

Tactical Supply Chain Planning under a Carbon Tax Policy Scheme: A Case Study

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Abstract

Greenhouse gas emissions are receiving greater scrutiny in many countries due to international forces to reduce anthropogenic global climate change. Industry and their supply chains represent a major source of these anthropogenic emissions. This paper presents a tactical supply chain planning model that integrates economic and carbon emission objectives under a carbon tax policy scheme. A modified Cross-Entropy solution method is adopted to solve the proposed nonlinear supply chain planning model. Numerical experiments are completed utilizing data from an actual organization in Australia where a carbon tax is in operation. The analyses of the numerical results provide important organizational and policy insights on (1) the financial and emissions reduction impacts of a carbon tax at the tactical planning level, (2) the use of cost/emission tradeoff analysis for making informed decisions on investments, (3) the way to price carbon for maximum environmental returns per dollar increase in supply chain cost.

Keywords: Green Supply Chain; Environmental Sustainability; Carbon Tax Policy Scheme; Carbon Pricing; Cap-and-Trade Market; Carbon Trading; Nested Integrated Cross-Entropy.

1. Introduction

Environmental issues are forcing management to be proactive rather than reactive in a variety of inter- and intra-organizational functions. Most manufacturing organizations have traditionally focused on internal environmental measures that they must, due to regulatory mandates, abide by or risk being penalized. This reactionary focus has evolved to more proactive measures such as improving environmental performance by focusing on efficiency and cost reduction, e.g. waste minimization (Sarkis et al., 2011). These proactive measures provide positive and joint economic and environmental returns, the so-called ‘win-win’ opportunities. These more proactive and competitively oriented opportunities may still be relatively short-sighted due to an internal and direct cost focus only (Sarimveis et al., 2008). Organizations have increasingly recognized that even more substantial environmental and economic savings can be achieved outside the organizational boundaries and immediate facility (Fahimnia et al., 2013b; Varsei et al., 2014). In addition, tangible environmentally proactive goals have expanded to integrate other more intangible factors such as improving image.

Research and practice in the area of green (environmentally sustainable) supply chain management (GSCM) has continued to grow (Brandenburg et al., 2014; Seuring et al., 2008; Tang and Zhou, 2012). In fact, recent practitioner-oriented research has shown that executives are more than ever concerned with greening their supply chains (SCs) (Lacy et al., 2010; Vlachos et al., 2007). Although GSCM is a critical organizational sustainability issue, it presents the largest gap between which organizational sustainability programs they *wish* to implement and what they *are* implementing. A major barrier causing this gap is convincing suppliers that

collaboration on greening issues is paramount to a healthy SC, implying an evidential need for long-term competitive and economic improvements that SC members will accrue.

Much of the research in this field, especially in the general GSCM literature, rather than its specific elements such as reverse logistics or green purchasing, has focused on general descriptive and qualitative analysis through empirical evaluations and case studies (Seuring and Müller, 2008). Formal modeling research has not seen the same level of research and development (Seuring, 2013). Formal modeling of GSCMs can certainly help steward and convince SC participants of the benefits of greening and its effectiveness (Brandenburg, et al., 2014).

The GSCM formal modeling that does exist has tended to focus less on operational and tactical levels of analysis, and more so on decision-making at strategic levels (Fahimnia et al., 2013b). For example, some strategic issues such as selection of greener suppliers and partnering have seen major decision modeling effort in this field (Bai and Sarkis, 2010a, b). Broader SC issues, such as integrated internal production management, transportation and warehousing, have not seen significant research from a formal modeling perspective, although the growth of research in this area has increased (Brandenburg, et al., 2014). This lack of GSCM research is especially true for optimization techniques relying on mathematical programming (Brandenburg et al., 2014; Srivastava, 2007). Models that can incorporate a broader set of SC activities and functions are still relatively rare, when compared to other GSCM decision modeling efforts such as strategic supplier selection.

Optimization models, because of the additional environmental dimensions, in addition to operational business concerns, tend to become complex. The focus on tactical issues, which

include a variety of internal and external relationships in their management, introduces additional complexities. Focusing on not only the modeling, but solution approaches for these efforts requires additional investigation since much of the research focuses on the formulation and not necessarily solution characteristics. This type of focus can provide greater promise for improving operational activities and planning from both economic and environmental perspectives, as well as the greater acceptance of GSCM initiatives.

Noting that this gap exists in the literature, we introduce in this paper a comprehensive tactical SC planning model that seeks to focus on both business operational and environmental performance. Business performance is based on traditional cost factors related to production, inventory, and logistics costs. The environmental factors in this paper focus on one of the more serious concerns within the environmentally aware community: carbon emissions. We adopt Nested Integrated Cross-Entropy (NICE) method to solve a nonlinear green SC planning model in an actual case situation where real world data is utilized to evaluate the impacts of a carbon tax on the economic and emissions performance of an organization.

The motivation for this research is manifold: (1) organizations need to help make decisions related to GSCM; (2) formal models for GSCM, especially at the tactical and operational levels are virtually non-existent and can help organizations make GSCM decisions; and (3) these models can become complex and investigating the application of new solution techniques can help in their adoption and broader acceptance. Thus, the objective is to help address these major issues, providing a contribution to managerial, social, and modeling research.

To help set the foundation for this study, we first provide an overview of the GSCM literature in Section 2 with a particular emphasis on characteristics and modeling efforts in this field. Section

3 introduces a green SC optimization model to address some of the issues identified in the literature. A CE-based solution methodology is discussed in Section 4 along with experimental runs in Section 5 using data from an actual case problem. Analysis of the numerical results and the managerial and policy insights gained are presented in Section 5. Conclusions are outlined in Section 6 with a clear identification of the significant work left for future investigation in this area.

2. GSCM Modeling Efforts

Focus on GSCM research has been increasing at a relatively rapid pace over the past decade due to the necessity by industry of observing and focusing on environmental issues (Sarkis et al., 2011; Seuring and Müller, 2008). Multifaceted environmentally-oriented forces have caused organizations across a broad variety of industries to take notice of the need for expanding their focus beyond their organizational boundaries when it comes to environmental considerations (Sarkis, 2012). These forces include governmental regulations, community norms, consumer expectations, and competitor benchmarking, to name a few (Fahimnia et al., 2014a; Zhu et al., 2011). The response has been evolving over the years with significant research developing amongst many methodological streams, empirical approaches, case studies, and formal modeling efforts (Brandenburg et al., 2014; Min and Kim, 2012).

A critical issue is that GSCM has encountered many variations in its definition and terminology over the years. A comprehensive list characterizing this concept includes: sustainable supply network management, sustainable/green/ecological SCs, supply and demand sustainability in

corporate social responsibility networks, sustainable/green purchasing and procurement, and green/sustainable logistics. As can be seen, the scope can be very ambiguous and extensive. A slightly broader GSCM focus will define it as integrating environmental concerns into the inter-organizational practices. For the scope of this study (i.e. tactical SC planning and optimization), we define this scope around three critical stages of internal operations management, external logistics, and inventory management.

Some of the more rigorous attempts at GSCM-related modeling have occurred in the ‘closing-the-loop’ or reverse logistics portions of the GSCM literature (Chaabane et al., 2012; Diabat et al., 2013; Fahimnia et al., 2013b). Yet, much of that literature has focused on cost-based measures or traditional financial metrics optimization, e.g. revenue generation or cost reduction (Chung and Wee, 2011; Quariguasi Frota Neto et al., 2009; Rubio et al., 2007). Interestingly, in many of these models, environmental measures have taken a minor role, if any, to operational and financial measures. Some other research efforts have started to close the gaps in formal modeling literature by investigating specific aspects of GSCM (Brandenburg et al., 2014; Seuring, 2013). Such modeling efforts are limited not because of the insignificance of the work, but more because of the complexities involved in GSCM (Sundarakani et al., 2010) some of which we face in this study.

Some recent GSCM modeling efforts have focused on designing networks with emissions and life-cycle analysis considerations (Bojarski et al., 2009; Diabat et al., 2013; Wang et al., 2011). There are also studies with narrower focus on specific SC operations such as green supplier selection (Bai and Sarkis, 2010b; Lee et al., 2009; Yeh and Chuang, 2011) and fleet management (Ubeda et al., 2011). Mixed-integer linear programming (MILP) frameworks have been popular

for addressing sustainable SC design issues with material balance constraints from traditional operations and SC topics, to new technology introduction modeling (Chaabane et al., 2012). These strategic perspectives are introduced to determine the most effective SC design, while modeling efforts related to green SC planning at the tactical level are not well established in this literature set (Fahimnia et al., 2013a; Fahimnia et al., 2014a).

Some models have also considered joint strategic and operational aspects of designing an environmentally conscious SC (Hugo and Pistikopoulos, 2005). These few existing GSCM-oriented models still require significant life-cycle analysis information (Bojarski et al., 2009), with operational investigations left out of the modeling effort. They also usually tend to focus on single, general objective modeling approaches not explicitly considering multiple economic and environmental objectives. Linking up the operational with strategic dimensions of environmentally-oriented SC planning requires medium term, tactical planning approaches.

Given the current and increasing interest in the development of formal analytical models to aid industry and advance research in GSCM, we seek to contribute to this body of knowledge in the following ways. First, we develop a realistic model motivated not only by theoretical considerations but by real word practical requirements faced by an actual organization. Second, our modeling effort and contribution seeks to focus on two critical organizational objectives at the *tactical planning* level, economic (or business oriented) and environmental dimensions. Third, we also contribute by providing additional supports for managerial acceptance of this model and further understanding of a unique CE-based solution technique. We utilize the model and solution method to investigate how a carbon taxing mechanism influences the economic and environmental performance of an actual organization from the manufacturing sector.

3. Mathematical Modeling

We model a GSCM problem where multiple product types (i) are produced in different manufacturing plants (m) by travelling through a set of machine centers (g). Machine center g has its own production cost and emissions rate for processing product i . Finished products are then distributed to the warehouses (w) and from there to the end-users (e) in various geographical locations. Products can be shipped using different transport modes (k). Shipment costs and emissions generation rates may vary from one model of transport to another. The objective is to determine the tactical planning decisions, including production and distribution allocation strategies for the next planning horizon T (comprising t time periods) such that the overall SC cost and carbon emissions are minimized.

An bi-objective optimization model is developed in this section in which the first objective concerns the economic dimensions of SC and the second objective focuses on environmental aspects. Objective 1 minimizes the overall SC costs including production costs in regular-time and overtime on a set of machine centers, inventory holding costs in manufacturing sites and warehouses, transportation costs, and shortage/penalty costs. Objective 2 minimizes the total production and transport air emissions (i.e. carbon-equivalent emissions). The following assumptions are considered for mathematical modeling of this problem:

- Variety of product types (i) to be produced is known.
- Number, location, and capacity of plants (m) and warehouses (w) are known.
- Number and location of end-users (e), also identified as customer zones or retailers, are known.

- Demand is deterministic and aggregate demand for all product types in the concerned periods is assumed to be known for the next planning horizon.
- The forecasted demand for each product has to be satisfied, sooner or later, during the planning horizon. Shortage/penalty cost is incurred if the demand for a certain product at one period is backordered.
- A product type can be supplied from more than one manufacturing plant; however, the shipment of products between manufacturing plants is not allowed.
- Capacity limitations for regular-time and overtime production (capacity hours of machine centers), capacity of raw material supply, limitations in storage capacity at manufacturing plants and warehouses as well as distribution capacities are known.
- The required workforce is hired on casual/temporary bases. The hourly-paid wages are higher in the first period of plant opening. The rates will remain unchanged for the succeeding periods from the second period. The higher first-period wages reflect the one-off training/admin fees charged by labor hire services as well as the learning progress of labors.
- Transportation costs and emissions rates are proportional to transport distances.
- End-users are locations where products are delivered to the final customers with no holding capacity to store the products.
- Air emissions rate is known for processing a product on a machine center. This is determined according to the required processing time and the manufacturing technology used (e.g. older machines may take longer to process an item and produce more carbon emissions).
- Air emissions rates are known for different transport modes for the shipment of products from manufacturing plants to end-user.

The following indices and sets are used for the problem formulation.

Product index	i	Set of products	I
Manufacturing plant index	m	Set of manufacturing plants	M
Machine center index	g	Set of machine centers	G
Warehouse index	w	Set of warehouses	W
Transport mode index	k	Set of transport modes	K
End-user index	e	Set of end-users	E
Time-period index	t	Planning horizon	T

The input parameters include the followings:

d_{iet}	Forecasted demand for i in e at t
o_{mt}	Fixed costs of opening and operating m at t
o'_{wt}	Fixed costs of opening and operating w at t
h_{imt}	Unit holding cost for i in m at t
h'_{iwt}	Unit holding cost for i in w at t
hc_{imt}	Holding capacity (maximum units) in m for i at t
hc'_{iwt}	Holding capacity (maximum units) in w for i at t
p_{igmt}	Processing time (hrs) to produce a unit of i on g in m at t
l_{igmt}	Labor/hour cost (second-period onward) for regular-time production of i on g in m at t
l'_{igmt}	Labor/hour cost (second-period onward) for overtime production of i on g in m at t
l^{1st}_{igmt}	First-period labor/hour cost for regular-time production of i on g in m at t
l'^{1st}_{igmt}	First-period labor/hour cost for overtime production of i on g in m at t
r_{imt}	Cost of raw material for producing a unit of i in m at t
α_{imt}	Variable overhead cost of regular-time production of i in m at t
β_{imt}	Variable overhead cost of overtime production of i in m at t
sc_{iet}	Unit backordering (shortage) cost for i in e at t
s^{max}_{iet}	Maximum amount of shortage permitted for i in e at t
λ_{igmt}	Capacity hours for regular-time production of i on g in m at t
λ'_{igmt}	Capacity hours for overtime production of i on g in m at t

γ_{imt}	Capacity units of raw material supply for i in m at t
τ_{imwkt}	Unit transportation cost of i from m to w through k at t
τ'_{iwekt}	Unit transportation cost of i from w to e through k at t
τ''_{imekt}	Unit transportation cost of i from m to e through k at t
$\varepsilon^{\min}_{imwkt}$	Minimum allowed distribution of i from m to w through k at t
$\varepsilon^{\max}_{imwkt}$	Maximum allowed distribution of i from m to w through k at t
θ^{\min}_{iwekt}	Minimum allowed distribution of i from w to e through k at t
θ^{\max}_{iwekt}	Maximum allowed distribution of i from w to e through k at t
δ^{\min}_{imekt}	Minimum allowed distribution of i from m to e through k at t
δ^{\max}_{imekt}	Maximum allowed distribution of i from m to e through k at t
η_{im}	Inventory level of i in m at the start of planning horizon ($t=0$)
η'_{im}	Inventory level of i in m at the end of planning horizon ($t=T$)
φ_{iw}	Inventory level of i in w at the start of planning horizon ($t=0$)
φ'_{iw}	Inventory level of i in w at the end of planning horizon ($t=T$)
c_{igmt}	Estimated air emissions (kg/hr) to produce a unit of i on g in m at t
a_{imwkt}	Estimated air emissions (kg) for the shipment of i from m to w through k at t
a'_{iwekt}	Estimated air emissions (kg) for the shipment of i from w to e through k at t
a''_{imekt}	Estimated air emissions (kg) for the shipment of i from m to e through k at t
c^{\max}_{mt}	Maximum allowed air emissions generation (ton) in m at t
ρ	Emissions function coefficient
M	'Big M' standing for a very large number

Decision variables include continuous and binary variables. The continuous variables include:

Q_{imt}	Quantity of i produced in regular-time in m at t
Q'_{imt}	Quantity of i produced in overtime in m at t
J_{imwkt}	Quantity of i shipped from m to w through k during t
J'_{iwekt}	Quantity of i shipped from w to e through k during t
J''_{imekt}	Quantity of i shipped directly from m to e through k during t

X_{imt}	Inventory amount of i in m at the end of t
Y_{iwt}	Inventory amount of i in w at the end of t
S_{iet}	Quantity of i backordered in e at the end of t

The two binary variables determine whether a plant/warehouse is open or closed at each period:

$$G_{mt} = \begin{cases} 1, & \text{If } m \text{ operates in } t \\ 0, & \text{Otherwise} \end{cases}$$

$$G'_{wt} = \begin{cases} 1, & \text{If } w \text{ is open in } t \\ 0, & \text{Otherwise} \end{cases}$$

Using the above parameters and decision variables, objective function 1 (cost function) is formulated in Equation 1 representing the sum of production costs in regular-time and overtime (the nonlinear components of objective function 1), inventory holding costs in manufacturing plants and warehouses, transportation costs, and penalty/shortage costs of backordered demand.

$$\begin{aligned} Z_1 = & \sum_t \sum_m o_{mt} G_{mt} + \sum_t \sum_w o'_{wt} G'_{wt} + \sum_i \sum_m \sum_t \left[Q_{imt} \left(\sum_g P_{igmt} \{G_{m(t-1)} l_{igmt} + (1-G_{m(t-1)}) l_{igmt}^{1st}\} + r_{imt} + \alpha_{imt} \right) \right] + \\ & \sum_i \sum_m \sum_t \left[Q'_{imt} \left(\sum_g P_{igmt} \{G_{m(t-1)} l'_{igmt} + (1-G_{m(t-1)}) l'_{igmt}^{1st}\} + r_{imt} + \beta_{imt} \right) \right] + \sum_i \sum_m \sum_t h_{imt} X_{imt} + \sum_i \sum_w \sum_t h'_{iwt} Y_{iwt} + \\ & \sum_i \sum_m \sum_w \sum_k \sum_t J_{imvkt} \tau_{imvkt} + \sum_i \sum_w \sum_e \sum_k \sum_t J'_{iwekt} \tau'_{iwekt} + \sum_i \sum_m \sum_e \sum_k \sum_t J''_{imekt} \tau''_{imekt} + \sum_i \sum_e \sum_t S_{iet} s_{Ciet} \quad (1) \end{aligned}$$

Equation 1 consists of 10 components. Components 1 and 2 are the fixed costs of opening and operating plants and warehouses respectively. Components 3 and 4 (the nonlinear terms of objective function 1) express the regular-time and overtime production costs. The higher first-period wages are incorporated in these two components. Components 5 and 6 represent the inventory holding costs in manufacturing plants and warehouses respectively. Components 7-9 express the transportation costs for the distribution of items from plants to end-users. This can be

either directly from plants to end-users (component 9) or indirectly from plants to warehouses and from warehouses to end-users (components 7 and 8, respectively). Component 10 represents the sum of shortage costs if backlogging occurs at the end-users.

Objective function 2 (i.e. emissions function) is presented in Equation 2 formulating the generated manufacturing and transport air emissions.

$$Z_2 = \sum_i \sum_g \sum_m \sum_t Q_{imt} p_{igmt} c_{igmt} + \sum_i \sum_g \sum_m \sum_t Q'_{imt} p_{igmt} c_{igmt} + \sum_i \sum_m \sum_w \sum_k \sum_t J_{imwkt} a_{imwkt} + \sum_i \sum_w \sum_e \sum_k \sum_t J'_{iwekt} a'_{iwekt} + \sum_i \sum_m \sum_e \sum_k \sum_t J''_{imekt} a''_{imekt} \quad (2)$$

Equation 2 consists of 5 components. Components 1 and 2 express the manufacturing air emissions in regular-time and overtime. Components 3-5 formulate the emissions generated in transportation of products from plants to warehouses (component 3), warehouses to end-users (component 4), and plants to end-users (component 5).

The sum of cost function (Equation 1) and emissions function (Equation 2) forms the overall objective function presented in Equation 3. In this formulation, ρ is the emissions function coefficient (i.e. unit emissions price) which assigns a weight to objective function 2 converting the problem to a single-objective model.

$$Z = Z_1 + \rho Z_2 \quad (3)$$

The model is subject to the following constraints:

Restrictions on raw material supply:

$$Q_{imt} + Q'_{imt} \leq \gamma_{imt} \quad \forall i, m, t \quad (4)$$

Production capacity constraint (machine center capacity constraint) for regular-time and overtime production:

$$Q_{imt} P_{igmt} \leq \lambda_{igmt} \quad \& \quad Q'_{imt} P_{igmt} \leq \lambda'_{igmt} \quad \forall i, g, m, t \quad (5)$$

Storage capacity restriction in manufacturing plants:

$$X_{imt} \leq hc_{imt} \quad \forall i, m, t \quad (6)$$

Inventory balance in manufacturing plants:

$$X_{imt} - X_{im(t-1)} = Q_{imt} + Q'_{imt} - \sum_w \sum_k J_{imwkt} - \sum_e \sum_k J''_{imekt} \quad \forall i, m, t \quad (7)$$

Warehouse capacity restriction:

$$Y_{iwt} \leq hc'_{iwt} \quad \forall i, w, t \quad (8)$$

Inventory flow in warehouses:

$$Y_{iwt} - Y_{iw(t-1)} = \sum_m \sum_k J_{imwkt} - \sum_e \sum_k J'_{iwekt} \quad \forall i, w, t \quad (9)$$

Distribution capacity limits in manufacturing plants:

$$\mathcal{E}_{imwkt}^{\min} \leq J_{imwkt} \leq \mathcal{E}_{imwkt}^{\max} \quad \forall i, m, w, k, t \quad (10)$$

$$\mathcal{D}_{imekt}^{\min} \leq J''_{imekt} \leq \mathcal{D}_{imekt}^{\max} \quad \forall i, m, e, k, t \quad (11)$$

Distribution capacity constraint in warehouses:

$$\theta_{iwekt}^{\min} \leq J'_{iwekt} \leq \theta_{iwekt}^{\max} \quad \forall i, w, e, k, t \quad (12)$$

Demand satisfaction constraint:

$$\sum_m \sum_t Q_{imt} + Q'_{imt} = \sum_e \sum_t d_{iet} + \sum_m \eta'_{im} - \sum_m \eta_{im} + \sum_w \phi'_{iw} - \sum_w \phi_{iw} \quad \forall i \quad (13)$$

Maximum allowed backlog/shortage at end-users:

$$S_{iet} \leq s_{iet}^{\max} \quad \forall i, e, t \quad (14)$$

Inventory balance at end-users:

$$\sum_w \sum_k J'_{iwekt} + \sum_m \sum_k J''_{imekt} = d_{iet} - S_{iet} + S_{ie(t-1)} \quad \forall i, e, t \quad (15)$$

Constraint on the inventory level of finished products in manufacturing plants (Equation 16) and warehouses (Equation 17) at the start and end of the planning horizon:

$$X_{im0} = \eta_{im} \quad \& \quad X_{imT} = \eta'_{im} \quad \forall i, m \quad (16)$$

$$Y_{iw0} = \phi_{iw} \quad \& \quad Y_{iwT} = \phi'_{iw} \quad \forall i, w \quad (17)$$

Air emissions constraint in manufacturing plants:

$$\sum_i \sum_g P_{igmt} c_{igmt} (Q_{imt} + Q'_{imt}) \leq c_{mt}^{\max} / 1000 \quad \forall m, t \quad (18)$$

Restrictions on decision variables:

$$0 \leq Q_{imt} \leq G_{mt} M \quad \& \quad 0 \leq Q'_{imt} \leq G_{mt} M \quad \forall i, m, t \quad (19)$$

$$0 \leq J_{imwkt} \leq G_{mt} M \quad \& \quad 0 \leq J_{imwkt} \leq G'_{wt} M \quad \forall i, m, w, k, t \quad (20)$$

$$0 \leq J'_{iwekt} \leq G'_{wt} M \quad \forall i, w, e, k, t \quad (21)$$

$$0 \leq J''_{imekt} \leq G_{mt} M \quad \forall i, m, e, k, t \quad (22)$$

$$0 \leq X_{imt} \quad \forall i, m, t \quad (23)$$

$$0 \leq Y_{iwt} \quad \forall i, w, t \quad (24)$$

$$0 \leq S_{iet} \quad \forall i, e, t \quad (25)$$

The resulting model has $IT[3M+W+E+K(MW+ME+WE)]$ continuous variables, $T(M+W)$ binary variables and $I(1+M+W)+MT+IT[5M+3W+3E+GM+K(2MW+2ME+2WE)]$ constraints.

4. The NICE Solution Method

The *Cross-Entropy* (CE) method was first proposed by Rubinstein (1997) as a simulation method for estimating probabilities of rare events and was later adopted as an advanced optimization method to deal with both combinatorial and continuous optimization problems (Rubinstein, 1999). The idea of the CE is to start with an initial probability distribution over a feasible region and updating it adaptively based on a random sample collected from the feasible region. In consecutive iterations, the process should converge to some degenerate distribution that assigns a probability of 1 to an optimal solution. This convergence may cost a large number of iterations and hence the algorithm needs to be terminated at a local optimal solution where a predetermined condition is satisfied. More details on the CE method can be found in (Rubinstein and Kroese, 2004, 2007). Successful applications of the CE method have been reported in different optimization problems such as buffer allocation (Alon et al., 2005), capacitated lot-sizing (Caserta and Rico, 2009), vehicle routing (Wang and Qiu, 2012), project scheduling (Bendavid

and Golany, 2011), network design (Altıparmak and Dengiz, 2009) and more recently in SC planning (Esmailikia et al., 2014; Fahimnia et al., 2014b).

The GSCM model encountered in this paper is an MINLP model comprising both continuous and binary variables. We initially tried to adopt the Projection Adaptive Cross-Entropy (PACE) method proposed by Eshragh et al. (2011) to solve this model. According to PACE, to solve a nonlinear binary programming model, a sample of 0-1 variables is randomly generated at each iteration from which only those that result in feasible solutions are considered. For each feasible solution, with already-known binary variables, the problem is reduced to a linear programming model which is solvable using standard LP solvers. The corresponding optimal objective value is used to update the vector of probabilities in a standard CE algorithm. However, PACE was shown as unable to solve the proposed GSCM model due to the tight model constraints. Almost all samples of randomly generated binary variables in the first iteration lead to infeasible solutions. Obviously, it is impossible to update the probability vector with no sample in hand. Overall, PACE may only be an appropriate solution method for solving SC optimization problems when problem constraints are sufficiently loose to allow the generation of feasible solutions in the first iteration.

Fahimnia et al. (2014b) introduced NICE, a CE-based solution method, to tackle complex nonlinear SC planning problems. We adopt a similar technique to solve the MINLP model encountered in this paper. The proposed MINLP model would have feasible solutions when all 0-1 variables are equal to 1 (i.e. when all the manufacturing plants and warehouses are open in all periods and hence the SC operates at the full production and distribution capacity). NICE starts with setting all binary variables (G_{mt} and G'_{wt}) equal to 1 in iteration 1. This reduces the

MINLP model to a linear model. Obviously, all generated solutions in this initial sample are feasible with identical objective values. In the next iteration, only one of the binary variables is randomly set equal to zero and all the others remain equal to 1 (note that depending on the problem characteristics we may choose to limit the binary variables that can turn to zero). A sample of such solutions (i.e. solution with one zero binary variable) is generated and then used to update the probability distribution over the feasible region. Accordingly, iteration t involves a sample of solutions with $t-1$ binary variables equal to zero. The best found objective value in an iteration would be an optimal solution to the problem unless a better objective value is obtained in succeeding generations. A conservative termination condition would be to stop the algorithm when all the generated solutions in an iteration are infeasible. Alternatively, the process can be terminated when the ratio of infeasible solutions generated in a sample exceeds a predetermined value (say 95% of the overall population). To summarize the process of the modified CE method:

- Step 1 Set all binary variables (G_{mt} and G'_{wt}) equal to 1. This reduces the nonlinear GSCM model to a linear model. Find an optimal solution to this problem and set it as best found solution. Set the iteration counter (t) equal to 0;
- Step 2 Set $t = t + 1$;
- Step 3 Use the standard CE method to generate a sample of binary variables, each with exactly t zeros. Discard those leading to infeasible solutions. Use the sets of binary values to reduce the corresponding nonlinear GSCM models to linear programming models. Find an optimal solution for each linear model. If the best solution in this sample is better than the best found solution thus far, replace the latter with the former;
- Step 4 If the ratio of feasible solutions generated in Step 3 is less than $r\%$ (say 5%), STOP and

claim the best found solution as a local optimal solution for the GSCM problem; otherwise return to Step 2.

5. Model Implementation and Numerical Results

The modified CE algorithm presented in Section 4 is now implemented to solve a real world GSCM problem. Due to the massive data scale as well as the sensitivity of some of the supply and demand data, it is not possible to provide the detailed data used for our analysis. But, we try to provide a clear illustration of the production and distribution situations in EOF, the case company. EOF is engaged in the production and distribution of outdoor furniture in Australia. The product offerings at EOF (for the sake of this case study) include five families of stylish dining settings which may come in either seven or nine pieces. Each product is produced by passing through seven machine centers at one of the three manufacturing plants located in Sydney, Melbourne and Adelaide. Production costs are slightly lower in Adelaide, but more carbon emissions are generated due to older and less efficient machinery used. The plant in Melbourne has an intermediate position in terms of production costs, but is the greenest of the three. Production plants supply five customer zones (the end-users of EOF) in five different states including New South Wales, Victoria, Queensland, Western Australia, and South Australia, in order of their demand size. The distribution from plants to customer zones can be completed either directly or indirectly through four established warehouses. The available transport options (modes of transport) may vary from one route to another. External logistics companies provide the costs and emissions rates for each transport route and mode. The tactical planning horizon at EOF is one year comprising 12 one-month periods.

With five product families ($I=5$), three manufacturing plants ($M=3$), seven machine centers at each plant ($G=7$), four warehouses ($W=4$), three possible transport modes ($K=3$), five customer zones ($E=5$) and twelve time periods ($T=12$), the proposed MINLP model has 11,700 continuous variables, 84 binary variables and 20,776 constraints. The GSCM model and the modified CE algorithm were coded in MATLAB 7.13. The sample size in all experiments is set at 100 and the termination condition is when the ratio of infeasible solutions generated in a sample is more than 98% of the sample size (i.e. terminating the model when there are only two or less feasible solutions in a sample of 100).

Contextually, from a policy perspective, for the first time in Australian history, carbon taxing legislation passed the Australian Federal Parliament in November 2011. Carbon is priced at \$23 per ton in 2012 rising to \$24.15 in 2013 and \$25.40 in 2014. Using this model, we aim to study the impacts of the proposed carbon tax policy scheme on the economic and environmental performance of EOF which represents a broad range of Australian businesses within the discrete, durable parts manufacturing sector.

At a carbon price of \$23 per ton, the emissions function coefficient (ρ) in Equation 3 is set equal to 0.023, the cost of carbon pollution per kg. The numerical results obtained from the model run at the carbon price of \$23 per ton are presented in Table 1. The numerical results including the values of objective functions 1 and 2 and their components at each iteration provide insights on how the value of each component evolves in 23 iterations. The overall SC cost converges to a local optimal, completing 23 iterations in approximately 52 minutes. The local optimal solution (overall SC cost of \$8,170,645) is obtained in iteration 22, showing a 7.4% improvement compared to the objective value of \$8,821,143 in iteration 1, when all plants and warehouses are

open in all periods. Production cost is the primary contributor to the cost function constituting about 65% of the overall cost, whereas the major contributor to the emissions function is distribution emissions constituting about 60% of the overall emissions.

These initial results show that emissions cost ($\text{Obj Fn 2} * 0.023$) constitutes between 2.7% and 3.4% of the overall SC cost. This rather minor contribution of emissions cost would cause the emissions function to have a limited impact on the production and distribution decisions made by the model. This situation is witnessed by the fact that the 7.4% reduction in the overall SC cost over 23 iterations has caused an 11.8% increase in the value of objective function 2 (i.e. the carbon emissions generated by EOF). In short, the algorithm tends to minimize the more significant contributors to the goal function (Equation 3) and hence gives a higher priority to production and distribution costs in objective function 1 and a relatively lower priority to shortage cost in objective function 1 as well as emissions costs in objective function 2.

Table1. Numerical results at the carbon price of \$23 per ton

Iter	No of Feas Sol	Objective Function 1 (\$)				Objective Function 2 (kg)			Overall SC Cost (\$)	Emi Cost (\$)	Best Sol Found (\$)	Best Sol Found in Iter
		Obj Fn 1	Prod Cost	Dist Cost	Short Cost	Obj Fn 2	Prod Em	Dist Em				
1	100	8584353	5570490	3013863	0	10295216	4026178	6269038	8821143	236790	8821143	1
2	95	8538305	5504627	3033678	0	10540833	4118455	6422378	8780744	242439	8780744	2
3	97	8504320	5570489	2933831	0	10295191	4026176	6269015	8741109	236789	8741109	3
4	93	8466500	5474927	2991573	0	10531094	4118454	6412640	8708715	242215	8708715	4
5	86	8418758	5436299	2982459	0	10882965	4233803	6649162	8669066	250308	8669066	5
6	82	8386282	5441433	2944849	0	10923309	4256872	6666437	8637518	251236	8637518	6
7	79	8357816	5408099	2949717	0	10867298	4233802	6633496	8607764	249948	8607764	7
8	71	8332302	5515727	2816575	0	10531095	4118454	6412641	8574517	242215	8574517	8
9	71	8285675	5410249	2873276	2150	10848927	4225151	6623776	8535200	249525	8535200	9
10	69	8266916	5511239	2753524	2153	10291414	4017527	6273887	8503619	236703	8503619	10
11	60	8230959	5409368	2820090	1501	10975006	4279942	6695064	8483384	252425	8483384	11
12	50	8193571	5375620	2810597	7354	10982579	4271296	6711283	8446170	252599	8446170	12
13	50	8143729	5402935	2738972	1822	11020555	4291477	6729078	8397202	253473	8397202	13
14	49	8122042	5301725	2818160	2157	11426173	4444321	6981852	8384844	262802	8384844	14
15	40	8094049	5276372	2806889	10788	11264831	4375105	6889726	8353140	259091	8353140	15
16	36	8072478	5390609	2661293	20576	10957905	4282826	6675079	8324510	252032	8324510	16
17	20	8044332	5345357	2692586	6389	11346511	4406826	6939685	8305302	260970	8305302	17
18	19	7992250	5258701	2725499	8050	11738319	4509059	7229260	8262231	269981	8262231	18
19	13	7990681	5428779	2543561	18341	10692158	4187664	6504494	8236601	245920	8236601	19
20	17	7933349	5325278	2600971	7100	11334240	4428314	6905926	8194037	260688	8194037	20
21	8	7905267	5175904	2712813	16550	12030753	4638826	7391927	8181974	276707	8181974	21
22	10	7905906	5272373	2614808	18725	11510378	4421756	7088622	8170645	264739	8170645	22
23	4	7912097	5251931	2634746	25420	11560618	4470863	7089755	8177991	265894	8170645	22

For the sake of comparative analysis, we run the model in three optimization scenarios. The first scenario only minimizes the cost function (Equation 1). This scenario best represents the current situation at EOF; that is minimizing the SC non-environmental costs with no emissions consideration. The model outputs include the value of objective function 1 and its three components, objective function two and its two components, and the overall SC cost. The second scenario minimizes the emissions function (Equation 2) without considering the consequent economic impacts. The third scenario concerns the concurrent minimization of cost and emissions functions (Equation 3) considering a current carbon tax of \$23 per ton of emissions (2012 rate). Numerical results for the three optimization scenarios are shown in Table 2.

Table2. Numerical results for the three optimization scenarios

Opt Scenarios	Obj Fn 1 (\$)	Obj Fn 1 components			Obj Fn 2 (kg)	Obj Fn 2 components		Overall SC Cost
		Prod Cost (\$)	Dist Cost (\$)	Short Cost (\$)		Prod Em (kg)	Dist Em (kg)	
Cost-Only Optimization	7,788,619	5,242,576	2,530,439	15,604	11,841,063	4,587,628	7,253,435	8,060,963
Emissions-Only Optimization	10,688,849	6,618,534	3,616,623	453,692	71,32,311	4,017,523	3,114,788	10,852,892
Cost+Emissions Optimization	7,905,906	5,272,373	2,614,808	18,725	11,510,378	4,421,756	7,088,622	8,170,645

We also design six carbon tax scenarios to investigate the effectiveness of the current taxing mechanism in terms of its financial and emissions reduction impacts. Table 3 shows the numerical results in six scenarios. Scenarios 1, 2 and 3 represent the actual carbon tax situations in Australia in 2012, 2013 and 2014, respectively. The next three scenarios are hypothetical and are designed to examine how EOF will be affected by larger carbon prices. Analyses of these numerical results are presented in Section 6.

Table3. Numerical results for six carbon tax scenarios

Carbon Tax Scenarios	Obj Fn 1 (\$)	Obj Fn 1 components			Obj Fn 2 (kg)	Obj Fn 2 components		Overall SC Cost
		Prod Cost (\$)	Dist Cost (\$)	Short Cost (\$)		Prod Em (kg)	Dist Em (kg)	
\$23	7,905,906	5,272,373	2,614,808	18,725	11,510,378	4,421,756	7,088,622	8,170,645
\$24.15	7,986,443	5,513,574	2,467,676	5,193	11,354,959	4,383,852	6,971,107	8,260,665
\$25.40	8,077,204	5,420,950	2,644,216	12,038	11,266,152	4,385,063	6,881,089	8,363,364
\$46	8,150,891	5,410,154	2,710,874	29,863	10,362,401	4,269,014	6,093,387	8,622,961
\$115	8,238,118	5,397,808	2,795,827	44,483	9,715,376	4,273,526	5,441,850	9,131,933
\$230	8,635,482	5,522,033	3,084,622	28,827	7,837,213	4,213,620	3,623,593	10,438,041

6. Discussion: Organizational and Policy Insights

From Table 2, the cost-only and emissions-only scenarios show what happens at the two extremes. A minimum SC cost of just more than eight million dollars results when the emissions generation at EOF stays at its maximum (cost-only optimization). The reverse situation occurs in emissions-only optimization where the minimum carbon of approximately 7,132 tons is emitted at the maximum cost incurred. This result indicates that in the most optimistic scenario, carbon emissions at EOF can be reduced by about 40% at which the overall cost is increased by about 34%.

Not surprisingly, the results do show that without a regulatory requirement and a carbon taxing mechanism in place, the SC could be less costly to manage. Nevertheless, the emissions generated are also the highest when there is no penalty cost that encourages the internalization of the carbon emissions externality. At a carbon price of \$23 per ton, the overall SC cost is increased by 1.4% compared to a no-tax scenario. Arguably, a 1.4% increase in costs is not prohibitive, so long as there is equal application of the costs across organizations and industries.

The true social costs of emissions are difficult to measure, but there are arguments that the \$23 per ton is quite conservative. Researchers and governments have made estimates of the social cost of emissions. Many of these estimates are made through integrated assessment models (IAM's), which have their own limitations (Ackerman et al., 2009). The U.S. government, for example, has estimated that on average for 2015 the social cost per ton of carbon is \$37 per ton (U.S. Government, 2013). Although higher than current market trading prices, this governmental valuation has been considered a conservative estimate by watch groups and activists who felt that a number of social impacts were not considered in the evaluation (Howard, 2014).

Internal carbon prices are becoming an increasingly common business tool and are used by many firms for planning purposes (Economist, 2013). The Carbon Disclosure Project (CDP) found that 29 American companies and 20 German companies (large multinationals) have used an internal carbon price (Hörisch, 2013). This number is increasing. The U.S. corporate prices range from \$6-7 per ton of CO₂ equivalent at Microsoft to \$60 per ton of CO₂ equivalent at Exxon Mobil. Thus, even if mandatory carbon pricing and taxes were not in place, companies and their SCs need to be wary of the potential future costs associated with their operations.

If we look back at the general results for this study, clearly, there are conflicts between cost efficiencies and environmental emissions efficiencies, but not as much as potentially can exist. We admit that not all scenarios and real world situations will be like this, but an advantage of this type of analysis is that it allows organizations to determine whether 'win-win' opportunities do exist, and even compare their internal prices versus external carbon taxes. This type of cost tradeoff analysis may also be valuable from an investment perspective for organizations or a policy setting decision by policy makers. For example, the additional costs from taxing

emissions are at approximately \$265,000. This value can provide a margin for potential investments to reduce these emissions, or if it is lower than internal estimates of current and future prices continue to make emissions.

Alternatively, from these results policymakers can see that there is more potential for EOF to reduce emissions generated in transport and storage, by as much as 4 million kilograms. The total emissions generated at a carbon tax of \$23 per ton is still far away from the best-emissions scenario (emissions-only optimization), only reduced by 2.79% in comparison with the worst-emissions scenario (production cost-only optimization). For a carbon price of \$23 per ton, every 1% increase in the overall SC cost yields approximately 2% carbon emissions reduction. While this may be a fairly good start for a country like Australia where no environmental regulatory policies have been practiced in the past, a further refined carbon taxing mechanism may result in additional improvements in environmental performance of SCs. For example, in the aforementioned CDP study, it was generally found that the companies with long productive lives and those affected by regulatory policies (such as oil companies) tend to use higher prices (Economist, 2013). In this way that companies may identify their own risks and potential costs of carbon emissions, governments may decide that certain industries and products can be taxed differently. Broadly, governments may focus on industries, through their taxing system, by identifying what organizations can have the biggest influence on reducing emissions and focus the regulatory efforts on those organizations. Alternatively, governments may focus on certain products or materials that have larger carbon footprints identifying those that can most easily achieve reductions at relatively minimal SC costs.

The numerical results from the six carbon tax scenarios presented in Table 3 can also be used to evaluate tradeoffs in SC segments, not just overall SC performance. Numerical results in Table 3 indicate that improvement in carbon emissions at EOF is highly dependent on the environmental performance of the transport sector. Admittedly, manufacturing emissions reductions are relatively stable for optimal solutions over the range of carbon credit costs. This can be due predominantly to the manufacturing inflexibility at EOF, that is, there is little excess capacity which can be eliminated to reduce the carbon emissions in the manufacturing operations while still meeting business goals. Also, EOF may be already very efficient in its manufacturing operations leaving only little room for additional improvements in its environmental performance.

Numerically, we see that in the most-expensive-carbon scenario, the production emissions is reduced by about 5%, while the distribution emissions is down by about 50%. Therefore, the primary contributor to the carbon reduction at EOF is the distribution emissions generated through the external transportation and storage. An important managerial insight for EOF management is to focus investment on greener alternative transport options regardless of the level and type of environmental regulatory policies. On the other hand, although distribution emissions are where the greatest savings occur, the largest percentage increase in costs occurs in the shortage/backlog costs area (see the shortage costs for the three scenarios in Table 2). Thus, very high emissions penalties will not only increase costs throughout the company in terms of delivery and operations, but also customer service may be impeded in such cases.

This segmentation of the costs and optimization structure across the SC provides greater flexibility for management to focus on particular activities within the SC. A finer grained

analysis, e.g. specific machining centers or warehouses, can help organizations make finer-tuned choices. In addition, not only are the magnitude of reductions important, but the costs of reductions may play a significant role. Right now, the cost/emissions tradeoffs are completed by reducing certain activities. However, additional analysis may reveal that it might be more cost-efficient and competitively effective if investments are made in certain areas to help reduce the emissions rather than cutting back on production. Investments in more efficient manufacturing technology, better warehousing design, or improved transportation fleets can be amongst such alternatives. Cost and investment tradeoffs using this analysis can be important inputs into such decisions.

One primary and broad-based policy question is to determine the carbon price at which the maximum environmental performance can be achieved without substantial impacts on the economy and competitive positioning of firms. We now introduce Figure 1 to illustrate the influence of various carbon prices on the financial and environmental performance of EOF. The percentage values for each scenario are given compared to a situation with no carbon tax introduced. From this figure, the price range of \$40 to \$60 appears to be the most effective and efficient option in terms of emissions generation and cost escalation. Within this period, a dollar increase in SC cost has the greatest positive impact on the carbon pollution reduction. The 2012-2014 carbon tax rates seem to yield the lowest marginal environmental gain among these carbon tax scenarios.

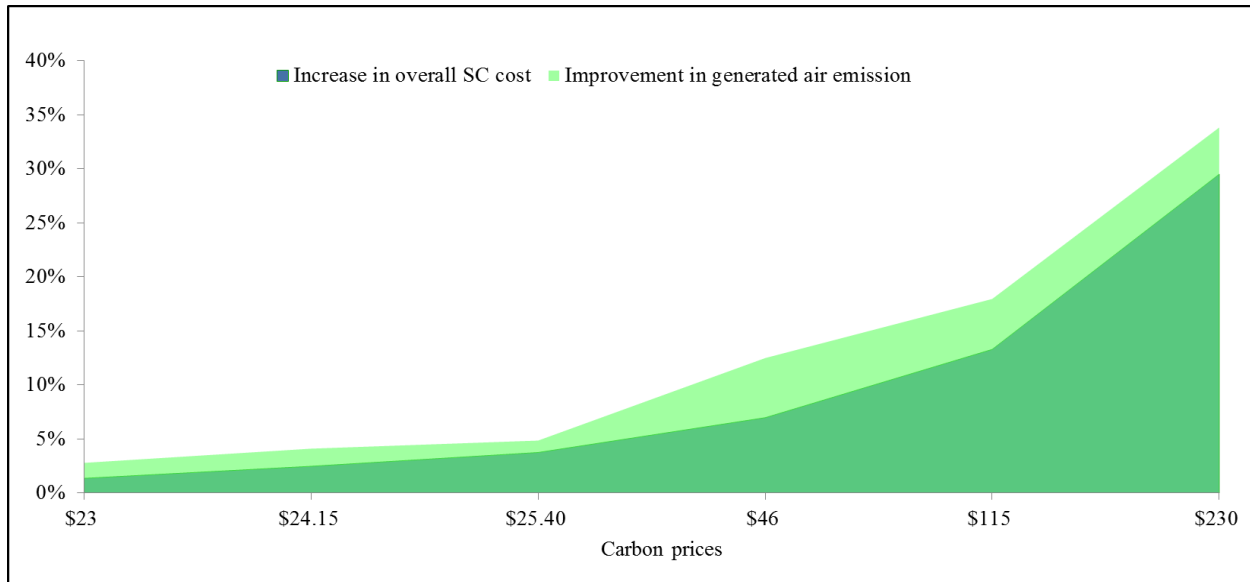


Fig1. SC cost increase versus carbon emissions reduction at various carbon prices

Given that EOF can represent discrete, durable parts manufacturing sector in Australia, our numerical results suggest that the government can take advantage of the maximum environmental returns per dollar investment offered in the carbon tax range of \$40 to \$60 per ton of emissions. While carbon prices above \$60 will still continue to improve the environmental impacts of SCs, it may impose unacceptable economic costs that may be inappropriate for the present time when the national economic conditions are weak and there exists significant uncertainty in the global economy.

It should be noted that important policy decisions such as these need more than simple cost-benefit analysis (Hockley, 2014). The methodology can provide the necessary scientific, economic, and mathematical support to aid governments in making more robust decisions. How the data and assumptions are generated is also important. In this situation the various parameters were determined through corporate information and estimates. Utilizing additional tools to help

generate estimates, such as more accurate social costs of carbon emissions, can be integrated into these decision tools.

The application of these tools to broader policy instruments such as regional emissions, such as ozone or sulfur emissions, using various permitting, rather than taxing, approaches can prove beneficial to policymakers. One aspect of these tools that was not explicitly considered is the regional considerations of SCs. Some regions, due to greater economic or population growth, may be unduly affected by regulatory policies such as carbon taxes (Sathaye and Shukla, 2013). Integrating geographical considerations and altering carbon taxes to more evenly distribute burden areas, especially poverty-stricken and underprivileged areas, can be utilized in these models. Although integration of these factors can be considered in these models, care must be taken that pollution havens and free-rider concerns do not cause these areas to be regions over represented with greater carbon or toxic emissions.

7. Conclusions

This article investigated the potential impacts of a carbon tax policy scheme on the financial and emissions reduction performance of SCs at the tactical planning level. A green SC planning model was presented incorporating realistic economic and environmental objectives and constraints. A modified CE-based optimization algorithm was designed to solve the developed MINLP model. The analyses from model implementation in an Australian case study indicate that a carbon tax of \$23 per ton of emissions generated imposes a minor reduction of less than 3% in carbon emissions when the overall SC cost is increased by about 1.5%. Additional

reductions in carbon emissions may be made through designing a more effective carbon pricing/trading mechanism in the future. For example, the most effective level of pricing can be first determined to cause true industry and SC reductions and then for transition to a cap-and-trade market, caps can be adjusted in such a way that the equilibrium market price is comparable to the carbon tax. Some economists have argued that setting hard caps and minimum prices for trading prices is similar to carbon taxing (Wara, 2014). This is just one example of identifying appropriate pricing that will be most economically and environmentally effective.

From an organizational perspective, it was shown in this paper that there are certain areas across the SC where investments can be made to reduce emissions. But, there are also business goals that need to be met. With this model, not only can key decisions be made on investments, but also the model identifies on which costs organizations should focus. For instance, transport emissions were shown to be the primary contributor to the overall carbon emissions. Less carbon-intensive transport options may not only result in reduced carbon emissions, but such an investment may also help reduce shortage costs and improve customer service. However, if there are subcontractors and partner organizations in the SC, particular efforts to collaborate on identifying the best solutions and sharing the burdens can be more effectively completed since the influence of the regulatory measures may not be equal across SC partners.

For the related policymakers, the findings of this research can be used as inputs for the design of more effective carbon tax or trading mechanisms. The numerical results for an Australian SC from discrete, durable parts manufacturing sector indicate that the maximum environmental returns per dollar increase in SC cost occur in the price range of \$40 to \$60. A carbon price above \$60 may impose unacceptable economic costs that may be inappropriate in a situation

where national economic conditions are weak and there exists significant uncertainty in the global economy.

The model and methodology presented in this paper has its limitations and these limitations allow for future improvements. More advanced models can be developed allowing for multi-period investments addressing the volatility of carbon pricing. Even carbon taxes may have unforeseen influences, such as where the emissions may shift along the SC. Incorporating uncertainties into these deterministic models, such as likelihood of emissions and costs shifting along the SC given variations in carbon taxes, can be investigated. Bayesian analysis which can help identify potential uncertainties integrated with these deterministic models is one potential direction for future research.

As the shift from carbon taxing to a carbon market trading environment occurs, there are greater uncertainties involved in the value of the carbon credits. This uncertainty will require a larger sensitivity analysis for evaluating the impact of the carbon prices/credits on the market. But, given the limitations and problems associated with cap-and-trade markets, both relating to uncertainties and political issues (Wara, 2014), considering mixed regulatory policies can be integrated into these types of decision tools. For example, investigations are required on introducing minimal carbon prices (taxes) in hybrid cap-and-trade systems.

Regional and variable carbon taxes may occur to help economic development in certain areas. Although these might be perverse types of incentives, these subsidies can be utilized by governments to enhance economic wellbeing in certain areas by shifting some of the environmental burden reductions to other regions which can more readily afford the taxes or more easily eliminate the carbon emissions. This type of regional modeling can be integrated

into the carbon tax model. Alternatively, a hybrid regulatory scheme can be investigated, instead of choosing between carbon tax and cap-and-trade system. The differences in these types of policies can be examined by developing and comparing deterministic versus stochastic modeling efforts.

Overall, there are many opportunities for further research, some of which are based on utilizing and advancing this model in a carbon tax environment, but also some that may integrate a wide variety of estimation and decision support tools. This field is still fertile and aiding both industries and governments in making these decisions is still an important requirement for economic and environmental improvements.

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