) and penalty ($\delta$) times the carbon emission costs, $Z_{co2}$. The deterministic model (D1.2) to be solved in this case is given below, where $Z_{base}$ is the cost given by equation (1).

\[
\text{Minimize } Z_{tax} = Z_{base} + \delta Z_{co2} 
\]

Where

\[
Z_{co2} = \sum_{p \in P} \sum_{n \in N} \sum_{t \in T} \sum_{e \in E} e_{ph} Z P_{ph} + \sum_{q \in Q} \sum_{i \in I} \sum_{e \in E} e_{ql} Z Q_{q} + \sum_{k \in K} \sum_{i \in I} \sum_{e \in E} e_{ki} Z K_{k} + \\
\sum_{r \in R} \sum_{n \in N} \sum_{t \in T} \sum_{w \in W} e_{rn} Z R_{r} + \sum_{w \in W} \sum_{n \in N} \sum_{t \in T} \sum_{m \in M} e_{wn} Z W_{w} + \sum_{p \in P} \sum_{e \in E} \sum_{q \in Q} \sum_{m \in M} \sum_{i \in I} e_{pq} Z P Q_{pq} + \\
\sum_{q \in Q} \sum_{c \in C} \sum_{e \in E} \sum_{m \in M} \sum_{i \in I} e_{qc} Z Q C_{qc} + \sum_{c \in C} \sum_{e \in E} \sum_{k \in K} \sum_{i \in I} \sum_{m \in M} e_{ck} Z C K_{ck} + \\
\sum_{k \in K} \sum_{r \in R} \sum_{e \in E} \sum_{i \in I} \sum_{m \in M} \sum_{e \in E} e_{kr} Z K R_{kr} + \sum_{r \in R} \sum_{e \in E} \sum_{i \in I} \sum_{m \in M} \sum_{e \in E} e_{wr} Z W R_{wr} \leq C_{max} 
\]

Subject to: Constraints (2) – (51)

Robust counterpart of the base model is developed under various uncertainty sets based on carbon tax policy as shown in Table 4.
Table 4. Robust counterpart of the base model under various uncertainty sets based on carbon tax policy

<table>
<thead>
<tr>
<th>Uncertainty set</th>
<th>Objective function</th>
<th>Constraints</th>
</tr>
</thead>
<tbody>
<tr>
<td>Box (R1.2)</td>
<td>$W_{TAX}^{BP}$</td>
<td>$W^D + W^N + \delta Z_{CO2} \leq W_{TAX}^{BP}$, (2) – (51), (64) – (68), and (111)</td>
</tr>
<tr>
<td>Polyhedral (R2.2)</td>
<td>$W_{TAX}^{BP}$</td>
<td>$W^D + Z^N + \delta Z_{CO2} \leq W_{TAX}^{BP}$, (2) – (51), (71) – (87), and (111)</td>
</tr>
<tr>
<td>Interval+polyhedral (R3.2)</td>
<td>$W_{TRD}^{BP}$</td>
<td>$W^D + p^N + Z^N + \pi (Z_{CO2} - C_{max}) \leq W_{TRD}^{BP}$, (2) – (51), (90) – (107), and (111)</td>
</tr>
</tbody>
</table>

5.3 Model with Carbon Cap-and-Trade Policy

Under this policy, a firm has a carbon cap as in the previous policy. However, it is allowed to trade its carbon allowance. If a firm emits less than its prescribed carbon cap ($Z_{CO2} < C_{max}$), then it sells the unused amount of carbon emission with a market of $\pi$. On the other hand, if a firm emits more than its prescribed carbon cap ($Z_{CO2} > C_{max}$), then it purchases additional carbon emission credit with a market price of $\pi$ in order to maintain its supply chain activities. The deterministic model formulation (D1.3) under this policy is given below.

\[
\text{Minimize } Z_{trade}
\]

where

\[
Z_{trade} = Z_{base} + \pi (Z_{CO2} - C_{max})
\]  
(112)

Subject to: Constraints (2) – (51)

Robust counterpart of the base model is developed under various uncertainty sets based on carbon cap-and-trade policy as shown in Table 5.

Table 5. Robust counterpart of the base model under various uncertainty sets based on carbon cap-and-trade policy

<table>
<thead>
<tr>
<th>Uncertainty set</th>
<th>Objective function</th>
<th>Constraints</th>
</tr>
</thead>
<tbody>
<tr>
<td>Box (R1.3)</td>
<td>$W_{TAX}^{BP}$</td>
<td>$W^D + W^N + \pi (Z_{CO2} - C_{max}) \leq W_{TAX}^{BP}$, (2) – (51), (64) – (68), and (111)</td>
</tr>
<tr>
<td>Polyhedral (R2.3)</td>
<td>$W_{TAX}^{BP}$</td>
<td>$W^D + Z^N + \pi (Z_{CO2} - C_{max}) \leq W_{TAX}^{BP}$, (2) – (51), (71) – (87), and (111)</td>
</tr>
<tr>
<td>Interval+polyhedral (R3.3)</td>
<td>$W_{TRD}^{BP}$</td>
<td>$W^D + p^N + Z^N + \pi (Z_{CO2} - C_{max}) \leq W_{TRD}^{BP}$, (2) – (51), (90) – (107), and (111)</td>
</tr>
</tbody>
</table>

Table 6 summarizes all four deterministic models with their objective functions and constraints.

Table 6. Summary of the four deterministic models under various carbon policies

<table>
<thead>
<tr>
<th>Model Name</th>
<th>Objective Function</th>
<th>Constraints</th>
</tr>
</thead>
<tbody>
<tr>
<td>Base Model (D1)</td>
<td>(1)</td>
<td>(2) – (51)</td>
</tr>
<tr>
<td>Carbon Cap (D1.1)</td>
<td>(108)</td>
<td>(2) – (51) &amp; (109)</td>
</tr>
<tr>
<td>Carbon Tax (D1.2)</td>
<td>(110)</td>
<td>(2) – (51) &amp; (111)</td>
</tr>
<tr>
<td>Carbon Cap-and-Trade (D1.3)</td>
<td>(112)</td>
<td>(2) – (51) &amp; (111)</td>
</tr>
</tbody>
</table>

6. COMPUTATIONAL RESULTS

6.1 Test Instances

In this section, two random numerical examples of different sizes are considered to validate the proposed model. The size of each test problem is shown in Table 7. The randomly generated nominal data are given in Table 8. This validation protocol is adopted from Pishvaee et al., 2011 and Keyvanshokooh et al., 2016.
Mohammed et al. RO for CLSCN Design with Carbon Policies Under Uncertainty

Table 7. Test instances’ size

<table>
<thead>
<tr>
<th>Instance size</th>
<th>P</th>
<th>Q</th>
<th>C</th>
<th>K</th>
<th>R</th>
<th>W</th>
<th>L</th>
<th>N</th>
<th>M</th>
<th>H</th>
<th>T</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>3</td>
<td>5</td>
<td>10</td>
<td>7</td>
<td>3</td>
<td>3</td>
<td>4</td>
<td>8</td>
<td>3</td>
<td>2</td>
<td>2</td>
</tr>
<tr>
<td>2</td>
<td>5</td>
<td>10</td>
<td>15</td>
<td>10</td>
<td>7</td>
<td>7</td>
<td>4</td>
<td>8</td>
<td>3</td>
<td>2</td>
<td>4</td>
</tr>
</tbody>
</table>

Table 8. The distributions from which the parameters used in the test instances are generated

<table>
<thead>
<tr>
<th>Parameters related to facilities</th>
<th>Carbon emissions due to facilities</th>
</tr>
</thead>
<tbody>
<tr>
<td>Parameter</td>
<td>Range</td>
</tr>
<tr>
<td>(D_c^t)</td>
<td>Uniform(100,400)</td>
</tr>
<tr>
<td>(R_c^t)</td>
<td>Uniform(65,260)</td>
</tr>
<tr>
<td>(f_{ph})</td>
<td>Uniform (30000,60000)</td>
</tr>
<tr>
<td>(f_{q})</td>
<td>Uniform (10000,12000)</td>
</tr>
<tr>
<td>(f_{k})</td>
<td>Uniform (2500,5000)</td>
</tr>
<tr>
<td>(f_{r})</td>
<td>Uniform (20000,30000)</td>
</tr>
<tr>
<td>(f_{w})</td>
<td>Uniform (4000,5000)</td>
</tr>
<tr>
<td>(SP_p)</td>
<td>Uniform (85000,95000)</td>
</tr>
<tr>
<td>(SQ_p)</td>
<td>Uniform (50000,60000)</td>
</tr>
<tr>
<td>(SK_p)</td>
<td>Uniform (30000,40000)</td>
</tr>
<tr>
<td>(SR_p)</td>
<td>Uniform (100000,1200000)</td>
</tr>
<tr>
<td>(SW_p)</td>
<td>Uniform (600000,800000)</td>
</tr>
<tr>
<td>(c_{k}^{c_{ph}})</td>
<td>Uniform (7.8)</td>
</tr>
<tr>
<td>(c_{k}^{c_{ph}})</td>
<td>Uniform (12,15)</td>
</tr>
<tr>
<td>(c_{k}^{c_{ph}})</td>
<td>Uniform (2,4)</td>
</tr>
<tr>
<td>(c_{k}^{c_{ph}})</td>
<td>Uniform (2,5)</td>
</tr>
<tr>
<td>(c_{k}^{c_{ph}})</td>
<td>Uniform (3,4)</td>
</tr>
<tr>
<td>(c_{k}^{c_{ph}})</td>
<td>Uniform (5,6)</td>
</tr>
<tr>
<td>(c_{k}^{c_{ph}})</td>
<td>Uniform (1,2)</td>
</tr>
<tr>
<td>(\phi_{in})</td>
<td>Uniform (6,8)</td>
</tr>
<tr>
<td>(\alpha_n)</td>
<td>80%</td>
</tr>
<tr>
<td>(\gamma_{ph11})</td>
<td>Uniform (5.5, 6.5)</td>
</tr>
<tr>
<td>(\gamma_{ph21})</td>
<td>Uniform (2.5, 3.5)</td>
</tr>
<tr>
<td>(\gamma_{q11})</td>
<td>Uniform (0.6, 0.9)</td>
</tr>
<tr>
<td>(\gamma_{k1})</td>
<td>Uniform (0.2, 0.4)</td>
</tr>
<tr>
<td>(\gamma_{r1})</td>
<td>Uniform (1.5, 2.5)</td>
</tr>
<tr>
<td>(\gamma_{w1})</td>
<td>Uniform (0.5, 0.8)</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Transportation mode capacities, in tons</th>
<th>Costs and carbon emissions of transportation modes</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mode Type</td>
<td>Min. Capacity</td>
</tr>
<tr>
<td>Heavy duty truck</td>
<td>100</td>
</tr>
<tr>
<td>Mid-size truck</td>
<td>100</td>
</tr>
<tr>
<td>Light truck</td>
<td>100</td>
</tr>
<tr>
<td></td>
<td></td>
</tr>
<tr>
<td>Mode</td>
<td>Cost ($ / ton-km)</td>
</tr>
<tr>
<td>Heavy duty truck</td>
<td>0.125</td>
</tr>
<tr>
<td>Mid-size truck</td>
<td>0.118</td>
</tr>
<tr>
<td>Light truck</td>
<td>0.110</td>
</tr>
</tbody>
</table>

At first, deterministic and robust models are solved using nominal data. Six uncertainty levels are considered for each size of the test instance. These levels are \(\psi = 0.2, 0.4, 0.6, 0.8, 1.0\) and 1.2 for the box uncertainty set and \(\Gamma = \psi \cdot |J_i|\) for the polyhedral and interval+polyhedral uncertainty sets. All mathematical models are coded in GAMS 24.5.6 coupled with CPLEX 12.6 MIP solver on a laptop with Intel Core i5 with 2.40 GHz processor and 4GB of RAM. The optimal objective function value along with the number of constraints and variables including binary and continuous variables as well as CPU time is summarized in Table 9. The results obtained in deterministic models with the robust models are compared to evaluate the performance and desirability of the solutions obtained by both models. The objective function values (total costs) of the robust models are greater than the values obtained from deterministic models. The additional costs are incurred due to a larger solution space to accommodate any realization of uncertain data. As the degree of uncertainty level increases, the value of objective function worsens. A comparison of the robust model using different uncertainty sets (box, polyhedral, interval+polyhedral) indicates that objective function value robust model associated with box uncertainty set is always less than the robust models for the two other uncertainty sets which imply that ‘box’ uncertainty set is smaller and fully covered by both ‘polyhedral’ and ‘interval+polyhedral’ uncertainty sets. When the uncertainty level reaches \(\Gamma = |J_i|\) (i.e., \(\psi = 1\)), the objective function value based on the ‘interval+polyhedral’ and ‘polyhedral’ uncertainty set is equal because in this condition both of them have the same uncertainty set. For the ‘interval+polyhedral’ set where \(\Gamma \geq |J_i|\), the subscription between the polyhedron and the interval remains unchanged and does not increase thereafter. Figure 3 depicts this issue clearly. In the context of computational time, the robust models have higher computational time compared with deterministic models (especially in the larger problem size). This is because of the complexity of the robust models. Moreover, among the three
robust models, the polyhedral uncertainty set has higher computational time, and this is due to the complexity of the polyhedral model (a large number of variables and constraints). It is noticeable that the higher computational time for the proposed robust model is acceptable considering the strategic temper of the CLSC network design problem.

Table 9. Summary of test results

<table>
<thead>
<tr>
<th>Test problem level</th>
<th>Test problem</th>
<th>Objective function value in Millions</th>
<th>CPU time (in seconds)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Deterministic Box (ѱ)</td>
<td>Polyhedral (Γ=ѱ*</td>
</tr>
<tr>
<td>1</td>
<td>0</td>
<td>6.41</td>
<td>5.13</td>
</tr>
<tr>
<td>0.2</td>
<td>0.2</td>
<td>6.69</td>
<td>6.77</td>
</tr>
<tr>
<td>0.4</td>
<td>0.4</td>
<td>6.97</td>
<td>7.12</td>
</tr>
<tr>
<td>0.6</td>
<td>0.6</td>
<td>7.25</td>
<td>7.45</td>
</tr>
<tr>
<td>0.8</td>
<td>0.8</td>
<td>7.54</td>
<td>7.86</td>
</tr>
<tr>
<td>1</td>
<td>1</td>
<td>8.24</td>
<td>8.61</td>
</tr>
<tr>
<td>1.2</td>
<td>1.2</td>
<td>9.11</td>
<td>9.57</td>
</tr>
<tr>
<td>2</td>
<td>0</td>
<td>8.27</td>
<td>473.38</td>
</tr>
<tr>
<td>0.2</td>
<td>0.2</td>
<td>8.73</td>
<td>8.97</td>
</tr>
<tr>
<td>0.4</td>
<td>0.4</td>
<td>9.13</td>
<td>9.45</td>
</tr>
<tr>
<td>0.6</td>
<td>0.6</td>
<td>9.83</td>
<td>10.25</td>
</tr>
<tr>
<td>0.8</td>
<td>0.8</td>
<td>10.21</td>
<td>10.71</td>
</tr>
<tr>
<td>1</td>
<td>1</td>
<td>10.92</td>
<td>11.78</td>
</tr>
<tr>
<td>1.2</td>
<td>1.2</td>
<td>11.51</td>
<td>12.76</td>
</tr>
</tbody>
</table>

Figure 3. Objective function values of problem 1

6.1 CLSC Network Design

This section presents the strategic design of the CLSC network with respect to various carbon policies. Facility selection decisions of CLSC network under different policies vary with respect to changes in supply chain total cost and carbon emissions as shown in Table 6 where the value ‘1’ represents that a facility is opened and ‘0’, otherwise. CLSC network design of all models is designed for the first problem, and the value of uncertainty level is ψ=0.2 for the box uncertainty set, and Γ=0.2*|Ji| of the polyhedral and interval+polyhedral uncertainty sets.

Tables 10-12 show the optimal CLSC network design structure of all the models at different values of carbon cap under carbon cap policy. From Table 10, it is observed that with increasing carbon cap level, new facilities are opening. The reason for adding new facilities to the network is that the firm uses available carbon credits by increasing supply chain strategic and operational activities in order to satisfy customers demand and minimize the total cost. Once the carbon cap reaches 550 tons, the total cost becomes the lowest. After this cap, firm not requires additional carbon credits to reduce the total cost, i.e., firm
reaches its maximum capacity of carbon cap utilization, due to this, there are no further changes in supply chain network structure.

Table 10. CLSC network design under carbon cap policy

<table>
<thead>
<tr>
<th>Facility type</th>
<th>Carbon cap</th>
<th>Carbon cap</th>
<th>Carbon cap</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>100</td>
<td>400</td>
<td>≥ 700</td>
</tr>
<tr>
<td>PCs</td>
<td>[1 1 0]</td>
<td>[1 1 0]</td>
<td>[1 1 1]</td>
</tr>
<tr>
<td>DCs</td>
<td>[0 1 0 1 0]</td>
<td>[1 0 0 1 0]</td>
<td>[0 1 0 1 0]</td>
</tr>
<tr>
<td>CCs</td>
<td>[1 0 1 0 1 0]</td>
<td>[1 0 1 0 1 0]</td>
<td>[0 0 1 0 1 1 0]</td>
</tr>
<tr>
<td>RCs</td>
<td>[0 1 1]</td>
<td>[0 1 1]</td>
<td>[1 0 1]</td>
</tr>
<tr>
<td>DDs</td>
<td>[1 1 1]</td>
<td>[1 1 1]</td>
<td>[1 1 1]</td>
</tr>
</tbody>
</table>

Table 11 presents the optimal CLSC network design structure of all the models at different values of carbon tax rate under carbon tax policy. When there is no carbon tax rate imposed, the CLSC network design structure is the same as the base model network structure. As carbon tax rate increases, supply chain strategic and operational activities are significantly reduced, i.e. aim to minimize total cost and carbon emissions which leads to closing the opened facilities.

Table 11. CLSC network design under carbon tax policy

<table>
<thead>
<tr>
<th>Facility type</th>
<th>Carbon tax rate ($/ton)</th>
<th>Carbon tax rate ($/ton)</th>
<th>Carbon tax rate ($/ton)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>10 30 50</td>
<td>10 30 50</td>
<td>10 30 50</td>
</tr>
</tbody>
</table>

Table 12 depicts the optimal CLSC network design structure of all the models at different values of carbon price (buying and selling price) under carbon trade policy. In this policy, a firm allows to buy and sell carbon credits in order to main supply chain operations. From Table 12 as we can see that at particular carbon market price the optimal CLSC network design structure is same for all carbon caps. At a higher level of carbon market prices, some of the opened facilities were closed.
The reason for this is that at higher carbon market prices, the firm has enough incentives to sell carbon credits and make the profits rather than by increasing SC activities (strategic and operational).

### Table 12. CLSC network design under carbon trade policy

<table>
<thead>
<tr>
<th>Facility Type</th>
<th>Deterministic when ( \pi = 5 )</th>
<th></th>
<th>Robust (Box) when ( \pi = 5 )</th>
<th></th>
<th>Robust (Box) when ( \pi = 15 )</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Carbon cap</td>
<td></td>
<td>Carbon cap</td>
<td></td>
<td>Carbon cap</td>
<td></td>
</tr>
<tr>
<td></td>
<td>100 400 700</td>
<td></td>
<td>100 400 700</td>
<td></td>
<td>100 400 700</td>
<td></td>
</tr>
<tr>
<td>PCs</td>
<td>[1 1 0] [1 1 0] [1 1 0]</td>
<td></td>
<td>[1 1 1] [1 1 1] [1 1 1]</td>
<td></td>
<td>[1 1 1] [1 1 1] [1 1 1]</td>
<td></td>
</tr>
<tr>
<td>DCs</td>
<td>[0 1 0 1 0] [0 1 0 1 0] [0 1 0 1 0]</td>
<td></td>
<td>[1 1 0 0 1] [1 1 0 0 1] [1 1 0 0 1]</td>
<td></td>
<td>[0 1 0 1 0] [0 1 0 1 0] [0 1 0 1 0]</td>
<td></td>
</tr>
<tr>
<td>CCs</td>
<td>[0 1 0 1 0 0] [0 1 1 0 0 0] [0 1 1 0 0 0]</td>
<td></td>
<td>[1 0 1 0 0 0 1] [1 0 1 0 0 0 1] [1 0 1 0 0 0 1]</td>
<td></td>
<td>[1 0 1 0 0 0 1] [1 0 1 0 0 0 1] [1 0 1 0 0 0 1]</td>
<td></td>
</tr>
<tr>
<td>RCs</td>
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Where PCs = production centers; DCs=distribution centers; CCs=collection centers; RCs=recycling centers; DDs=disposal centers; 1 = a facility is opened and 0, otherwise

### 6.2 Results of Carbon Cap Model

In this section, we study the effect of a strict carbon cap on objective function values and carbon emissions for deterministic and robust models on CLSC network strategic and tactical decisions. Numerical results of all the models are designed for the first problem, and the value of uncertainty level is \( \psi=0.2 \) for the box uncertainty set, and \( \Gamma=0.2*|JI| \) of the polyhedral and interval+polyhedral uncertainty sets.

Figure 4 indicates that while increasing the carbon cap, objective function value reduces to a certain level then it becomes constant. As cap value decreasing from 550 tons to 50 tons, supply chain operational activities need to be adjusted in order to meet the carbon emission requirements. In other words, the cost of maintaining production and transportation activities at low cap levels is high as compared to the cost at higher cap levels to meet customer demand.

Figure 5 shows the effect of a carbon cap on total carbon emissions. As carbon cap increases, carbon emission is also increased. The shape of the curve indicates that there is a linear relationship between them which implies that carbon emissions can be reduced significantly with a slightly increase in the objective function value. This is due to the fact that carbon cap constraint (53) in section 5.1 is a tight constraint which directly impacts on the total carbon emissions.

![Figure 4. Objective function value vs carbon cap](image1)

![Figure 5. Carbon emission vs carbon cap](image2)
6.3 Results of Carbon Tax Model

This section presents the effect of carbon tax on objective function values and carbon emissions for deterministic and robust models on CLSC network operational decisions. Figure 6 depicts a direct/linear relationship between a carbon tax and the total cost (as tax rate increases, the total cost also increases). On the other hand, carbon emissions reduce significantly, as carbon tax rate increases as shown in Figure 7. This significant reduction in carbon emissions reflects that the firm seeks to modify its SC activities to reduce the carbon emissions. As the further increase of carbon tax rate, emission curve eventually becomes almost flatten. This indicates that there are no further operational changes required/exist in SC which impacts the carbon emissions.

![Figure 6. Objective function value vs carbon tax](image)

![Figure 7. Carbon emission vs carbon tax](image)

6.4 Results of Carbon Cap-and-Trade Model

In this section, we study the effect of carbon prices on supply chain total cost (objective value) for deterministic and all robust models. Figure 8 and 9 shows the relationship between carbon cap and the total cost at different carbon prices. From the graphs, as carbon market price increases, total cost becomes high when the cap is low, and when the cap is high, the total cost becomes low. This is because when at low cap levels, it costs firms to buy additional carbon credits to maintain supply chain operations which result in higher supply chain costs. When the market price is high, the firm has enough incentive to make profits by selling carbon credits and shortens supply chain operations so that cap does not affect much as the results lower supply chain costs.

![Figure 8. Objective function value vs carbon cap](image)

![Figure 9. Carbon emission vs carbon cap](image)

Thus, the impact of carbon trade policy heavily depends on how to allocate the cap and what the market price is. In this policy, carbon emissions maintain constant level though varying carbon cap. This is because there is a carbon market exists under this policy that a firm can sell unused carbon credits to the market and make the additional source of income and can buy the carbon credits from the market to maintain SC operations.
7. SENSITIVITY ANALYSIS

In this section, sensitivity analysis is performed for both deterministic and robust models to show the impact of uncertain parameters (demand, return rate, processing costs, and transportation costs) in the behavior of the proposed model. All the sensitivity analysis is designed for the first problem, and the value of uncertainty level is \( \psi = 0.2 \) for the box uncertainty set, and \( \Gamma = 0.2 \| \mathbf{J} \| \) of the polyhedral and interval+polyhedral uncertainty sets.

Figure 10 and 11 depict the sensitivity analysis for the processing costs and transportation costs respectively. As shown in these figures, by increasing the value of processing costs and transportation costs, the objective function value for all the model’s increases and behavior of the curves are in the linear pattern. On the other hand, the difference between the deterministic and robust models is not major significant. Also, box and interval+polyhedral uncertainty sets are completely covered by the polyhedral uncertainty set.

The sensitivity analysis of customer’s demand and used product return rate is depicted in Figure 12 and 13 respectively. As shown in Figure 12, the objective function is more sensitive to the demand, i.e., as the mean demand increases the objective function value increases with the steeper slope as compared to processing costs and transportation costs.

Figure 13 depicts the behavior of return quantities with respect to objective function values, as return quantity increases the objective function value decreases, this is due to fact that the more return quantities imply, the less procurement of raw materials or new components with presumption that procurement cost of new components are always higher that of collection and recycling costs of return quantities.
8. CONCLUSIONS

With increasing pressure due to various rules and regulations on low carbon development, it has become important as well as challenging for firms worldwide to incorporate carbon footprint management into their business decisions. In this context, this paper proposed a series of optimization models considering different carbon policies to show how carbon emissions considerations can be incorporated into quantitative strategic and operational models to address a multi-period, multi-product CLSC network design problem. A MILP formulation is used to formulate the proposed model. Besides, to design a realistic network, a set-based robust optimization methodology is proposed to handle uncertainty in the processing costs, transportation costs, customer demand, and return quantities. Subsequently, the tractable robust counterpart of the proposed model is extended to compare the difference among various uncertainty sets. In the set-based robust optimization, to overcome the worst possible combination of values at the same time (box uncertainty set), two uncertainty sets with an adjustable degree of conservatism (polyhedral and interval-polyhedral) are used. To make supply chain requirements more realistic, we incorporated decisions on selection of technologies at facilities and transportation modes options, as well as capacity limits on production, distribution, and storage.

Computational experiments show that the robust model considers additional cost (robustness price) and a higher computational time compared with the deterministic model in order to stabilize the model against the uncertain environment. The model extends further to investigate the impact of different carbon policies such as strict carbon cap, carbon tax, and carbon cap-and-trade on the supply chain strategic and operational decisions. Numerical results provide insightful observations about the impact of different carbon policies on optimal design of CLSC, supply chain total costs, and carbon emissions.

Optimal CLSC network structure under a carbon cap, carbon tax, carbon trade policies have been examined. As carbon cap increases, open new facilities until the carbon cap reaches 550 kilotons. The reason for this increase in strategic activities of a firm because the firm is willing to minimize SC total cost and reduce carbon emissions by utilizing allocated carbon allowances. Due to a linear (direct) relationship between the total cost and carbon tax in carbon tax policy, strategic activities of the firm are significantly reduced (closing the opened facilities) as carbon tax rate increases that is to minimize supply chain total cost and reduce carbon emissions. Due to having both buying and selling flexibility in carbon cap-and-trade policy, firm strategic activity (open new facilities) is the same for all carbon cap levels at particular carbon credit price.

Supply chain operational decisions heavily depend on the carbon capsize under carbon cap policy. Because in this policy, carbon emissions can be reduced significantly with a slight increase in the total cost, also carbon emissions are the lowest under this policy. Under carbon tax policy, supply chain activities are directly proportional to the carbon tax rate. This policy provides more flexibility but imposes huge financial burden on the firms to reach certain emission target compared to other two policies. However, once tax policy is adopted, the supply chain total cost is insensitive to targeted emission goal, which is different from other two policies. Carbon trade policy heavily depends on carbon market price and cap allocation. Results indicate that among three carbon cap policies, carbon cap-and-trade policy is more flexible and efficient than other two policies. Under this policy, firms can be sold unused carbon units to the market and make additional income when carbon cap size is large. In other words, this policy motivates the firms to emit fewer carbon units even when the carbon allowance is available more than needed. Due to the existence of a carbon market in the carbon trade policy, it is more favorable among all other policies and attractive to many countries. We performed sensitivity on processing costs, transportation costs, customer demand, and on return quantities to analyze their effect on the proposed model. Results reveal that the proposed model is more sensitive to customer demand and return quantities than processing costs and transportation costs.

Some managerial implications with respect to the proposed robust model and carbon policies. The proposed robust optimization model should be useful for managers to achieve a robust SCND which can withstand any possible uncertainty. Numerical examples provide evidence that the proposed model can produce significant savings in supply chain operations. Without considering inherent uncertainties in the environment may result in sub-optimal or infeasible solutions. Robust optimization overcomes many disadvantages (e.g., lack of historical data to fit appropriate probability distributions, the probability of an infeasible solution in some realization, and computational complexities in large-scale problems).

Finally, the proposed robust models with three different uncertainty sets and carbon policies can be valuable for decision makers (DMs). Each of the selected uncertainty set has its own characteristics, and DMs can apply them based on their respective situations. Indeed, DMs have flexibility to design a robust supply chain network based on their favorable robustness. To have tighter constraints and a more conservative model, box uncertainty is recommended. Alternatively, to reduce the level of conservative solutions, polyhedral uncertainty is recommended since it provides an adjustable degree of conservatism. Finally, for uncertainty with a known bounded distribution, DMs will have the flexibility to design a set size that leads to the desired robustness (feasible and acceptable solutions). This study guides DMs to decide which policy to be chosen well in advance to minimize overall supply chain cost as well as carbon emission across the supply chain.
REFERENCES


APPENDIX – I

The following notations are used for the mathematical formulation of the model.

**Sets and subscripts**

- **P** set of candidate locations for production centers PCs, \{1,2, \ldots p \ldots\}
- **Q** set of candidate locations for distribution centers DCs, \{1,2, \ldots q \ldots\}
- **C** set of markets, \{1,2, \ldots c \ldots\}
- **K** set of candidate locations for collection centers CCs, \{1,2, \ldots k \ldots\}
- **R** set of candidate locations for recycling centers RCs, \{1,2, \ldots r \ldots\}
- **W** set of candidate locations for disposal deports DDs, \{1,2, \ldots w \ldots\}
- **L** set of product types, \{1,2, \ldots l \ldots\}
- **N** set of component types, \{1,2, \ldots n \ldots\}
- **M** set of transportation modes, \{1,2, \ldots m \ldots\}
- **H** set of production technologies, \{1,2, \ldots h \ldots\}
- **T** set of periods in the planning horizon, \{1,2, \ldots t \ldots\}

**Parameters**

- \( D_{cl}^{ts} \) Demand for product \( l \) by market \( c \) in time period \( t \)
- \( R_{cl}^{ts} \) EOL returns of product \( l \) from market \( c \) in time period \( t \),
- \( \mu_{l}^{f} \) Proportion of EOL product \( l \) returned after \( f \) years of service, \( f=0 \) means in the same year, \( \sum_{f=0}^{F_{l}} \mu_{l}^{f} \leq 1 \).
- \( F_{l} \) Maximum life of product \( l \)
- \( \varphi_{ln} \) Number of units of component \( n \) in a unit of product \( l \)
- \( \alpha_{n} \) Fraction of component \( n \) that could be recycled
- \( t_{plh} \) Time to produce a unit of product \( l \) using technology \( h \)
- \( trn_{n} \) Time to recycle a component \( n \)
- \( vl_{l} \) Space required to store a unit of product \( l \).
- \( vn_{n} \) Space required for disposal of one unit of component \( n \)
- **M** A large scalar

**Capacities of facilities**

- \( SP_{p} \) Production capacity of the PC in location \( p \), in hrs
- \( SQ_{q} \) Storage capacity of the DC in location \( q \), in m³
- \( SK_{k} \) Storage capacity of the CC in location \( k \), in m³
- \( SR_{r} \) Recycling capacity of the RC in location \( r \), in hrs
- \( SW_{w} \) Storage capacity of the DD in location \( w \), in m³
Load capacities of transportation mode

\( tpq_{pqm}, Tpq_{pqm} \) \text{Min. and Max. load capacity of transportation mode } m \text{ between the PC in location } p \text{ and DC in location } q, \text{ in tons} \\
\( tqc_{qcm}, Tqc_{qcm} \) \text{Min. and Max. load capacity of transportation mode } m \text{ between the DC in location } q \text{ and market } c, \text{ in tons} \\
\( tck_{ckm}, Tck_{ckm} \) \text{Min. and Max. load capacity of transportation mode } m \text{ between market } c \text{ and in location CC } k, \text{ in tons} \\
\( tkr_{kmr}, Tkr_{kmr} \) \text{Min. and Max. load capacity of transportation mode } m \text{ between the CC in location } k \text{ and RC in location } r, \text{ in tons} \\
\( trp_{rpm}, Trp_{rpm} \) \text{Min. and Max. load capacity of transportation mode } m \text{ between the RC in location } r \text{ and the PC in location } p, \text{ in tons} \\
\( trw_{rwm}, Trw_{rwm} \) \text{Min. and Max. load capacity of transportation mode } m \text{ between the RC in location } r \text{ and the DD in location } w, \text{ in tons} \\

Fixed Costs

\( f_{ph} \) \text{Fixed cost of constructing a PC in location } p \text{ with technology } h \\
\( f_{q} \) \text{Fixed cost of constructing a DC in location } q \\
\( f_{k} \) \text{Fixed cost of constructing a CC in location } k \\
\( f_{r} \) \text{Fixed cost of constructing a RC in location } r \\
\( f_{w} \) \text{Fixed cost of constructing a DD in location } w \\

Unit costs

\( cpo_{np}^{t} \) \text{Unit purchasing cost of new component } n \text{ from suppliers for the PC in location } p \text{ in time period } t \\
\( cmp_{ph}^{t} \) \text{Unit production cost of product } l \text{ at the PC in location } p \text{ using technology } h \text{ in time period } t \\
\( chp_{pm}^{t} \) \text{Unit holding cost of component } n \text{ at the PC in location } p \text{ in time period } t \\
\( cha_{ql}^{t} \) \text{Unit holding cost of product } l \text{ at the DC in location } q \text{ in time period } t \\
\( ccc_{kl}^{t} \) \text{Unit collection cost of EOL product } l \text{ at CC in location } k \text{ in time period } t \\
\( crc_{rm}^{t} \) \text{Unit recycling cost of component } n \text{ at the RC in location } r \text{ in time period } t \\
\( cdw_{wn}^{t} \) \text{Unit disposal cost of scrapped component } n \text{ at the DD in location } w \text{ in time period } t \\
\( tpq_{pqlm}^{t} \) \text{Cost of shipping a unit of product } l \text{ from the PC in location } p \text{ to the DC in location } q \text{ using transportation mode } m \text{ in time period } t \\
\( tqc_{qctm}^{t} \) \text{Cost of shipping a unit of product } l \text{ from the DC in location } q \text{ to market } c \text{ using transportation mode } m \text{ in time period } t \\
\( tck_{cklm}^{t} \) \text{Cost of shipping a unit of retuned product } l \text{ from market } c \text{ to the CC in location } k \text{ using transportation mode } m \text{ in time period } t \\
\( tkr_{krmm}^{t} \) \text{Cost of shipping a unit of returned product } l \text{ from the CC in location } k \text{ to the RC in location } r \text{ using transportation mode } m \text{ in time period } t \\
\( trp_{rpmn}^{t} \) \text{Cost of shipping a unit of recycled component } n \text{ from the RC in location } r \text{ to the PC in location } p \text{ using transportation mode } m \text{ in time period } t
$trw_{rwnm}^t$ Cost of shipping a unit of scrapped component $n$ from the RC in location $r$ to the DD in location $w$ using transportation mode $m$ in time period $t$.

**Parameters related to carbon emission**

$ep_{pht}^t$ Carbon emission in kg due to the production of one unit of product $l$ at the PC in location $p$ with technology $h$ in time period $t$.

$eq_{ql}^t$ Carbon emission in kg due to storing of one unit of product $l$ at the DC in location $q$ in time period $t$.

$ek_{kl}^t$ Carbon emission in kg due to a collection of one unit of returned product $l$ at the CC in location $k$ in time period $t$.

$er_{rn}^t$ Carbon emission in kg due to recycling of one unit of component $n$ at the RC in location $r$ in time period $t$.

$ew_{wn}^t$ Carbon emission in kg due to the disposal of one unit of component $n$ at the DD in location $w$ in time period $t$.

$epq_{lqptm}^t$ Carbon emission in kg for shipping one unit of product $l$ from the PC in location $p$ to DC in location $q$ using transportation mode $m$ in time period $t$.

$eqc_{qcim}^t$ Carbon emission in kg of shipping product $l$ from the DC in location $q$ to market in location $c$ using transportation mode $m$ in time period $t$.

$eck_{cklm}^t$ Carbon emission in kg of shipping returned product $l$ from market in location $c$ to the CC in location $k$ using transportation mode $m$ in time period $t$.

$ekr_{krtl}^t$ Carbon emission in kg of shipping returned product $l$ from the CC in location $k$ to the RC in location $r$ using transportation mode $m$ in time period $t$.

$erp_{rpnm}^t$ Carbon emission in kg of shipping recycled component $n$ from the RC in location $r$ to the PC in location $p$ using transportation mode $m$ in time period $t$.

$erw_{rnwm}^t$ Carbon emission in kg of shipping scrapped component $n$ from the RC in location $r$ to the DD in location $w$ using transportation mode $m$ in time period $t$.

$C_{max}$ Maximum allowed carbon emission (carbon cap).

$\delta$ The carbon tax rate per unit (amount of tax paid per unit emitted).

$\pi$ The carbon price (buying and selling).

**Decision variables**

**Binary variables**

$Z_{ph} 1$ if a PC is constructed in candidate location $p$ that uses technology $h$, $0$ otherwise.

$Z_{Qq} 1$ if a DC is constructed in candidate location $q$, $0$ otherwise.

$Z_{Kk} 1$ if CC is constructed in candidate location $k$, $0$ otherwise.

$Z_{Rr} 1$ if RC is constructed in candidate location $r$, $0$ otherwise.

$Z_{Ww} 1$ if DD is constructed in candidate location $w$, $0$ otherwise.

$YPQ_{pqt}^t 1$ if transportation mode $m$ is used between the PC in location $p$ and the DC in location $q$ in time period $t$, $0$ otherwise.
Mohammed et al. RO for CLSCN Design with Carbon Policies Under Uncertainty

\( YQ_{qcm} \) 1 if transportation mode \( m \) is used between the DC in location \( q \) and the market in location \( c \) in time period \( t \), 0 otherwise

\( YCK_{ckm} \) 1 if transportation mode \( m \) is used between the market in location \( c \) and the CC in location \( k \) in time period \( t \), 0 otherwise

\( YKR_{krm} \) 1 if transportation mode \( m \) is used between the CC in location \( k \) and the RC in location \( r \) in time period \( t \), 0 otherwise

\( YRP_{rpm} \) 1 if transportation mode \( m \) is used between the RC in location \( r \) and the PC in location \( p \) in time period \( t \), 0 otherwise

\( YRW_{rwm} \) 1 if transportation mode \( m \) is used between the RC in location \( r \) and the DD in location \( w \) in time period \( t \), 0 otherwise

Continuous variables

\( Q_{np} \) Quantity of new component \( n \) purchased by the PC in location \( p \) in time period \( t \).

\( Q_{phl} \) Quantity of product \( l \) produced in the PC in location \( p \) using technology \( h \) in time period \( t \)

\( QPQ_{pqlm} \) Quantity of product \( l \) shipped from the PC in location \( p \) to the DC in location \( q \) using transportation mode \( m \) in time period \( t \)

\( QQC_{qclm} \) Quantity of product \( l \) shipped from the DC in location \( q \) to the market in location \( c \) using transportation mode \( m \) in time period \( t \)

\( QCK_{cklm} \) Quantity of returned product \( l \) shipped from the market in location \( c \) to the CC in location \( k \) using transportation mode \( m \) in time period \( t \)

\( QKR_{krim} \) Quantity of returned product \( l \) shipped from the CC in location \( k \) to the RC in location \( r \) using transportation mode \( m \) in time period \( t \)

\( QRP_{rpm} \) Quantity of component \( n \) shipped from the RC in location \( r \) to the PC in location \( p \) using transportation mode \( m \) in time period \( t \)

\( QRW_{rwm} \) Quantity of disposable component \( n \) shipped from the RC in location \( r \) to the DD in location \( w \) using transportation mode \( m \) in time period \( t \)