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Carbon market sensitive robust optimization model for closed loop supply chain network design under uncertainty

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Abstract. The adoption of closed-loop supply chain (CLSC) network is one of the effective approaches to reduce carbon emissions. In current globalization, inherent uncertainty exists in business environment so there is a need to be design robust supply chains. This paper proposes a deterministic mixed integer linear programming (MILP) model integrating economics and carbon emission considerations including selection of production technologies and transportation mode as a part of CLSC network strategic and tactical decisions. The robust counterpart of the proposed deterministic model is developed based on three alternative uncertainty sets to represent the imprecise input parameters. The robust counterpart is used to study the supply chain performance by considering the two most globally practiced carbon regulatory policies; carbon tax policy and carbon trading policy. Numerical results show that total cost of the proposed robust optimization model under each uncertainty set is greater than the total cost of deterministic model. The additional cost is due to solution space of each uncertainty set to accommodate any uncertainty level. As uncertainty level increases the overall supply chain cost worsen. Moreover, the results suggest that carbon tax rate has direct relation with overall supply chain cost whereas having carbon market trading flexibility in carbon trading policy, this policy is more efficient policy as compared to carbon tax policy. Furthermore, the proposed robust optimization model is useful for mangers to achieve not only a robust supply chain network design which can withstand any possible uncertainty level but also significant reduction in carbon emissions by choosing suitable carbon-efficient policy.

1. Introduction

Climate change, global warming, environmental issues and energy crisis led to environmental regulations and stringent government legislations by policy makers around the globe. For example, China has pledged to cutting emission intensity by 40–45 % by 2020 [1]. Malaysia has committed to cut its emissions up to 45% by 2030 [2]. Other organizations, such as the United Nations (UN) and the European Union (EU) have initiated a wide range of emission reduction mechanisms including carbon cap, carbon tax, and carbon trading to curb the carbon emissions and other greenhouses gases (GHG). Among them, the carbon tax and carbon trading are regarded as the most widely adopted mechanisms, have been broadly adopted by the UN, the EU, and many other counties [3]. Under carbon tax mechanism, its aims to control carbon emission by taxing (monetary penalty) per unit of generated carbon emission. According to a latest report by world bank [4], over 40 countries have implemented carbon taxes. Under carbon trading policy (also known as cap-and-trade), if a firm generates carbon emission less than the pre-allocated carbon cap, it can sell unused carbon amount in the carbon trading market and make profit. Similarly, if the emitted carbon is more than prescribed carbon cap it can buy additional carbon amount in a carbon trading market to maintain its supply chain activities. The goal of this policy is either to have firms buy carbon credits or invest in emission reduction projects and technology to minimize GHG emissions.

Later said initiatives such as investing in energy efficient facilities and equationuipment, energy saving projects, and using low pollution energy sources implement at firm level to reduce GHG emissions. Such efforts have been effective; however, other potentially more significant approaches such as optimizing firm's strategic (opening/closing a facility), frequationuency of transportation between the facilities, and operational decisions of a firm in business practices in a complex supply chain, particularly in CLSC, are frequationuently ignored. For example, facility location decisions, production and transportation quantities, and transportation mode selection decisions influence GHG emissions, which in turn effect overall emissions of the final product [5,6]. These approaches might reduce carbon emissions more with a lower cost than the cost of investing in energy efficient projects and technologies. However, the existing supply chain models are focusing on economic objective only. So, it is necessary to integrate carbon emissions into supply chain decisions that could aid organizations, firms, policy-makers, and even NGO's in evaluating supply chain's strategic, tactical and operational evaluations from carbon regulatory mechanisms. Moreover, the configuration of CLSC logistic network under uncertainty is highly necessary to coop with uncertain parameters such that the impact of parameter fluctuations on network configuration will be less. To deal with uncertainty in input parameters, robust optimization methodology has attracted researchers' attention [7].

This paper proposes a deterministic MILP model for a multi-period, multi-product CLSC network design problem, decisions on production technology and transportation mode selection are incorporated in the model. A robust counterpart of proposed model is developed to handle 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 (I+P) uncertainty sets. The proposed model is further extended by integrating carbon regulatory policies including carbon tax policy and carbon trading policy to examine the effect of these policies on supply chain strategic as well as tactical decisions.

A brief review of recent literature follows in Section 2. In section 3, we provide problem description, assumption, and model formulation. Robust counterpart of proposed model under three uncertainty sets is explained in Section 4. In Section 5, numerical results are presented for analysis purpose. Finally, conclusions are made in Section 6.

2. Literature Review

Recently, few papers proposed supply chain models by incorporating carbon emission regulations on supply chain planning decisions. Benjaafar *et al* [8] presented supply chain models by integrating various carbon policies and analyzed the effect of total cost and emissions on supply chain inventory management decisions. Few authtors [5,9] investigated the effect of carbon emission policies on CLSC network design and planning decisions. The main limitation in their work is all parameters assumed to be deterministic.

In recent years, few researchers paid attention to uncertainty issues of CLSC network design using robust optimization methodology [10,11]. Li *et al* [12] studied set-based robust optimization techniques for both LP and MILP problems. They proposed few novel uncertainty sets such as box, polyhedral, and I+P set. Uncertainty set provides flexibility not only to decision makers for adjusting set-size to a requationuired level that leads to desired robustness in their decision but also to overcome the worst-case scenario of uncertain data [7]. This type of approach for handling uncertainty is very rarely used in supply chain network design (SCND) problems. Considering above gap in the literature, this research is a step further in this direction.

3. Problem Definition and Modelling

A proposed CLSC network is shown in figure 1. It consists of suppliers, production centers (PCs), distribution centers (DCs), and markets (CZs) in the forward network, while collection centers (CCs), recycling centers (RCs), and disposal centers (WCs) in the reverse network.

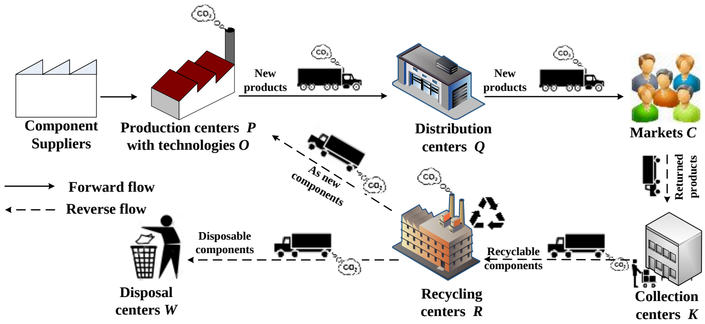

Figure 1. A proposed CLSC network

In the forward network, PCs $p \in P$ procure components from both RCs $r \in R$ and suppliers. Multiple products $l \in L$ are produced in PCs using potential technologies $o \in O$. At PCs, both production cost and emission rate depend on type of potential technologies to use because each technology differs in terms of investment cost and amount of emission. Final products are shipped to CZs $c \in C$ using different transportation modes $m \in M$ via DCs $q \in Q$. 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 (satisfy minimum quality requationuirements), it shipped to PCs. Logistic activities carried out using different transportation modes $m \in M$ varies in unit transportation cost and emission rate.

Other assumptions are stated as the following.

i. The number, capacity and potential location of PCs, DCs, CCs, RCs, and WCs are known.
ii. Product demand, returns, variable costs, and transportation costs are considered as uncertain.
iii. Transshipment cost is not allowed.
iv. Emission rate at facilities as well as emission rate of transportation mode is known.

Consider the CLSC network is denoted by $G=(N,A)$ where N and A denotes the set of nodes and the set of Arcs respectively. The node set $N = F \cup C$, where F is the set of potential facilities consisting of PCs, DCs, CCs, RCs, and WCs; i.e., $F = P \cup Q \cup K \cup R \cup W$; and C is the set of customer zones. Arc represents a link or connection between any two nodes in the network. The arc set $\mathrm{A} = A^f \cup A^r$, where A^f is the set of arcs between the facilities in the forward network; $A^f = \{ij : (i \in P, j \in Q), (i \in Q, j \in C), (i \in C, j \in K\}$, and A^r is set of arcs between the facilities in the reverse network; $A^r = \{ij : (i \in C, j \in K), (i \in K, j \in R), (i \in R, j \in P)$, $(i \in R, j \in W)\}$, while A^l is set of arcs in which products flow is carried out $A^l = \{ij : (i \in P, j \in Q), (i \in Q, j \in C), (i \in C, j \in K), (i \in K, j \in R)\}$, whereas A^n is set of arcs in which component flow is carried out $A^n = \{ij : (i \in R, j \in P), (i \in R, j \in W)\}$, A^{fr} is set of arcs that connect between forward and reverse supply chain network $A^{fr} = \{ij : (i \in C, j \in K)\}$, whereas A^{rf} is set of arcs that connect between reverse and forward supply chain network $A^{rf} = \{ij : (i \in R, j \in P)\}$.

The parameters used for configuring CLSC network are as follows. The demand for the product $l \in L$ by customer $c \in C$ in time period $t \in T$ is denoted by d_{cl}^t. Customer returned product or end-of-life product in time period $t \in T$, is denoted r_{cl}^t. Each potential facility $p \in P$ of the proposed supply chain network has a capacity limit associated with component/product, is denoted by η_i. The proportion of components $n \in N$ in a product $l \in L$ is denoted by φ_{ln}. $\alpha_n$specifies the percentage of recyclable components in recycling centers. The cost parameters include fixed cost, processing cost and logistic cost associated with cost of opening and operating facility (fc_i), cost of processing a product/component at facility (ci_{il}^t) and cost of using transportation mode (tc_{ijnm}^t), respectively. Finally, the amount of carbon emission generated by facilities as well as transportation modes is denoted by ef_i and ec_{ijlm}^t respectively.

Three sets of decision variables are considered for the CLSC network configuration decisions. First set of binary variables are on hand for determining which of processing facility *i* to open is denoted by z_i. Second set of binary variables are for choosing which of transportation mode *m* between node *i* and node *j* in period *t*, is denoted by y_{ijm}^t. Third set of decision variables are for determining the amount of products at process/production facilities as well as the amount of products and components shipped from node *i* to node *j* using transportation mode *m* in period *t*, denoted by x_{ijlm}^t. In addition, the decision variable for unmet demands for product *l* at market *c* in period *t* is denoted by δ_{il}^t.

Given these definitions, the two objective functions can be formulated using MILP. The first objective function, shown in equation (1), formulates the overall supply chain cost (excluding carbon emission cost). Equation (1) is the summation of total ten components: the first two components represent fixed cost of opening production centers with available technologies and fixed of cost of opening potential facilities, respectively. The third and fourth components represent purchasing cost and production cost, respectively. The components 5-7 represent collection cost of returned products, recycling cost of components and the cost of land-filling, respectively. The eight component represents the shortage cost at customer zones. Finally, the ninth and tenth components represent the transportation cost.

$$\boldsymbol{Z_1} = \sum_{i\in P}\sum_{o\in O} fc_{io}z_{io} + \sum_{i\in F} fc_i z_i + \sum_{n\in N}\sum_{i\in P}\sum_{t\in T} ci_{ni}^t\, x_{ni}^t + \sum_{i\in P}\sum_{o\in O}\sum_{l\in L}\sum_{t\in T} ci_{iol}^t\, x_{iol}^t + \sum_{i,j\in A^{fr}}\sum_{l\in L}\sum_{m\in M}\sum_{t\in T} cc_{jl}^t\, x_{ijlm}^t + \sum_{i,j\in A^{rf}}\sum_{n\in N}\sum_{m\in M}\sum_{t\in T} cr_{in}^t\, x_{ijnm}^t + \sum_{i,j\in A^{kw}}\sum_{n\in N}\sum_{m\in M}\sum_{t\in T} cw_{j\prime n}^t\, x_{ijnm}^t + \sum_{i\in C}\sum_{l\in L}\sum_{t\in T} \pi_{il}^t\delta_{il}^t + \sum_{i,j\in A^l}\sum_{l\in L}\sum_{m\in M}\sum_{t\in T} tc_{ijlm}^t\, x_{ijlm}^t + \sum_{i,j\in A^n}\sum_{n\in N}\sum_{m\in M}\sum_{t\in T} tc_{ijnm}^t\, x_{ijnm}^t \quad (1)$$

The second objective function, shown in equation (2), formulates the carbon emission cost. Notation Z_2 representing the overall carbon emission resulted in from summation of four components. The first two components represent the emission due to production using one of the two selected technologies and emissions at rest of the potential facilities for various activities, respectively. The third and fourth components represent the emission due to transportation in the forward and reverse logistics network, respectively.

$$\boldsymbol{Z_2} = \sum_{i\in P}\sum_{o\in O} ef_{io}z_{io} + \sum_{i\in F\setminus P} ef_i z_i + \sum_{i,j\in A^l}\sum_{l\in L}\sum_{m\in M}\sum_{t\in T} ec_{ijlm}^t\, x_{ijlm}^t + \sum_{i,j\in A^n}\sum_{n\in N}\sum_{m\in M}\sum_{t\in T} ec_{ijnm}^t\, x_{ijnm}^t \quad (2)$$

The goal of this research is to minimize the overall supply chain cost regardless of environmental regulations in place. Obviously, the supply chain costs are formulated differently depending on the type of regulatory policy selected. This paper considers the two most commonly selected regulatory policies around the globe; (1) carbon tax policy, and (2) carbon trading policy. Overall supply chain cost under each regulatory policy can be formulated as per Zakeri *et al* [3] in equation (3) and (4) respectively by considering the above two objective functions in equation. (1) and (2).The goal of:

Carbon tax policy: *Minimize* $Z_1 + \delta\, Z_2$ (3)

Carbon trading policy: *Minimize* $Z_1 + \pi\, (Z_2 - C_{max})$ (4)

Carbon tax policy in equation (3), a monetary penalty (taxing) δ is imposed per unit emit of carbon emission in supply chain activities. Whereas in trading policy in equation (4), as per the definition provided in introductory section, if a firm generates carbon emission less than the pre-allocated carbon cap ($Z_2<C_{max}$), it allows to sell unused amount of carbon in the carbon trading market with a market of π and makes profit. Similarly, if the emitted carbon is more than prescribed carbon cap ($Z_2>C_{max}$), it allows to buy additional amount of carbon with a market price of π to continue its business activities.
Constraints of the model starting with flow balancing equations are as follows.

$$\sum_{i\in R}\sum_{m\in M} x_{ijnm}^t + x_{nj}^t = \sum_{l\in L}\sum_{o\in O} \varphi_{ln}\, x_{jol}^t, \qquad \forall\ j\in P, n\in N, t\in \quad (5)$$

$$\sum_{o\in O} x_{ihl}^t = \sum_{j\in Q}\sum_{m\in M} x_{ijlm}^t, \ \forall\ i\in P, l\in L, t\in T \quad (6)$$

$$\sum_{i\in P}\sum_{m\in M} x_{ijlm}^{t} = \sum_{i\in C}\sum_{m\in M} x_{jilm}^{t}, \ \forall\ j \in Q, l \in L, t \in T \tag{7}$$
$$\sum_{i\in C}\sum_{m\in M} x_{ijlm}^{t} = \sum_{i\in R}\sum_{m\in M} x_{jilm}^{t}, \ \forall j \in K, l \in L, t \in T \tag{8}$$
$$\sum_{i\in P}\sum_{m\in M} x_{jinm}^{t} = \sum_{i\in K}\sum_{l\in L}\sum_{m\in M} \alpha_n \varphi_{ln} x_{ijlm}^{t}, \qquad \forall j \in R, n \in N, t \in T \tag{9}$$
$$\sum_{i\in W}\sum_{m\in M} x_{jinm}^{t} = \sum_{i\in K}\sum_{l\in L}\sum_{m\in M} (1-\alpha_n)\varphi_{ln} x_{ijlm}^{t}, \ \forall j \in R, n \in N, t \in T \tag{10}$$

Constraints (5)-(7) are balancing equationuations of flow for each type of component and product in the forward network. Similarly, constraints (8)-(10) are flow balancing equationuations for the reverse network.

$$\sum_{i\in Q}\sum_{m\in M} x_{ijlm}^{t} + \delta_{cl}^{t} \geq d_{jl}^{t} \qquad \forall j \in C, l \in L, t \in T \tag{11}$$

Constraint (11) ensures that the demand for all customer zones is taken into account, and imposing huge penalty for unsatisfied demand.

$$\sum_{j\in K}\sum_{m\in M} x_{ijlm}^{t} = r_{il}^{t}, \ \forall\ i \in C, l \in L, t \in T \tag{12}$$

Constraint (12) ensures that the returned of each product in each time period equationuals the returned products collected at CCs.

$$\sum_{l\in L} tp_{lo}\, x_{iol}^{t} \leq \eta_i\, z_{io}, \qquad \forall i \in P, o \in O, t \in T \tag{13}$$
$$\sum_{j:(i,j)\in A^l}\sum_{l\in L}\sum_{m\in M} vl_l\, x_{ijlm}^{t} \leq \eta_i\, z_i, \ \forall i \in (Q,K), t \in T \tag{14}$$
$$\sum_{j:(i,j)\in A^n}\sum_{n\in N}\sum_{m\in M} vn_n x_{ijnm}^{t} \leq \eta_i\, z_i, \forall i \in (R,W), t \in T \tag{15}$$

Constraints (13)-(15) are capacity constraints on facilities that ensure production and process capacities in the forward and reverse network.

$$\sum_{t\in T}\sum_{o\in O} z_{io}^{t} \leq 1, \qquad \forall i \in P \tag{16}$$

Constraint (16) ensures at most one technology can be installed in each PC.

$$\sum_{j:(i,j)\in A^l}\sum_{l\in L}\sum_{m\in M}\sum_{t\in T} x_{ijlm}^{t} \leq M \sum_{o\in O} z_{io}, \ \forall\ i \in P \tag{17}$$
$$\sum_{j:(i,j)\in A^n}\sum_{n\in N}\sum_{m\in M}\sum_{t\in T} x_{ijnm}^{t} \leq M \sum_{o\in O} z_{io}, \ \forall\ i \in P \tag{18}$$
$$\sum_{j:(i,j)\in A^l}\sum_{l\in L}\sum_{m\in M}\sum_{t\in T} x_{ijlm}^{t} \leq M z_i, \ \forall\ i \in (Q,K) \tag{19}$$
$$\sum_{j:(i,j)\in A^n}\sum_{n\in N}\sum_{m\in M}\sum_{t\in T} x_{ijnm}^{t} \leq M z_i, \ \forall\ i \in (R,W) \tag{20}$$

Constraints (17) – (20) allow the existence of entering and exiting flows of products/components to a given facility only if the facility is a part of the network.

$$y_{ijm}^{t} \leq \sum_{o\in O} z_{io}, \quad \forall\ j: (i,j) \in A, i \in P, m \in M, t \in T \tag{21}$$
$$y_{jim}^{t} \leq \sum_{o\in O} z_{io}, \quad \forall\ j: (j,i) \in A, i \in P, m \in M, t \in T \tag{22}$$
$$y_{ijm}^{t} \leq z_i, \ \forall\ j: (i,j) \in A, i \in F\backslash P, m \in M, t \in T \tag{23}$$
$$y_{jim}^{t} \leq z_i, \ \forall\ j: (j,i) \in A, i \in F\backslash P, m \in M, t \in T \tag{24}$$

Constraints (21)–(24) 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.

$$\sum_{l\in L} x_{ijlm}^{t} \geq trmn_{ijm} y_{ijm}^{t}, \ \forall (i,j) \in A^l, m \in M, t \in T \tag{25}$$
$$\sum_{l\in L} x_{ijlm}^{t} \leq trmx_{ijm} y_{ijm}^{t}, \ \forall (i,j) \in A^l, m \in M, t \in T \tag{26}$$
$$\sum_{n\in N} x_{ijnm}^{t} \geq trmn_{ijm} y_{ijm}^{t}, \ \forall (i,j) \in A^n, m \in M, t \in T \tag{27}$$
$$\sum_{n\in N} x_{ijnm}^{t} \leq trmx_{ijm} y_{ijm}^{t}, \ \forall (i,j) \in A^n, m \in M, t \in T \tag{28}$$

Constraints (25)–(28) ensure that shipment quantity should be between the minimum and maximum capacity of selected transportation mode.

4. Robust Optimization Method

Robust optimization provides a framework to handle imprecise input data and immunizes optimal solution (always insures feasibility) for any realization of uncertain parameters within a given uncertainty set [7]. Robust counterpart is a worst-case formulation of the nominal problem with uncertain parameters. Li *et al* [12] mentioned uncertainty sets with 1-norm, ∞-norm, and 1∩∞-norms which based on robust set-based methodology. Where φ and Γ are the adjustable parameters for the size of the sets.

$U_{box} = \{\rho | \rho_\infty \leq \varphi\} = \{\rho | |\rho_j| \leq \varphi, \forall\, j \epsilon J\}$

$U_{polyhedra} = \{\rho | \rho_1 \leq \Gamma\} = \{\rho | \sum_{J_i} |\rho_j| \leq \Gamma\}$

$U_{box+polyhedra} = \{\rho | \sum_{J_i} |\rho_j| \leq \Gamma, |\rho_j| \leq \varphi, \forall\, j \epsilon J_i\}$

Consider the following linear optimization model.

$Minimize\ \sum_j c_j x_j$

$subject\ to$: $\sum_j a_{ij} x_j \leq b_i, \forall\, i \epsilon I$ where $(a, b, c\ \epsilon\ U)$

Where the parameters *a*, *b*, *c* vary in a given uncertainty set *U*. Li *et al* [12] proposed robust counterpart of above linear model using three novel uncertainty sets called Box, Polyhedral, and Interval+Polyhedral (I+P) as shown in table 1. Based on robust counterpart formulations provided in table 1, this paper developed the robust counterpart of the proposed MILP model under three uncertainty sets by considering uncertainty in product demand, returns, variable costs and transportation costs.

Table 1. Robust counterpart under various uncertainty sets

Box	Polyhedral	Interval + polyhedral (I+P)
$Minimize\ W$ $subject\ to$: $\sum_j c_j x_j + \varphi \sum_{J_i} \bar{c}_j x_j \leq W$ $\sum_j a_{ij} x_j + \varphi \left[\sum_j \bar{a}_{ij} x_j + \bar{b}_i\right] \leq b_i, \forall\, i \epsilon I$ Note that the box uncertainty set has a special case known as interval uncertainty set and it is when φ=1.	$Minimize\ W$ $subject\ to$: $\sum_j c_j x_j + \Gamma Z \leq W$ $Z \geq \bar{c}_j x_j, \forall\, j \epsilon J_i$ $\sum_j a_{ij} x_j + \Gamma z_i \leq b_i, \forall\, i \epsilon I$ $z_i \geq \bar{a}_{ij} x_j, \forall\, i \epsilon I, j \epsilon J_i$ $z_i \geq \bar{b}_i, \forall\, i \epsilon I$	$Minimize\ W$ $subject\ to$: $\sum_j c_j x_j + \Gamma Z + \sum_{j \epsilon J_i} p_{j0} \leq W$ $Z + p_{j0} \geq \bar{c}_j x_j, \forall\, j \epsilon J_i$ $Z, p_{j0} \geq 0$ $\sum_j a_{ij} x_j + \sum_{J_i} p_{ij} + p_{i0} + \Gamma z_i \leq b_i, \forall\, i \epsilon I$ $z_i + p_{ij} \geq \bar{a}_{ij} x_j, \forall\, i \epsilon I, j \epsilon J_i$ $z_i + p_{i0} \geq \bar{b}_i, \forall\, i \epsilon I$ $z_i, p_{ij}, p_{i0} \geq 0$

5 Numerical Results

In this section, we discuss important observations related to the design of CLSC. A numerical example is used for this purpose. We examined the impact of carbon tax and carbon trade policy parameters on overall supply chain cost and emission.

The concerned CLSC network in this study composes of the simple problem consisting of three PCs (*P*=3), one of the two potential technologies (*O*=2), produce four different types of product (*L*=4). Each product made of eight components (*N*=8), five DCs (*Q*=5), and ten CZs (*C*=10) in the forward network. In the reverse network, seven CCs (*K*=7), three RCs (*R*=3), and three WCs (*W*=3). For logistic activities, transportation mode selection decision plays significant role in reducing carbon emission. Different modes of transportation such as rail, water, air, and road, each of which has varies in carbon emission per ton-mile [13]. This work considers only road transportation modes (*M*=3) with limited transportation capacities. Modes 1, 2 and 3, respectively, represent light, medium-size and heavy trucks. The parameters of the proposed model are generated using uniform distribution for deriving insights as shown in table 2. Both deterministic and robust models are solved by CPLEX 12.6.3 on a computer with 4GB RAM and Intel core i5 2.4GHz CPU.

At first, robust model under three uncertainty sets are solved using nominal data and comparison made which depicted in figure. 2. From the figure 2, the following observations are made. (i) Objective function associated with box uncertainty set is smaller than the other two sets. It implies that box set is fully covered by the rest of the two. (ii) When uncertainty level reaches one (i.e., ψ=1), the objective function value associated with polyhedral and I+P sets become equal. This is due to both sets have same uncertainty set Γ=ψ*|Ji| in this condition. (iii) Objective function value of I+P set remains unchanged after ψ=1. results show that total cost of the proposed robust optimization model under each uncertainty set is greater than the total cost of deterministic model. The additional cost is due to solution space of each uncertainty set to accommodate any uncertainty level.

Table 2. The values of the parameters used

Parameters related to facilities

Parameter	Range
d_{cl}^{t}	Uniform(100,400)
r_{cl}^{t}	Uniform(65,260)
tpl_{lh}	Uniform(8,12)
trn_n	Uniform(1,2)
vl_l	Uniform(6,8)
vn_n	Uniform(0.8,2)
α_n	80%

Costs and carbon emissions of transportation modes

Mode	Cost ($ / ton-km)	CO_2 emission factor (kg/km)
Light truck	0.110	0.0236
Mid-size truck	0.118	0.0452
Heavy duty truck	0.125	0.0824

In summary, objective function values associated with three uncertainty sets of the robust model are greater than the objective function value obtained by deterministic model. The additional cost is due to solution space of each uncertainty set to accommodate any uncertainty level. As uncertainty level increases the objective function value worsen because each uncertainty set has its own characteristics.

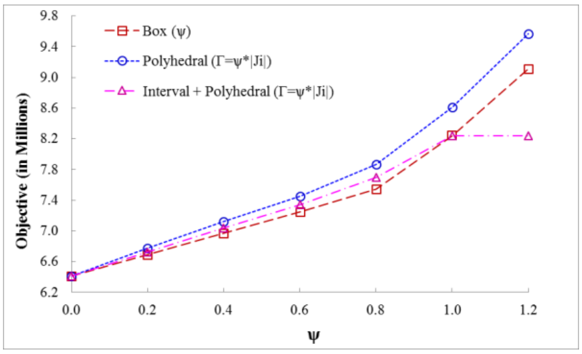

Figure 2. Objective Function Values under three sets

5.1 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 3 depicts a direct/linear relation between overall supply chain cost and carbon tax rate.

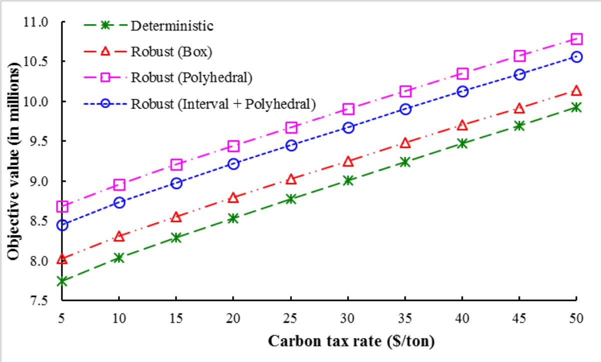

Figure 3. Objective function vs Carbon tax rate

In figure 4, as carbon tax rate increases, emission reduces significantly. This significant reduction in carbon emission reflects that the firm seeks to modify its supply chain activities to reduce the emission. As further increase of carbon tax rate, emission becomes constant. This indicates that there are no further operational changes required/exist in supply chain which impacts the carbon emissions.

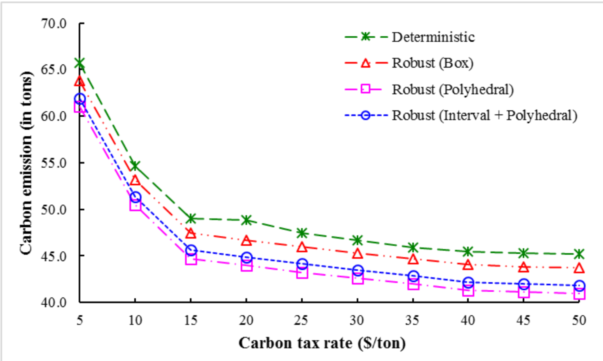

Figure 4. Carbon emission vs Carbon tax rate

5.2 Results of Carbon trading Model

In this section, we examine the effect of carbon prices on overall supply chain cost (objective value) for deterministic and robust models. From figure 5, at carbon price 5$/ton, 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 firm to buy additional carbon credits to keep supply chain activities which leads to higher supply chain cost. When the market price is high, 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.

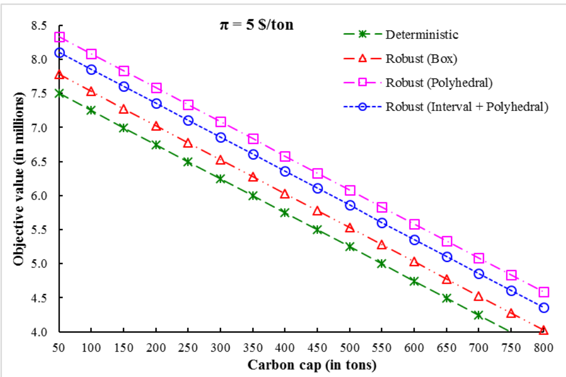

Figure 5. Objective function vs Carbon cap

While increasing carbon cap at particular carbon price, carbon emission becomes constant. However, increasing carbon price influences reducing in carbon emission as shown in figure 6. This type of behavior is due to flexibility in carbon trading, because at high carbon prices firm motivates either by selling unused carbon credits and make profit or by reducing purchase of additional carbon credits to keep in the business.

5.3 Discussion

In this section, we discuss about current work compared with previous studies in the literature. Deterministic MILP model for a multi-period multi product CLSC network design problem is discussed in the literature[6].

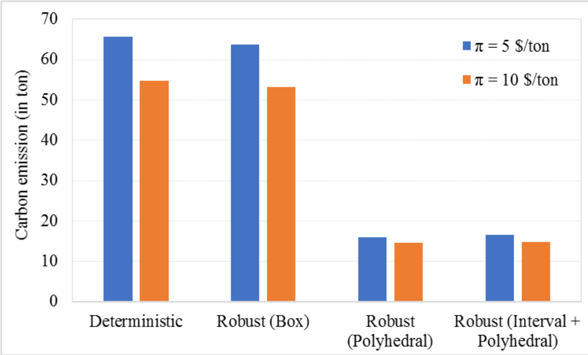

Figure 6. Carbon emission vs carbon price

However, integrating economics and carbon emission considerations for designing CLSC network and a set-based robust optimization methodology based on three alternative uncertainty sets to represent the imprecise input parameters are hardly discussed in the literature. Moreover, to make supply chain management becomes more realistic, we incorporated decisions on selection of production technologies and transportation modes. These decisions play vital role in making CLSC strategic and operational decisions due to trade-off between investment cost and carbon emission. Investment cost on low technology equipment is low but generate high carbon emission various investment cost of high technology equipment is high but emit low carbon emissions. Moreover, transportation is a major source of carbon emissions. We assume that each transportation mode has varies in capacity level and carbon emission i.e., small vehicles emit less carbon emission, but unit cost of transportation is high as compared to heavy trucks and vise-versa.

6. Conclusions

This paper proposed a deterministic MILP model for a multi-period CLSC network design problem, decisions on production technology and transportation mode selection are incorporated in the model. A robust counterpart of proposed model is developed to handle uncertainty in input data. Box, polyhedral, and I+P uncertainty sets are used to deal with uncertainties. The proposed model is further extended to include carbon emissions into supply chain design and planning decisions by integrating carbon tax and carbon trading regulatory policies.

Numerical results provide some useful observations. Results show that the robust model associated with various uncertainty sets incurs additional cost compared with deterministic model. This additional cost is due to immunize the model against any uncertainty. Carbon tax and carbon trading policies influence supply chain cost and reduce carbon emission. Specifically, overall supply chain cost is directly proportional to carbon tax rate under carbon tax policy however carbon emission reduces while increasing carbon tax rate but after certain point it becomes constant (insensitive) to carbon tax rate. This policy easy to implement but it put financial burden to the firm. Whereas carbon trading policy mainly depends on carbon market price and carbon cap allocation. This policy provides flexibility in buying and selling unused amount of carbon credits. Due to existence of carbon trading feature, this policy is more favorable to the organizations, firms, policy-makers, and even NGO around the globe.

The proposed robust optimization model considering two carbon policies has some useful managerial implications. (1) The proposed robust optimization model should be useful for mangers to achieve a robust SCND which can withstand any possible uncertainty within set limit. (2) Each uncertainty set that used in the proposed robust model has its own characteristic which implies decision makers have flexibility to design a robust CLSC network based on desired set. (3) Managers of the firm can decide which policy need to choose well in advance to minimize overall supply chain cost as well as emission while making supply chain related decisions.

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