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How green is a lean supply chain?

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ABSTRACT: This article presents a supply chain planning model that can be used to investigate tradeoffs between cost and environmental degradation including carbon emissions, energy consumption and waste generation. The model also incorporates other aspects of real world supply chains such as multiple transport lot sizing and flexible holding capacity of warehouses. The application of the model and solution method is investigated in an actual case problem. Our analysis of the numerical results focuses on investigating relationship between lean practices and green outcomes. We find that (1) not all lean interventions at the tactical supply chain planning level result in green benefits, and (2) an agile supply chain is the greenest and most efficient alternative when compared to strictly lean and centralized situations.

KEY WORDS: Green Supply Chain; Environmental Sustainability; Lean; Agile; Flexible; Nonlinear Mathematical Programming; Cross-Entropy Method; Case Study

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1. Introduction

Governments and industries are seeking ways to decouple economic development and growth from commensurate environmental burden. This 'green growth' philosophy was a central discussion at the recent United Nations Conference on Sustainable Development, also called Rio+20. Decoupling economic growth and environmental degradation is not an easy goal to achieve. Yet at the national level, examples to grow without corresponding increases in environmental pressure do exist (Dittrich et al., 2012; Vazquez-Brust and Sarkis, 2012). At the organizational level, efforts that have utilized eco-efficiency, ecological modernization and 'win-win' principles support the feasibility of achieving these goals (Sarkis and Cordeiro, 2012).

Investigations on the phenomena of jointly improving organizational environmental and economic performance have tended to focus on empirical studies to show that green growth results are realistic and achievable (Molina-Azorín et al., 2009; Zhu and Sarkis, 2004). However, such results do not inevitably occur without design, planning, and support. Research and development are required to help achieve these results and eventually contribute to decoupling economic and environmental growth (Fahimnia et al., 2014).

Green or environmentally sustainable supply chain management (SCM) has been viewed as one area where organizations and industry can make significant contribution to both economic and environmental development (Varsei et al., 2014). Descriptive research utilizing empirical and case study research on forward sustainable supply chains (SCs) has seen substantial development over the past couple of decades. Normative, prescriptive, and quantitative modeling efforts on the forward SC have received significantly less attention (Seuring, 2013; Seuring and Müller, 2008; Srivastava, 2007), although reverse logistics planning has received considerable investigation (Fahimnia et al., 2013d). The call for development and utilization of economic and optimization approaches to further socially supportive research such as sustainable SC research has continued (Sarkis, 2012b; Seuring, 2013). We seek to contribute to this call for additional analytical and modeling normative research with our current study.

The specific focus of this study is on ecologically and economically balancing and optimizing material manufacture and movement across a multi-tiered SC. Our modeling effort is based on a real world situation that has actually encountered issues raised in this investigation. The complexity of the modeling effort limits how effectively these models can be solved. Efficient solution techniques are needed for solving complex green SC modeling efforts (Grossmann and Guillén-Gosálbez, 2010). To address this complexity, we introduce a solution method, named Nested Integrated Cross-Entropy (NICE), that is able to find quality and relatively rapid solutions to the complex mixed-integer nonlinear model encountered in this study. The proposed model and the NICE solution procedure allows for investigating the locus of decision parameters that can prove useful to management seeking to balance the economic and environmental dimensions. One specific case situation, investigated in this paper, is studying various scenarios adjusting the SC 'leanness'.

We make several contributions to this important and growing field of green SCM. First, we introduce a multidimensional optimization model for tactical SCM that is applicable to real world situations. We then utilize a novel solution approach to provide quality solutions to this complex nonlinear problem within a relatively short model runtime. Our third major contribution involves the execution of this model to provide practical insights into the decision environment facing managers, focusing on critical issues related to the lean-and-green debate. These insights set the stage for additional investigation and model development in future research.

The remainder of the paper is composed of the followings sections. In Section 2 a background review of literature in this area and previous models which we use as a foundation is presented. Section 3 presents the mathematical model. Section 4 overviews the Nested Integrated Cross Entropy (NICE) solution method. Section 5 provides an execution of the model using real case data with results and initial analysis.

Section 6 provides a discussion of the results with a focus on the issue of SC leanness-versus-greenness. Section 7 is the concluding section which includes a summary of the study and results, research and managerial implications, model and study limitations, and guidance for future research.

2. Foundational Literature Background

Green SCM has been defined as the explicit consideration of ecological dimensions in the planning, operations, and management of SCs (Zhu and Sarkis, 2004). Organizations are under varied and increasing pressures from a broad spectrum of stakeholders to manage their SC functions in more environmentally efficient and effective ways (Darnall et al., 2008; Fahimnia et al., 2009; Testa and Iraldo, 2010; Zhu and Sarkis, 2007). When adding the environmental and social concerns into modeling and management research effort, design, planning and management problems become geometrically more complex (Nikolopoulou and Ierapetritou, 2012). The research and modeling for SCM optimization in general is a relatively non-trivial exercise (Fahimnia et al., 2013a) and it becomes even more complex for greening of SCs. Organizations and researcher guidance is paramount to helping make practical and theoretical progress in this field.

One important factor in improving the tractability of the modeling for greening the SC is an explicit definition of the boundaries and flows of the problem (Sarkis, 2012a). In this paper, we clearly define an important boundary to include forward SC participants including manufacturers, warehouses, and end-users. The flows in the model include materials, energy, and waste flows. Models for evaluating and optimizing environmental and economic performance of organizational operational activities can range from machines in a production center (Sloan, 2011), to a large global closed loop SCM system (Hugo and Pistikopoulos, 2005). But, even the most comprehensive surveys show that the relative investigation of green SC topics with analytical modeling and optimization is secondary to qualitative and empirical studies (Seuring, 2013; Seuring and Müller, 2008). Although some emergent analytical modeling research for green SCM does exist, a vast majority of literature focuses on cost minimization objective and relatively fewer articles incorporate multiple objectives and explicitly integrate economic and environmental goals (Brandenburg et al., 2014; Melo et al., 2009).

Our modeling effort in this paper fits within the tradeoff mode of modeling literature. The literature that seeks to jointly model environmental and financial/business objectives is not extensive. Recent reviews have been completed by Brandenburg et al. (2014), Benjaafar et al. (2013), Tang and Zhou (2012), and Dekker et al. (2012). Most of this literature focuses on cost minimization as a financial objective. Profit maximization is the only other financial objective which requires consideration of sales revenue and pricing. Managing greenhouse gas emissions has been the most common environmental objective. This is not surprising given the greater global focus on carbon emissions as the primary contributor to climate change. Some of the bi-objective models focusing on cost and carbon emission minimizations have been presented by Ferretti et al. (2007), Nagurney and Nagurney (2010), Pinto-Varela et al. (2011), Abdallah et al. (2011), Wang et al. (2011a), Elhedhli and Merrick (2012), Chaabane et al. (2012), Pishvaee et al. (2012), Fahimnia et al. (2013c), and (Fahimnia et al., 2013d). But, not all emissions studies are only on carbon. For example, Nagurney and Nagurney (2010) use general emissions in a strategic network design problem, where a variety of emissions, even solid wastes, are used to design a green SC network. A couple of other studies, such as Pinto-Varela et al. (2011) and Yeh and Chuang (2011), utilize a set of green scoring or ecological indicators that are broader in perspective than carbon emission alone.

The preponderance of this literature uses numerical experiments or simulated data to validate the developed models (see for example Ferretti et al. (2007), Nagurney and Nagurney (2010), Pinto-Varela et al. (2011), Abdallah et al. (2011), Wang et al. (2011a), and Elhedhli and Merrick (2012)). Only some of the more recent studies have incorporated real data from organizations and industry (Fahimnia et al., 2013c; Fahimnia et al., 2013d; Mallidis et al., 2012; Pishvaee et al., 2012). There are also case or sector specific models such as Ferretti et al. (2007) who present SC cost and environmental expressions for molten aluminum substitution into the SC. Even though specific to a particular industry case, the expressions can help set the foundation for other industries.

Apart from these initial classifications, the published works can also be discussed based upon the level of planning and analysis. The tradeoff between cost and emission performance has been a major focus in strategic SC decision making. Such modeling efforts may include green infrastructure modeling (Harris et al., 2011), green SC network design, particularly in closed-loop situations (Chaabane et al., 2012; Elhedhli and Merrick, 2012; Frota Neto et al., 2008; Wang et al., 2011b) as well as studies with a narrower focus on specific SC operations such as green supplier selection (Bai and Sarkis, 2010; Lee et al., 2009; Yeh and Chuang, 2011) and transport mode selection (Hoen et al., 2014). These models only capture a broad, strategic dimension and thus the levels of analysis present very aggregate solutions. Integrating tactical and operational product level considerations in these modeling efforts is relatively immature (see for example Fahimnia et al. (2014), Fahimnia et al. (2013d), and Pan et al. (2013)).

We also realize that multi-objective SCM modeling efforts result in major complexity and that a model, to be accepted by industrial practitioners and researchers, needs to arrive at quality solutions in a relatively tolerable length of time. The opportunity to investigate various scenarios and parameters requires improved solution procedures. The use of linear solvers such as CPLEX has made this possible where small and medium size problems can be presented in a linear form (Dhaenens-Flipo and Finke, 2001; Fahimnia et al., 2013a; Ferrio and Wassick, 2008; Gunnarsson et al., 2007). Alternatively, various heuristics methods have been proposed for tackling large and nonlinear models that are difficult or impossible to solve optimally using the standard solvers (Esmaeilikia et al., 2014a; Fahimnia et al., 2013b; Jayaraman and Ross, 2003; Naso et al., 2007; Yang et al., 2007). The design of such heuristics is generally problem specific and a generic heuristic method may not fit the purpose for solving all ranges of combinational optimization problems (Esmaeilikia et al., 2014b).

As evidenced by the many issues and potential dimensions of green SC research, this study aims to address, in some form, the various gaps and limitations in the current literature. We clearly bound our decision environment to focus analysis on a critical aspect of the SC which includes the production, storage, and delivery of products, the three core elements in almost all SCs. Our explicit focus is on the forward SC, which has received less modeling investigation than reverse logistics aspects of environmentally oriented modeling (Seuring and Müller, 2008). We also focus on tactical SC planning which has received less modeling attention compared to strategic design of networks. In addition, we provide a more comprehensive evaluation of environmental factors (by considering carbon emissions, energy and wastes as model objectives) and jointly balance these efforts against economic concerns. Balancing these dimensions can help organizations decide how far they should take each based on organizational, community, and competitive pressures and requirements, a very important step towards decoupling economic growth and environmental degradation at the SC level. Finally, we take advantage of the binary and nonlinear structure of our mathematical model and introduce a modified Cross-Entropy (CE) method to solve the encountered model in this research. To the best of our knowledge, this is one of the early attempts in applying CE in solving optimization problems in the context of SCM, and especially in green SCM literature.

3. Model Development

The schematic view of the proposed SC under investigation is shown in Figure 1. Multiple product types (*i*) are produced in different manufacturing plants (*m*) by travelling through a set of machine centers (*g*). Older and more outdated machinery makes a plant cheaper to run, but is less energy/carbon efficient and generates more production waste. Finished products are then distributed to end-users in dispersed geographical locations (*e*) through a set of established warehouse (*w*). Different truck sizes can be used in transport including small, medium, and heavy trucks. Smaller trucks are leaner (smaller lot size deliveries) requiring less storage space in warehouses, but may be economically and environmentally inefficient to use. The choice of small, medium or large warehouses determines the available storage space at each location.

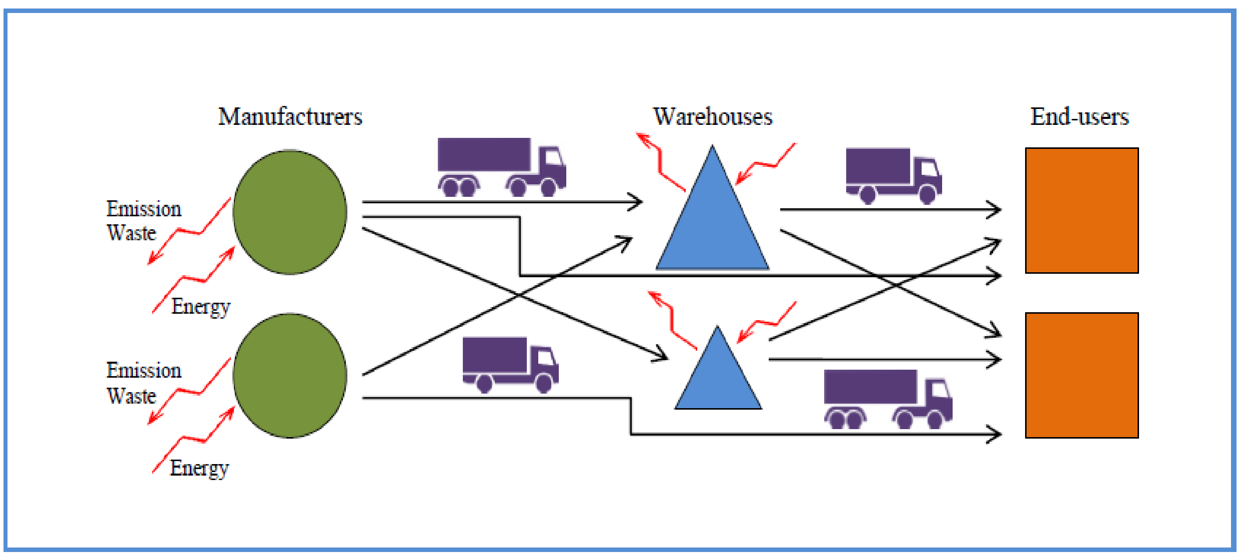

Fig. 1. The boundaries of the SC under investigation

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) in a way to minimize the overall SC cost while reducing the negative environmental impacts (i.e. carbon emissions, energy consumption, production and storage waste generation). A multi-objective optimization model is developed in which the first objective concerns the economic dimensions of SC and the next three objectives focus on the associated environmental aspects.

The following key assumptions are considered for the purpose of mathematical modeling:

- 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) are known.
- Demand is deterministic and the 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. A penalty cost is incurred if the demand for a certain product at one period is backordered. The backlog/backordered demand must be satisfied in the subsequent periods before the end of the planning horizon.
- Capacity limitations for regular time and overtime production (capacity hours of machine centers), capacity of raw material supply, limitations in storage capacity at manufacturers 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 after plants opening due to the training costs and hiring/admin fees. The rates will remain unchanged for the succeeding periods from the second period.
- Transportation costs and emission rates are available for small, medium and heavy trucks.
- End-users are the locations where products are delivered to the final customers with no space to store the products.

- Carbon emission, energy consumption and waste generation rates are available for processing products on each machine center. These costs are generally functions of the machine's useful life, processing time and manufacturing technology used.
- Carbon emission, energy consumption and waste generation rates are available for storing products in plants and warehouses.

3.1 Parameters and decision variables

Indices used in this model include *i* for product type, *m* for manufacturing plant, *g* for machine center, *w* for warehouse, *e* for end-user and *t* for time period. The input parameters are given in Appendix A. The continuous and binary decision variables include the followings:

Decision variables:

Q_{imt} Quantity of *i* produced during regular-time in *m* at *t*

Q'_{imt} Quantity of *i* produced during overtime in *m* at *t*

F_{ijkt} Quantity of *i* shipped from *j* to *k* during *t* $(jk \in \{mw, we, me\})$

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 (backlog amount) in *e* at the end of *t*

Binary Decision variables:

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

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

We also use the following auxiliary binary variables to assist in formulating variations in warehouse sizes and truck types.

$$G^{s}_{wt} = \begin{cases} 1, & \text{If warehouse } w \text{ is chosen to be small size in period } t \\ 0, & \text{Otherwise} \end{cases}$$

$$G^{m}_{wt} = \begin{cases} 1, & \text{If warehouse } w \text{ is chosen to be medium size in period } t \\ 0, & \text{Otherwise} \end{cases}$$

$$G^{ts}_{ijkt} = \begin{cases} 1, & \text{If a small truck is used to ship } i \text{ from } j \text{ to } k \text{ at } t \\ 0, & \text{Otherwise} \end{cases} \qquad jk \in \{mw, we, me\}$$

$$G^{tm}_{ijkt} = \begin{cases} 1, & \text{If a medium truck is used to ship } i \text{ from } j \text{ to } k \text{ at } t \\ 0, & \text{Otherwise} \end{cases} \qquad jk \in \{mw, we, me\}$$

3.2 Formulation of objective functions

Using parameters and decision variables defined in Section 3.1, the four objective functions can be formulated as a mixed-integer nonlinear programming (MINLP) model. *Objective function 1* (Equation 1) is the cost function that expresses the manufacturing, transport, inventory holding and backlog costs. The nonlinear components appear in terms 3 and 4 of Equation 1.

$$\begin{aligned} Z_1 = {} & \sum_m \sum_t o_{mt}\, G_{mt} + \sum_w \sum_t o'_{wt}\, c^{oc}_{wt}\, G'_{wt} + \\ & \sum_i \sum_m \sum_t [(\sum_g p_{igmt}\, \{l_{igmt}\, G_{m(t-1)} + l^{1st}_{igmt}(1 - G_{m(t-1)})\} + r_{imt} + \alpha_{imt}) Q_{imt}] + \\ & \sum_i \sum_m \sum_t [(\sum_g p_{igmt}\, \{l'_{igmt}\, G_{m(t-1)} + l'^{1st}_{igmt}(1 - G_{m(t-1)})\} + r_{imt} + \beta_{imt}) Q'_{imt}] + \\ & \sum_i \sum_m \sum_t h_{imt}\, X_{imt} + \sum_i \sum_w \sum_t h'_{iwt}\, c^{hc}_{iwt}\, Y_{iwt} + \\ & \sum_i \sum_{jk\in\{mw,we,me\}} \sum_t \tau_{ijkt}\, c^{tc}_{ijkt}\, F_{ijkt} + \sum_i \sum_e \sum_t sc_{iet}\, S_{iet} \end{aligned} \tag{1}$$

Where:

$$c^{oc}_{wt} = \begin{cases} 1\,, & \text{If } w \text{ is set to a small size} \\ cm^{oc}_{wt}\,, & \text{If } w \text{ is set to a medium size} \\ cl^{oc}_{wt}\,, & \text{If } w \text{ is set to a large size} \end{cases} \tag{2}$$

$$c_{iwt}^{hc} = \begin{cases} 1, & \text{If } w \text{ is set to a small size} \\ cm_{iwt}^{hc}, & \text{If } w \text{ is set to a medium size} \\ cl_{iwt}^{hc}, & \text{If } w \text{ is set to a large size} \end{cases} \quad (3)$$

$$c_{ijkt}^{tc} = \begin{cases} 1, & F_{ijkt} \leq stc_i \\ cm_{ijkt}^{tc}, & stc_i < F_{ijkt} \leq mtc_i \\ ch_{ijkt}^{tc}, & mtc_i < F_{ijkt} \leq htc_i \end{cases} \quad jk \in \{mw, we, me\} \quad (4)$$

Using the axillary variables, the step functions in Equations 2-4 can be mathematically formulated as:

$$c_{wt}^{oc} = G_{wt}^{s} + cm_{wt}^{oc}\, G_{wt}^{m} + cl_{wt}^{oc}\,(1 - G_{wt}^{s} - G_{wt}^{m}) \qquad G_{wt}^{s} + G_{wt}^{m} \leq 1 \quad (5)$$

$$c_{iwt}^{hc} = G_{wt}^{s} + cm_{iwt}^{hc}\, G_{wt}^{m} + cl_{iwt}^{hc}\,(1 - G_{wt}^{s} - G_{wt}^{m}) \quad (6)$$

$$c_{ijkt}^{tc} = G_{ijkt}^{ts} + cm_{ijkt}^{tc}\, G_{ijkt}^{tm} + ch_{ijkt}^{tc}\,(1 - G_{ijkt}^{ts} - G_{ijkt}^{tm}) \qquad jk \in \{mw, we, me\} \text{ and } G_{ijkt}^{ts} + G_{ijkt}^{tm} \leq 1 \quad (7)$$

Objective function 2 (emission function in Equation 8) formulates the generated carbon pollution in manufacturing, transport and inventory holding.

$$Z_2 = \sum_i \sum_g \sum_m \sum_t p_{igmt}\, a_{igmt}\left(Q_{imt} + Q'_{imt}\right) + \sum_i \sum_m \sum_t a_{imt}^{m} X_{imt} + \sum_i \sum_w \sum_t a_{iwt}^{w}\, c_{iwt}^{a} Y_{iwt} + \sum_i \sum_{jk \in \{mw,we,me\}} \sum_t a_{ijkt}^{ce}\, c_{ijkt}^{ce}\, F_{ijkt} \quad (8)$$

Where:

$$c_{iwt}^{a} = \begin{cases} 1, & \text{If } w \text{ is set to a small size} \\ cm_{iwt}^{a}, & \text{If } w \text{ is set to a medium size} \\ cl_{iwt}^{a}, & \text{If } w \text{ is set to a large size} \end{cases} \quad (9)$$

$$c_{ijkt}^{ce} = \begin{cases} 1, & F_{imwt} \leq stc_i \\ cm_{ijkt}^{ce}, & stc_i < F_{ijkt} \leq mtc_i \\ ch_{ijkt}^{ce}, & mtc_i < F_{ijkt} \leq htc_i \end{cases} \quad jk \in \{mw, we, me\} \quad (10)$$

The mathematical formulation of the step functions 9 and 10 can be given as:

$$c_{iwt}^{a} = G_{wt}^{s} + cm_{iwt}^{a}\, G_{wt}^{m} + cl_{iwt}^{a}\,(1 - G_{wt}^{s} - G_{wt}^{m}) \quad (11)$$

$$c_{ijkt}^{ce} = G_{ijkt}^{ts} + cm_{ijkt}^{ce}\, G_{ijkt}^{tm} + ch_{ijkt}^{ce}\,(1 - G_{ijkt}^{ts} - G_{ijkt}^{tm}) \qquad jk \in \{mw, we, me\} \quad (12)$$

Objective function 3, energy function, is presented in Equation 13 which formulates the consumed energy in manufacturing and inventory holding in plants and warehouses.

$$Z_3 = \sum_i \sum_g \sum_m \sum_t p_{igmt}\, b_{igmt}\left(Q_{imt} + Q'_{imt}\right) + \sum_i \sum_m \sum_t b^m_{imt}\, X_{imt} + \sum_i \sum_w \sum_t b^w_{iwt}\, c^b_{iwt}\, Y_{iwt} \quad (13)$$

Where:

$$c^b_{iwt} = \begin{cases} 1\,, & \text{If } w \text{ is set to a small size} \\ cm^b_{iwt}\,, & \text{If } w \text{ is set to a medium size} \\ cl^b_{iwt}\,, & \text{If } w \text{ is set to a large size} \end{cases} \quad (14)$$

The mathematical formulation of Equation 14 is presented in Equation 15.

$$c^b_{iwt} = G^s_{wt} + cm^b_{iwt}\, G^m_{wt} + cl^b_{iwt}\,(1 - G^s_{wt} - G^m_{wt}) \quad (15)$$

Objective function 4 (waste function) is presented in Equation 16 formulating the generated wastes in manufacturing and inventory holding in plants and warehouses.

$$Z_4 = \sum_i \sum_g \sum_m \sum_t u_{igmt}\left(Q_{imt} + Q'_{imt}\right) + \sum_i \sum_m \sum_t u^m_{imt}\, X_{imt} + \sum_i \sum_w \sum_t u^w_{iwt}\, c^u_{iwt}\, Y_{iwt} \quad (16)$$

Where:

$$c^u_{iwt} = \begin{cases} 1\,, & \text{If } w \text{ is set to a small size} \\ cm^u_{iwt}\,, & \text{If } w \text{ is set to a medium size} \\ cl^u_{iwt}\,, & \text{If } w \text{ is set to a large size} \end{cases} \quad (17)$$

The step function in Equation 17 can be mathematically presented as:

$$c^u_{iwt} = G^s_{wt} + cm^u_{iwt}\, G^m_{wt} + cl^u_{iwt}\,(1 - G^s_{wt} - G^m_{wt}) \quad (18)$$

The goal of the proposed optimization model is to minimize the value of Z in Equation 19.

$$Z = \rho_1 Z_1 + \rho_2 Z_2 + \rho_3 Z_3 + \rho_4 Z_4 \quad (19)$$

3.3 Model constraints

The proposed model is subject to the following constraints:

1. Capacity constraints:

- Restrictions on raw material supply:

$$Q_{imt} + Q'_{imt} \leq \gamma_{imt} \qquad \forall\, i, m, t \tag{20}$$

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

$$p_{igmt}\, Q_{imt} \leq \lambda_{igmt} \quad \& \quad p_{igmt}\, Q'_{imt} \leq \lambda'_{igmt} \qquad \forall\, i, g, m, t \tag{21}$$

- Stack buffer capacity restriction in manufacturing plants:

$$X_{imt} \leq hc^{m}_{imt} \qquad \forall\, i, m, t \tag{22}$$

- Warehouse capacity restriction:

$$Y_{iwt} \leq hc^{ws}_{iwt}\, G^{s}_{wt} + hc^{wm}_{iwt}\, G^{m}_{wt} + hc^{wl}_{iwt}(1 - G^{s}_{wt} - G^{m}_{wt}) \qquad \forall\, i, w, t \tag{23}$$

- Maximum allowed shortage at end-users:

$$S_{iet} \leq S^{max}_{iet} \qquad \forall\, i, e, t \tag{24}$$

2. Balance constraints:

- Inventory balance at plants:

$$X_{imt} - X_{im(t-1)} = Q_{imt} + Q'_{imt} - \sum\nolimits_{k \in \{w,e\}} F_{imkt} \qquad \forall\, i, m, t \tag{25}$$

- Inventory balance at warehouses:

$$Y_{iwt} - Y_{iw(t-1)} = \sum\nolimits_{m} F_{imwt} - \sum\nolimits_{e} F_{iwet} \qquad \forall\, i, w, t \tag{26}$$

- Inventory balance at end-users:

$$\sum\nolimits_{j \in \{m,w\}} F_{ijet} = d_{iet} - S_{iet} + S_{ie(t-1)} \qquad \forall\, i, e, t \tag{27}$$

- Demand satisfaction constraint:

$$\sum_m \sum_t (Q_{imt} + Q'_{imt}) = \sum_e \sum_t d_{iet} + \sum_m \eta'_{im} - \sum_m \eta_{im} + \sum_w \varphi'_{iw} - \sum_w \varphi_{iw} \quad \forall\, i \quad (28)$$

3. *Emissions, energy and waste constraints:*

- Emissions generation constraint in manufacturing plants:

$$\sum_i \sum_g p_{igmt}\, a_{igmt}(Q_{imt} + Q'_{imt}) + \sum_i a^m_{imt}\, X_{imt} \leq a^{maxm}_{mt} \quad \forall\, m, t \quad (29)$$

- Emissions generation constraint in transport:

$$\sum_i \sum_{jk\in\{mw,we,me\}} c^{ce}_{ijkt}\, a^{ce}_{ijkt}\, F_{ijkt} \leq a^{maxa}_t \quad \forall\, t \quad (30)$$

- Emissions generation constraint in warehouses:

$$\sum_i a^w_{iwt}\, c^a_{iwt} Y_{iwt} \leq a^{maxw}_{wt} \quad \forall\, w, t \quad (31)$$

- Energy use constraint in manufacturing plants:

$$\sum_i \sum_g p_{igmt}\, b_{igmt}(Q_{imt} + Q'_{imt}) + \sum_i b^m_{imt}\, X_{imt} \leq b^{maxm}_{mt} \quad \forall\, m, t \quad (32)$$

- Energy use constraint in warehouses:

$$\sum_i b^w_{iwt}\, c^b_{iwt}\, Y_{iwt} \leq b^{maxw}_{wt} \quad \forall\, w, t \quad (33)$$

- Waste generation constraint in manufacturing plants and warehouses:

$$\sum_g \sum_m u_{igmt}(Q_{imt} + Q'_{imt}) + \sum_m u^m_{imt}\, X_{imt} + \sum_w u^w_{iwt}\, c^u_{iwt}\, Y_{iwt} \leq u^{max}_{it} \quad \forall\, i, t \quad (34)$$

4. *Other constraints:*

- Inventory level of finished products at stack buffers (Equation 35) and warehouses (Equation 36) at the start and end of the planning horizon (t=0 and t=T):

$$X_{im0} = \eta_{im} \quad \& \quad X_{imT} = \eta'_{im} \quad \forall\, i, m \quad (35)$$

$$Y_{iw0} = \phi_{iw} \quad \& \quad Y_{iwT} = \phi'_{iw} \quad \forall\, i, w \quad (36)$$

- Restrictions on decision variables:

$$0 \leq Q_{imt} \leq G_{mt}M \quad \& \quad 0 \leq Q'_{imt} \leq G_{mt}M \quad \forall\, i, m, t \quad (37)$$

$$0 \leq F_{imwt} \leq G_{mt}M \quad \& \quad 0 \leq F_{imwt} \leq G'_{wt}M \quad \forall\, i, m, w, t \quad (38)$$

$$0 \leq F_{iwet} \leq G'_{wt}\, M \quad \forall\, i, w, e, t \quad (39)$$

$$0 \leq F_{imet} \leq G_{mt}\, M \quad \forall\, i, m, e, t \quad (40)$$

$$0 \leq X_{imt} \qquad \forall\, i, m, t \tag{41}$$

$$0 \leq Y_{iwt} \qquad \forall\, i, w, t \tag{42}$$

$$0 \leq S_{iet} \qquad \forall\, i, e, t \tag{43}$$

4. The Nested Integrated Cross Entropy (NICE) method

Cross Entropy (CE) is a simulation-based optimization method initially proposed for estimating probabilities of rare events (Rubinstein, 1997). It was eventually redesigned and used to solve both combinatorial and continuous optimization problems (Rubinstein, 1999). CE starts with an initial probability distribution over a feasible region, for instance, a uniform distribution, and then updates the distribution adaptively based on a random sample collected from the feasible region. Such a revision process should converge to some degenerate distribution that assigns a probability of 1 to an optimal solution. Technical details on the CE method can be found in (Rubinstein and Kroese, 2004, 2007).

To help explain the CE method, let us consider the following binary nonlinear programming (BNLP) model:

$$\text{Minimize} \quad f(\boldsymbol{x})$$
$$\text{subject to} \quad A\boldsymbol{x} \leq \boldsymbol{b} \quad \text{and} \quad \boldsymbol{x} \in \{0,1\}^{\kappa}$$

where $f(\boldsymbol{x})$, A, and $\boldsymbol{b}$ are, respectively, nonlinear (non-convex) objective function, matrix of coefficients, and right hand side vector. All vectors are assumed to be vertical. Matrices, vectors, and scalars are respectively, denoted by capital, bold-small, and small fonts. If they involve randomness, the last two items will be switched to capital letters. For instance, X and $\boldsymbol{X}$ denote a random variable and a random vector, respectively. The concept of the CE method is to generate points adaptively from the feasible region $\{\boldsymbol{x}|A\boldsymbol{x} \leq \boldsymbol{b}\}$ such that, eventually, samples converge to an optimal solution. For this purpose, we define a probability vector $\boldsymbol{p}$ such that its i^{th} element is the probability that the random variable X_i is equal to one in an optimal solution. That is:

$$p_i := \Pr(X_i = 1).$$

The CE process starts with an initial probability vector $\boldsymbol{p}$ and adaptively generates samples from the feasible region according to the probability vector $\boldsymbol{p}$ and concurrently updating it. This learning process will continue until a termination rule is met (e.g., vector $\boldsymbol{p}$ converges to an almost zero-one vector). A major contribution of the CE method was introducing the updating scheme in the learning procedure. A standard CE method for the proposed BNLP model follows the following four-step algorithm:

Step 1. Choose an initial probability vector $\boldsymbol{p}_0$ with elements uniformly distributed, that is

$$p_i \coloneqq \frac{1}{2} \qquad \text{in which } i = 1,2, \dots, \kappa.$$

Generate n random solutions $\boldsymbol{X}_1, \boldsymbol{X}_2, \dots, \boldsymbol{X}_n$ with respect to probability vector $\boldsymbol{p}_0$. Obviously, each *random vector* $\boldsymbol{X}_i$ is a vector of length κ with random elements $X_1, X_2, \dots, X_\kappa$. Each of the random vectors $\boldsymbol{X}_i$ may or may not be feasible with respect to the feasible region $\{\boldsymbol{x}|A\boldsymbol{x} \leq \boldsymbol{b}\}$. Eliminate infeasible solutions from the sample and keep only the feasible ones. Sort the feasible solutions in ascending order with respect to their objective values. Now, consider the best m solutions where m is a ρ fraction of generated feasible solutions $(0 < \rho \leq 1)$. The latter is called *elite sample*.

Step 2. Use the best m generated feasible solutions found in previous step and calculate $\boldsymbol{p}_1^*$ and $\boldsymbol{p}_1$ by applying the following equations:

$$p_{i,1}^* = \frac{1}{m} \sum_{(1 \leq j \leq m: \boldsymbol{X}_j \ni i)} 1 \quad \text{for all } i = 1,2, \dots, \kappa,$$

$$\boldsymbol{p}_1 = (1 - \alpha)\boldsymbol{p}_0 + \alpha \boldsymbol{p}_1^*,$$

where summation over "$(1 \leq j \leq m: \boldsymbol{X}_j \ni i)$" denotes summation over the set of all elite solutions $\boldsymbol{X}_j$ that the element X_i is equal to 1 and α is a fixed smoothing parameter chosen from the interval (0,1).

Step 3. Generate n new solutions $\boldsymbol{X}_1, \boldsymbol{X}_2, \dots, \boldsymbol{X}_n$ with respect to probability vector $\boldsymbol{p}_1$ and repeat Step 1 and Step 2 again with $\boldsymbol{p}_0$ and $\boldsymbol{p}_1^*$ replaced with $\boldsymbol{p}_1$ and $\boldsymbol{p}_2^*$, respectively. Denote the final solution by $\boldsymbol{p}_2$. Denote the corresponding probability vector at stage t by $\boldsymbol{p}_t$.

Step 4. If for any $t > r$ and some r (say $r = 5$) the best found solution does not change, Stop and introduce it as a local optimal solution. Otherwise, repeat Steps 2-4 again.

The main issue with this algorithm is the acceptance/rejection decision, that is, cutting off the generated infeasible solutions and keeping only feasible ones from region $\{\boldsymbol{x}|A\boldsymbol{x} \leq \boldsymbol{b}\}$. If the rejection ratio is high (due to the geometric structure of the feasible region), the algorithm may cost a lot to ensure that, on average, there is significant number of feasible solutions in each sample. This issue is resolved in the modified CE method presented in this section.

Successful applications for 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 (Altiparmak and Dengiz, 2009) and multi-objective optimization (Bekker and Aldrich, 2011). To the best of our knowledge, our study is the first attempt investigating the application of the CE-method in a SC planning and optimization problem. Further, the effectiveness of the CE algorithm (in terms of runtime and solution quality) against the well-known evolutionary algorithms, such as Genetic Algorithms and Simulated Annealing, and against branch-and-bound algorithms in large-scale optimization problems have been investigated in some of past studies (Alon et al., 2005; Altiparmak and Dengiz, 2009; Caserta et al., 2008; Jung-Chieh et al., 2011).

The MINLP model presented in this paper has the following generic structure:

$$\text{Minimize} \quad f(\boldsymbol{x}, \boldsymbol{y})$$

$$\text{subject to} \quad A\begin{pmatrix}\boldsymbol{x}\\ \boldsymbol{y}\end{pmatrix} \leq \boldsymbol{b} \qquad \text{and} \qquad \boldsymbol{x} \in \{0,1\}^{\kappa}\ ,\ \boldsymbol{y} \geq \boldsymbol{0},$$

where $f(\boldsymbol{x}, \boldsymbol{y})$, A and $\boldsymbol{b}$ are, respectively, a nonlinear (non-convex) objective function, a matrix of coefficients, and the right hand side vector. The main difference between this model and the initial BNLP model is the inclusion of a continuous vector $\boldsymbol{y}$. In addition, in this model, decision variables are a combination of binary and continuous variables (i.e. elements of vectors $\boldsymbol{x}$ and $\boldsymbol{y}$). We define this model as a combined nonlinear programming (CNLP) model.

We initially attempted solving the proposed CNLP problem with the standard CE method explained above. The first was to generate continuous variables. One may suggest constructing a parametric probability density function for these continuous variables (analogous to binary variables) and update the parameters adaptively at each iteration. However, this approach can significantly increase the number of generated infeasible solutions with respect to the feasible region $\{\binom{\boldsymbol{x}}{\boldsymbol{y}} | A \binom{\boldsymbol{x}}{\boldsymbol{y}} \leq \boldsymbol{b}, \boldsymbol{y} \geq \boldsymbol{0}\}$. Eshragh et al. (2011) developed an algorithm to solve a CNLP model called the Projection-Adaptive Cross Entropy (PACE) method. Using the specific structure of the proposed CNLP model, binary variables were fixed to reduce the CNLP to a linear programming model. If it is infeasible, then the generated binary solution is discarded, otherwise optimal values of continuous variables with respect to the fixed binary variables are found by solving the resulting linear programming model.

We tried to adopt the same PACE approach, but then we encountered another problem. When randomly generating the binary decision variables and binary auxiliary variables, it was observed that all the generated solutions are infeasible in the first iteration. In other words, no feasible solution could be generated in iteration 1 for exploitation in the CE updating scheme in the successive iterations. To resolve this problem, we propose a new algorithm called the *Nested Integrated Cross Entropy (NICE)* method. NICE begins with dividing the binary variables involved in our MINLP model into two categories:

Type I. Binary decision variables including G_{mt} and G'_{wt} corresponding to opening/closing plants and warehouses at each period;

Type II. Auxiliary binary variables corresponding to step-functions of transport lot-sizing options (truck sizes) and inventory holding capacity options (warehouse sizes).

Nested generation of binary variables Type I: By setting all elements of the binary vectors G and G' equal to 1, our MINLP problem can have a feasible solution. This is when all plants and warehouses are open in all periods and so the SC operates at the full capacity. From a managerial perfective, this may not be wise decision to make, but it allows the use of all possible resources and capacities to satisfy the market demand (that is a feasible solution to the problem). Likewise, setting all elements of the binary decision variables G and G' equal to zero will undoubtedly result in our MINLP model becoming infeasible as the market demand cannot be satisfied in all periods. This observation became the motivation for generating the binary decision variables in a *nested* way.

We define a variable ω representing the number of Type I binary variables equal to zero. At the outset (iteration 1), ω is set equal to zero (that is all binary variables in vectors G and G' equal to 1). At each iteration, A sample of G and G' is generated such that each sample has exactly ω zero-elements. For this, we randomly choose ω elements of binary variables in vectors G and G' (according to their updated distributions based on the standard CE method) and set them equal to zero. The remaining elements are set equal to 1. Doing so, the majority of the generated solutions in early iterations are feasible. As ω becomes larger in the later iterations, the number of infeasible solutions grows such that eventually almost all the solutions in the sample are infeasible. The algorithm can be stopped at this stage being confident that further increase in the value of ω cannot improve the quality of the best found solution as no more feasible solutions can be generated.

Integration of the CE method with CPLEX solver: Through nested generation of binary decision variables Type I and projecting them in the proposed MINLP model, the nonlinear problem is reduced to a MILP model with linear objective function and constraints. The reduced model that contains the auxiliary binary variables (corresponding to the step-functions of truck sizes and warehouse sizes) can be solved using the CPLEX integer programming solver. The integration of the proposed nested CE algorithm with CPLEX will form the *Nested Integrated Cross Entropy (NICE)* algorithm. The four-step process of the proposed NICE algorithm is described below:

Step 1. Set $\omega = 0$ where ω is the number of binary variable Type I equal to zero in each generated random solution (i.e. all binary variables Type I are equal to one). Use CPLEX to find an optimal solution for the resulting MILP model and set it as the best found solution.

Step 2. Set $\omega = \omega + 1$ (i.e. one more binary variable is set equal to zero in each generated random solution). Use the standard CE algorithm to generate sample of binary variables Type I and project them in the MINLP model. The MINLP model is reduced to a MILP model. Discard those samples that make the model infeasible and keep the feasible ones. If no feasible solution is generated, go to Step 4.

Step 3. Use CPLEX to solve the resulting MILP models generated in Step 2. If the best solution among those optimal solutions is better than the best found solution in previous iterations, then replace the former with the latter. Return to Step 2.

Step 4. Stop and claim that the best found solution is a local optimal solution for the proposed MINLP model.

5. Model Implementation: A Case Analysis

5.1 The case company parameters

The case company, STA, is located in Australia. With over 40 years of manufacturing experience, STA is involved in the production and distribution of a wide range of tanks (e.g. steel/metal water tanks and farm storage tanks), high and low-pressure cylinders (e.g. automotive LPG and CNG cylinders) and other types of domestic/commercial metal containers. STA has three manufacturing plants in South Australia, Queensland and Victoria (M=3), each equipped with five machine centers (G=5). Plant 1, the largest of the three, has older machinery that is less expensive to operate, but is less energy-efficient and generates higher levels of carbon emissions and waste. Plant 2, the smallest of the three in size, is in an intermediate position in terms of production costs and emissions rates, and plant 3 has the highest operational costs but is the most efficient in the use of energy and materials.

Finished products are delivered to five retailers or customer locations across five Australian states (E=5) through six warehouses (W=6). Warehouses are leased annually based on the projected storage requirement (choice of small, medium and large warehouses). Due to the substantial difference between the storage capacity of small and medium warehouses, the initial model runs revealed that that the use of small warehouses in all six locations throughout the year cannot fully satisfy the forecasted demand. Holding costs and energy/carbon efficiency rates vary from one warehouse to another based upon the rental rates, insurance costs, salaries and labor availability, material handling equipment used, and energy sources available (this also explains the differences in cost and emission rates for storing products in plants). The maximum difference in holding costs is about 30% between the cheapest (South Australia) and the most expensive (New South Wales) alternatives. Emissions and energy consumption rates differ as much as 40% between the least green (Queensland) and greenest (Victoria) warehouses.

In transport, three truck types can be used for the direct and indirect shipment of products from plants to retailers. Small trucks have a maximum load-carrying capacity of two tons, medium trucks can handle up to four tons, and heavy trucks carry a maximum of six tons. For different truck types in different routes, per unit shipping costs and carbon emission rates can be as much as 20% and $40%, respectively. For a given route and truck type, the emission rates are calculated assuming full truckload shipping and using average travelling speed at each route (see Fahimnia et al. (2013c)). Loading and unloading emissions are not taken into consideration. Planning horizon is one year comprising 12 one-month periods (T=12). Production, inventory holding and transportation emission and energy consumption rates are assumed to remain unchanged during the planning horizon. Our analysis focuses on the SC planning for four of STA's nationally recognized product types including a kind of LPG cylinder, two most popular types of small and medium metal water tanks, and a medium metal farm storage tank (I=4).

Other production and distribution characteristics are described below.

- STA is currently leasing medium size *warehouses* in all six locations. For STA's relatively bulky products, a medium size warehouse can store an average of two small truckloads while a large warehouse can hold up to five loads. Small warehouses have shown to be unable to provide the required storage needs for the complete demand satisfaction.
- Small, medium and heavy *truck types* are the available transport alternatives. STA has been using a mixture of the three truck types with small trucks used in about 90% of all transports.
- A *carbon price* of $23 per ton of emission has recently been introduced by the Australian Government, implementation of which was commenced in July 2012. No emission cap has been introduced by the scheme and we accordingly impose no emissions limit to STA's manufacturing, storage and transportation operations.
- *Electricity* is considered as the primary energy source at STA manufacturing plants. Electricity is consumed in all production stages including welding, machining, forming, deep drawing, trimming, piercing, rolling, bolting, riveting and crane operations. Likewise, in warehouses, electricity is regarded as the sole energy source used for heating/cooling, lightings and lift-truck operations.
- *Electricity prices* vary from one location to another ranging from 21.5 cents/kilowatt-hour (c/kW-h) in Victoria to 24.3 c/kW-h in Queensland to 28.5 c/kW-h in South Australia.

The proposed mathematical model along with the NICE solution method was coded in MATLAB 7.13 recalling CPLEX for solving the related linear models. The multiple objective functions of the proposed mathematical model are converted into one weighted-sum objective function by expressing the emission, energy and waste values in equivalent dollar amount. Therefore, in Equation 27, ρ_1 is set equal to 1, ρ_2 is the cost of emissions per kg, ρ_3 is the cost of energy per kW-h, and ρ_4 is the cost of waste per unit. Local energy prices (part of ρ_3) are addressed through the adjustment of the energy usage in plants and warehouses. A sample size of 100 is used in all the experiments. With three manufacturing plants, six warehouses and 12 time periods, the number of binary variables for opening/closing plants and warehouses (G_{mt} + G'_{wt}) is equal to (3+6)*12=108. According to the NICE procedure outlined in Section 4, the first iteration seeks to find best possible production/distribution allocation strategies when all plants and warehouses are open (108 open plants/warehouses). The next iteration randomly closes one of the open plants/warehouses and finds the best value of Z (Equation 27) by solving the resulting linear model. This value is then compared to the best in-hand solution. The termination condition is the iteration that finds no feasible solution in the sample of 100 solutions (i.e. the ratio of infeasible solutions to the sample size is equal to 1).

5.2 Case study decision scenarios

We present the numerical results in three scenarios representing the possible integration of two warehousing and three transport decisions. These decision scenarios are developed to show the application of our model and solution method in tactical SC planning and to aid the greenness-versus-greenness discussion in Section 6. The aim is to determine optimal production and distribution allocation strategies in three warehouse-transport scenarios (WTSs). The storage and trucking characteristics of each WTS are shown in Table 1.

Table 1 The warehouse-transport scenarios (WTSs)

WTS1 (the lean situation)	Medium inventory holding capacity (medium warehouses)	+	Small/medium lot size deliveries (small/medium trucks)
WTS2 (the centralized situation)	Large inventory holding capacity (large warehouses)	+	Small/medium/large lot size deliveries (small/medium/heavy trucks)
WTS3 (the flexible situation)	Medium/large inventory holding capacity (medium/large warehouses)	+	Small/medium/large lot size deliveries (small/medium/heavy trucks)

A medium warehouse can store an average of two small truckloads while a large warehouse can hold up to four loads. Larger warehouses impose more expensive opening costs but have more inexpensive holding costs per item and are more environmentally efficient on a per unit basis. Specific opening costs, holding costs and energy/carbon efficiency rates are known for each warehouse size at each location. In transport, small, medium and heavy trucks have the load-carrying capacity of two, four and six tons respectively. This enforces that a medium size warehouse can only be fed by small or medium trucks (as in WTS1). Conversely, heavy trucks are assumed to supply warehouses with the minimum capacity to hold one heavy truckload. This would give a large warehouse the choice of being served by either truck types (as in WTS2). Specific shipping cost and carbon emission rates are available for each truck type. WTS3 will have the flexibility of leasing either medium or large warehouse at each location. However, the decision of leasing a medium or large warehouse at each location remains unchanged during the planning horizon (i.e. fixed annual leasing period).

A primary aim of this scenario set is to provide an analysis and discussion on whether SC *leanness* results in more *greenness*. The three scenarios can be evaluated from a lean perspective through the expected levels of inventory held in the SC. Smaller vehicles and warehouses are expected to be limited in the inventory they can carry, which would be emblematic of a leaner SC. Allowing for larger warehouses and trucks only is a relatively less lean scenario, representing a more centralized situation. Based on the definition of lean that focuses on average inventory levels, the leanest scenario is WTS1, the least lean is scenario WTS2, and WTS3 is more of a hybrid situation. Of course, we recognize that lean practice is based on more than just average inventory levels, but it is an important, if not the most important, dimension of organizational leanness (Carvalho et al., 2010; Pettersen, 2009; Shah and Ward, 2007).

5.3 Case Results

Detailed numerical results from the model implementation for the three WTSs are presented in Appendix B. For each scenario, the numerical results include the iteration number, number of feasible solutions at each iteration, overall SC cost (from Equation 27), best found solution and the iteration at which it is found, as well as the values of four objective functions and their constituting elements. Table 2 summarizes the numerical results and outlines the characteristics of the local optimal solution for each of the three scenarios. Also included in the numerical results are the average warehouse capacity utilization and truckload utilization. This will provide some insights for the leanness-versus-greenness discussion in Section 6. Model runtime for each scenario varies between 15 and 20 minutes for a sample size of 100.

Table 2 Solution characteristics at the local optimal point for the three WTSs

	Overall SC cost ($)	Generated emissions (kg)	Consumed energy (kW-h)	Generated wastes (units)	No of 'zero' binary variables	Average warehouse capacity utilization (%)	Average truckload utilization (%)
WTS1	32,488,231	26,358,552	2,930,322	846	24	71.5 (+/- 3%)	81.1 (+/- 5%)
WTS2	31,600,746	23,491,646	2,837,776	824	23	79.7 (+/- 3%)	82.5 (+/- 4%)
WTS3	31,482,940	23,185,519	2,663,075	765	22	83.3 (+/- 4%)	89.7 (+/- 4%)

6. Discussion – To be Lean or Not?

We start our discussion by illustrating in Figure 2 how the model converges to the local optimal solution for the three WTSs. The local optimal solution (lowest hit) is marked for each scenario. As discussed in Section 4, each iteration generates an additional zero binary variable (i.e. at each iteration, one more random plant/warehouse is closed in a random period) and finds the optimal solution to the resulting linear model. The model terminates when it finds no more feasible solution to the problem. At this point no more plants/warehouses can be closed (i.e. no more binary variables can be set equal to zero). The local optimal solution is where the SC cost is the lowest, after which no more improvement can be observed in the value of objective function Z (Equation 27). For instance, in WTS3, the demand can still be satisfied by closing the plants and warehouses in 34 instances (in Table B3, 34 iterations indicate 34 randomly closed plants/warehouses). However, the local optimal solution in this case is found in iteration 22 which implies that closing plants and warehouses in more than 22 instances produces no better solution. WTS3 hits its lowest found cost quicker than WTS1 and WTS2. WTS1 produces the worst figure in terms of both the solution quality and convergence speed.

The NICE method aims to satisfy the given demand by utilizing the available resources (i.e. it closes as many plants and warehouses in all periods as practicable to generate a feasible solution). With this rationale, one can safely assume that the approach is able to produce quality local optimal solutions as it uses the minimum possible resources to fulfil the demand. What we don't know at this time is the quality of the solutions found when compared to other solution methods. Our goal for this paper was to introduce the NICE method and its application in solving a real SC planning problem. Future research can focus on evaluating the performance of the NICE method against the more established heuristic algorithms in solving a range of small, medium and large nonlinear SC planning test problems.

Fig. 2. The convergence of overall SC cost in three WTSs

We now focus our analysis on the numerical results for SC costs which we split into non-environmental and environmental costs. Figure 3 shows the non-environmental costs for each of the three scenarios. The non-environmental costs include the cost of production, distribution and backlog excluding their corresponding environmental costs. Production cost is at its lowest in WTS2, while WTS3 shows the lowest distribution and backlog costs. Production, distribution and backlog costs are at their highest in WTS1, the leanest situation. Backlog cost (which can be viewed as a measure of customer service level) is reduced in WTS2 and even more in WTS3, the most flexible option. This is sensible as demands can be fulfilled more effectively when more flexible transport and warehouse options are available. There is about 16% difference in service level between the worst and best performing scenarios, corresponding to lead and flexible situations, respectively.

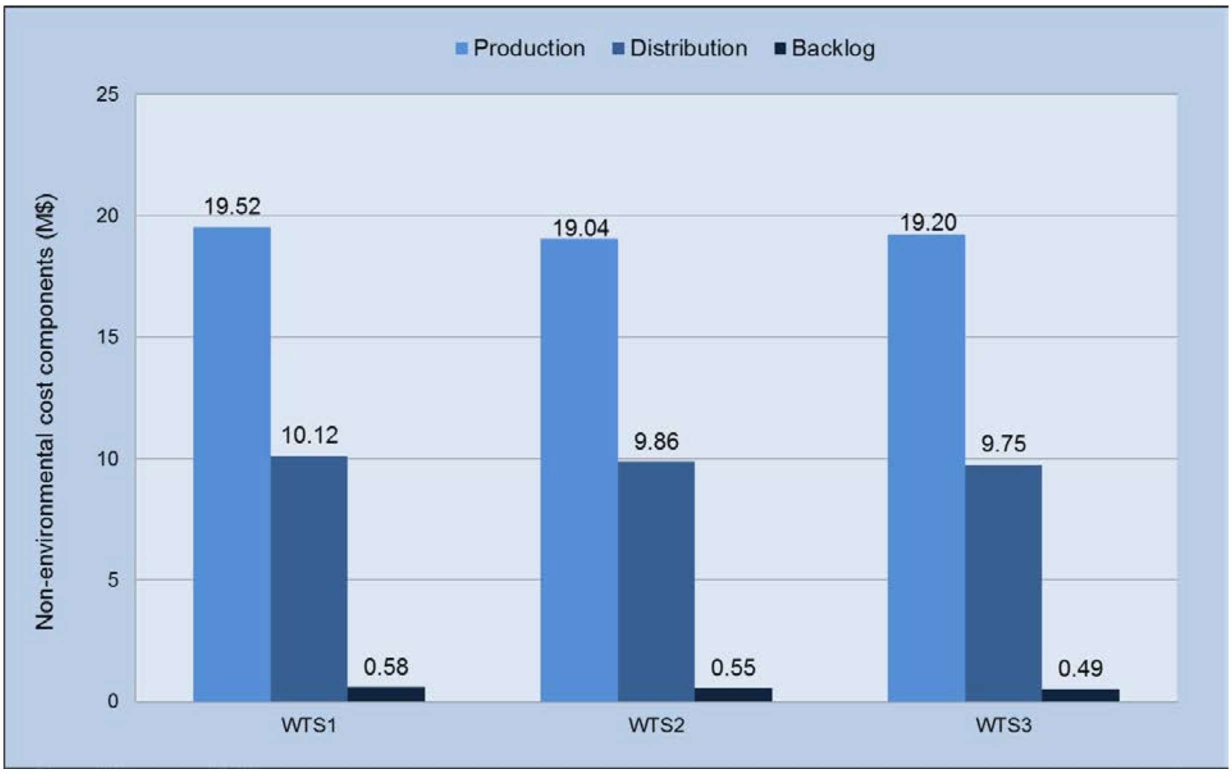

Fig. 3. Comparison of non-environmental costs in three WTSs

The overall environmental costs for each scenario include the costs of carbon emissions, energy consumption and waste generation. Figure 4 compares the environmental costs at the local optimal point for three WTSs. While WTS3 incurs the lowest cost of carbon, energy and waste, WTS1 results in the highest environmental cost. WTS2 results in slightly better performance than WTS1. Overall, these results point to a situation where lean practices are actually more detrimental to environmental performance. But, the least lean, more centralized larger warehouse and larger truck delivery situation for WTS2, performs only slightly better. The hybrid situation, allowing for the largest range of sizes, performs the best. The methodology takes advantage of these looser constraints allowing for a better choice balancing the waste costs and lessened carbon emissions per unit from larger warehouses against fewer emissions from larger truck deliveries. This finding indicates that the organization can take advantage of integrated lean and centralized situations for more efficient environmental performance. A strictly lean situation is shown be the worse alternative at the tactical planning level for this organization.

From the trends in Figure 3 and 4, it can be understood that more efficient economic and environmental performance may be resulted when a greater choice of warehouse sizes and transport modes are available. This result is not surprising due to fewer constraints on the choices available. In real world practice, the more varieties and choices available, the easier it is to improve. Yet, greater choice and variety may typically result in greater initial design costs, less continuity and standardization, and other costs of building flexibility into a system design.

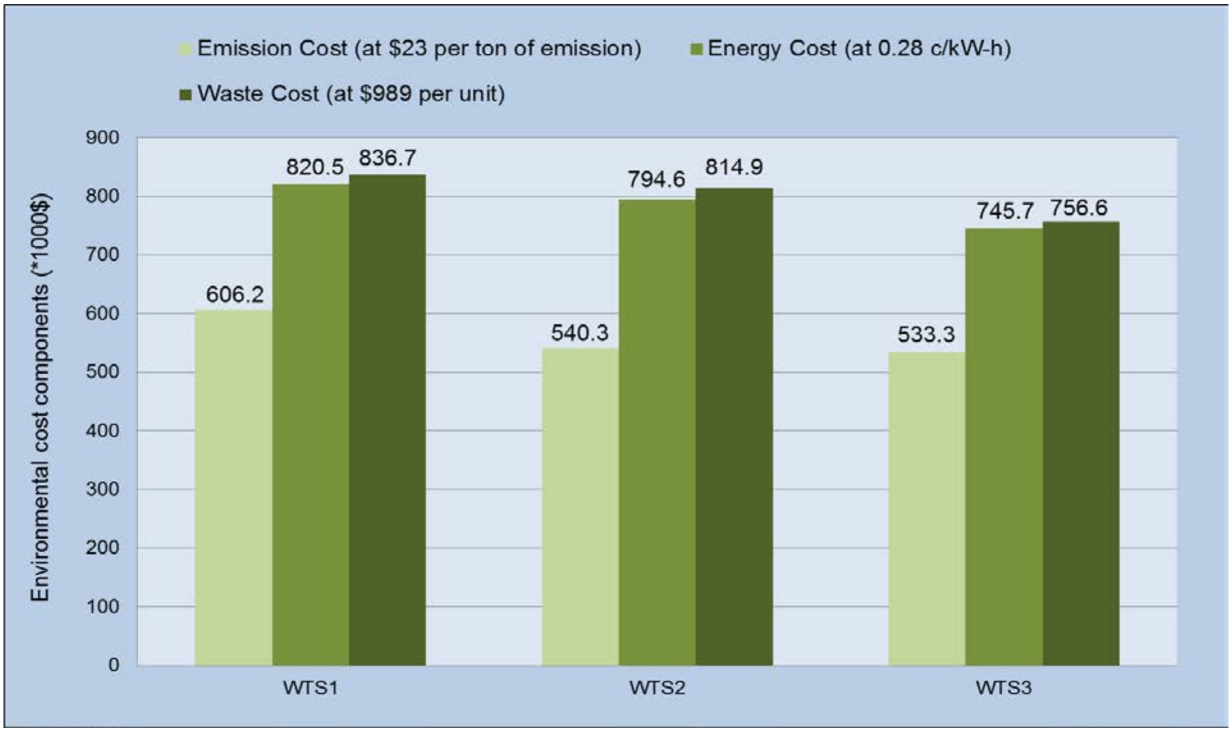

Fig. 4. Comparison of the environmental costs in three WTSs

Studies on the relationship between lean practices and green outcomes date back to when issues of relating manufacturing strategy and environmental concerns in organizations were evolving (Maxwell et al., 1993; Sarkis, 1995). Arguably, lean and green paradigms overlap by focusing on waste reduction and lead time reduction techniques (Dües et al., 2012). Most studies with a lean and green focus target efficient use of energy and resources and the reduction of waste (Carvalho et al., 2010; King and Lenox, 2001; Larson and Greenwood, 2004; Yang et al., 2011). There is however evidence that not all lean efforts can be positively related to environmental performance (Rothenberg et al., 2001; Zhu and Sarkis, 2004). Our results fall within this scope, but with a clear focus on tactical SC planning decisions. In this context, Cholette and Venkat (2009) showed that SC design and planning, especially with respect to transportation links and warehousing activities, can cause substantial variation in energy consumption and carbon emissions. While the focus on carbon emissions at the operational planning level has yet to be thoroughly investigated, our model provides a valuable exploratory tool for this purpose.

The lean-and-green debate argues that tradeoffs may exist depending on the environmental objective (waste reduction, carbon emission, energy consumption) and the SCM strategies (production, transportation, warehousing) of the lean practice. Thus, a decomposition of the costs and their location along the SC may provide greater insight into the lean-and-green debate. Noting this situation, we introduce Figure 5 which sets WTS1 as the baseline and illustrates the incremental percentage improvements in SC cost components by scenarios WTS2 and WTS3.

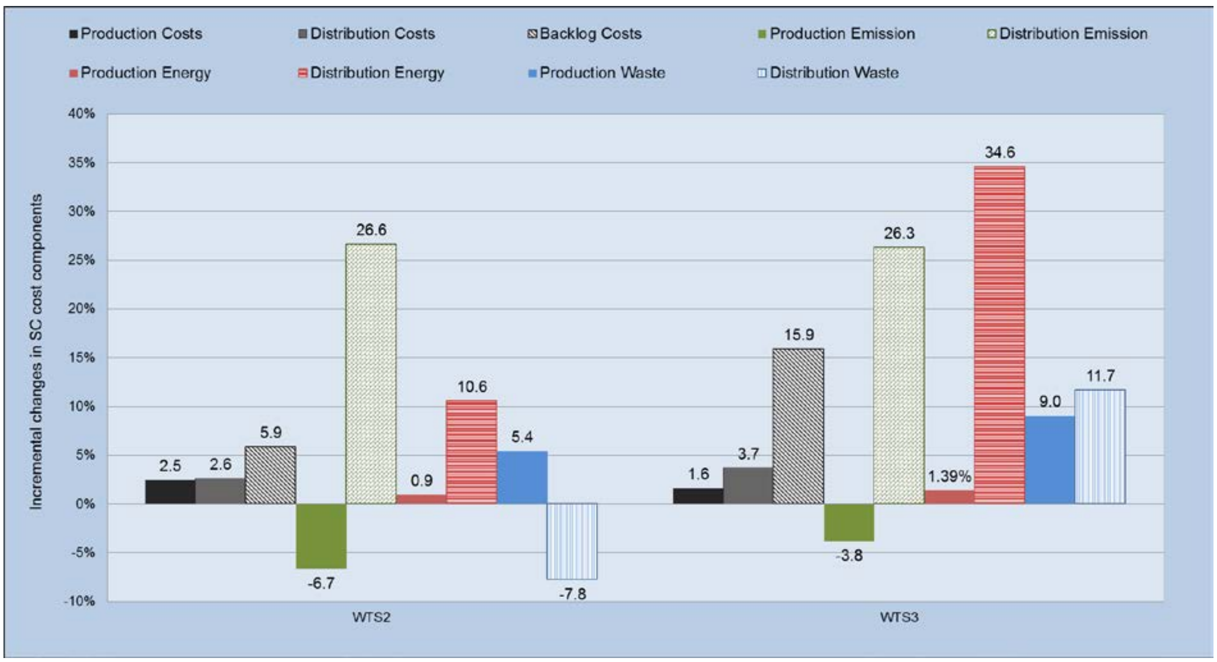

Fig. 5. Incremental changes in SC cost components compared to the baseline of WTS1

Figure 5 shows that the lean situation (WTS1) performs worse than the other two scenarios. In a more careful examination, we see that WTS1 actually performs better than both other scenarios on production function emissions (6.7% and 3.8% better performance than WTS2 and WTS3 respectively). Producing in smaller lot sizes to fill smaller trucks and warehouses reduces production emissions in this scenario. This result seems counter-intuitive since one of the aspects of smaller lot sizes in lean manufacturing is a greater number of set-ups which is typically non-value-adding. Larger production lot sizes will cause greater production emissions on average, if setup time is not considered. Future modeling efforts at the operational level can focus on the effects of setup time and number of setups to provide a clearer picture of the tradeoffs for production emissions (here, we focused on tactical aspects).

The centralized situation with a lean based transport and a non-lean based warehousing (WTS2) is more economically and environmentally efficient compared to the lean situation (WTS1). In the best case scenario, WTS3 results in smallest production/transport costs and least environmental impacts as it is more flexible both in transport and warehousing. This finding may be highly dependent on many factors such as the warehouse opening costs, economic and environmental cost of storage, the availability of different transport modes, as well as the shipment costs and emission rates.

One expected result that seems to hold is that distribution emissions are much improved in less lean scenarios (26.6% in WTS2, 26.3% in WTS2). This result is expected because in the lean situation smaller truck delivery sizes imply more and smaller deliveries with less emission efficient vehicles on a per unit basis. A similar reasoning is given for distribution energy use. But, the difference between WTS2 and WTS1, and WTS3 and WTS1 is much pronounced. This is a situation where greater truck-size flexibility allows WTS3 to more effectively eliminate less-than-truckload deliveries and waste. This is evidenced by nearly 90% average truckload utilization in WS3 (see Table 1). The situation of less efficiency due to limited larger truck size with WTS2 is clearer when comparing the distribution waste values. WTS2 is worse than WTS1 by 7.8%, whereas WTS3 is better than WTS1 by 11.7%.

Thus, we can see the tradeoffs a little more clearly overall in these situations. What we do not know at this time is the relative importance of each of these environmental performance results other than as a cost basis. Organizations can adjust the importance of each environmental dimension by assigning greater costs (objective function coefficients) to specific types of environmental emissions. These values are bound to change depending on industry, location and organization. For example, if the production and distribution waste is attributed to a hazardous or toxic material, then these wastes would get a much higher priority and thus larger coefficients. At this time, in Australia where the case company is located, carbon emissions are becoming a critical policy issue. Carbon taxes and a carbon trading market will make the situation a bit more dynamic, which points to allowing for the greatest flexibility in designing the SC. However, flexibility has value in situations where uncertainty exists. As the carbon taxes and carbon markets stabilize, organizations may seek to focus more on their business efficiencies as optimization of environmental emissions would be stabilized and optimized.

All these recommendations are based on assumptions that were considered for the development of the model and solution technique. Our analysis was at a tactical level with limited linkage to operational decisions and perspectives which may cause variation in the outcomes. Hierarchical linkage is a definite direction for future planning and design of an environmentally sound SC. Additional tweaking of the model, such as setup time delineations and delivery time and work flexibility costs, may provide additional nuanced evaluations from both economic and environmental perspectives.

7. Conclusions

This paper presented a multidimensional MINLP model for green SCM at the tactical planning level. The model can be used to explore tradeoffs between cost and environmental degradation including carbon emissions, energy consumption and waste generation. We took advantage of the model structure and introduced the NICE method, a CE-based solution technique, to solve the encountered MINLP model. Using real data from an actual SC, we showed how the model can be utilized to provide practical insights in a tactical SC decision environment facing operations, logistics and SC managers.

Our exploratory analysis focused on investigating critical issues related to the lean-and-green debate. While some lean interventions may inadvertently result in green benefits, especially through waste and lead time reductions, we found not all SC lean practices at the tactical planning level are in line with greening strategies and tactics. In fact, a strictly lean situation was shown be the worst environmentally sustainable alternative when compared to centralized (less lean) and flexible SC situations. We showed how organizations can take advantage of SC agility through integrated lean and centralized situations for more efficient environmental performance.

These results may however hold for the tactical SC planning only. Modeling efforts at the operational level that can investigate the effects of setup time and number of setups may provide a clearer picture of the tradeoffs between these situations. In addition, applying the model to strategic design issues, such as centralized versus decentralized warehousing and manufacturing designs, is a fertile direction for future research to answer more cost versus environmental tradeoffs. The dynamic nature of government policies and industrial competitiveness can also be integrated into future models as various emergent policies and markets evolve.

While we have shown the utility of our complex mathematical model and solution approach, our study is not without limitations. Although the model is realistic, and we have shown its application to a real world situation, some organizations may find that the data requirements and complexity of the model cumbersome. Allowing for model modular design and testing these models to identify the sensitivity of the results may allow for greater acceptance of the model. In the application of the model to the particular case of the lean-and-green debate, it was found that additional nuanced and detailed aspects of the model can be enhanced. This limitation is the opposite of our first limitation, in that additional complexity and considerations of the model can benefit additional study of various tradeoff questions facing policy makers and organizations. The NICE method can be more thoroughly tested against other established heuristics for solving nonlinear mathematical programming models. Our goal for this paper was to introduce this technique and future research directions would be to evaluate the efficiency of the NICE method and how to improve its performance.

The investigation of the influence of organizational decisions on sustainability of industries and communities is gaining increasing importance. The development and availability of new models and tools can help address many of these concerns. Given the multiple contributions of this work, we set the stage for additional and important future research directions, including new model and solution extensions, and potential for new applications and exploratory analyses.

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Appendix A Input parameters

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 small-size w at t
c^{oc}_{wt}	Warehouse opening coefficient for the choice of small/medium/large w at t
cm^{oc}_{wt}	Cost coefficient for opening medium-size w at t
cl^{oc}_{wt}	Cost coefficient for opening large-size w at t
h_{imt}	Unit holding cost for i in m at t
h'_{iwt}	Unit holding cost for i in small-size w at t
c^{hc}_{iwt}	Holding cost coefficient for the choice of small/medium/large warehouses for holding i in w at t
cm^{hc}_{iwt}	Cost coefficient for holding i in medium-size w at t
cl^{hc}_{iwt}	Cost coefficient for holding i in large-size w at t
hc^{m}_{imt}	Holding capacity (maximum units) of m for i at t
hc^{ws}_{iwt}	Holding capacity (maximum units) of small-size w for i at t
hc^{wm}_{iwt}	Holding capacity (maximum units) of medium-size w for i at t
hc^{wl}_{iwt}	Holding capacity (maximum units) of large-size w for i 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
p_{igmt}	Processing time (hrs) to produce a unit of i on g 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 backlog (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
stc_i	Capacity of small trucks for the shipment of product i
mtc_i	Capacity of medium trucks for the shipment of product i
htc_i	Capacity of heavy trucks for the shipment of product i
τ_{ijkt}	Unit transportation cost of i (using small trucks) from j to k at t ($jk \in \{mw, we, me\}$)
c^{tc}_{ijkt}	Transport coefficient for the choice of small/medium/heavy trucks for transportation of i from j to k at t ($jk \in \{mw, we, me\}$)
cm^{tc}_{ijkt}	Cost coefficient for using medium trucks for transportation of i from j to k at t ($jk \in \{mw, we, me\}$)
ch^{tc}_{ijkt}	Cost coefficient for using heavy trucks for transportation of i from j to k at t ($jk \in \{mw, we, me\}$)
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)
a_{igmt}	Estimated carbon emission to produce a unit of *i* on *g* in *m* at *t*
a^{ce}_{ijkt}	Estimated carbon emission for transferring *i* (using small trucks) from *j* to *k* at *t* ($jk \in \{mw, we, me\}$)
c^{ce}_{ijkt}	Carbon emission coefficient for the choice of small/medium/heavy trucks for transportation of *j* from *k* to *w* at *t* ($jk \in \{mw, we, me\}$)
cm^{ce}_{ijkt}	Carbon emission coefficient for using medium trucks for transportation of *i* from *j* to *k* at *t* ($jk \in \{mw, we, me\}$)
ch^{ce}_{ijkt}	Carbon emission coefficient for using heavy trucks for transportation of *i* from *j* to *k* at *t* ($jk \in \{mw, we, me\}$)
a^{m}_{imt}	Estimated carbon emission for holding one inventory unit of *i* in *m* at *t*
a^{w}_{iwt}	Estimated carbon emission for holding one inventory unit of *i* in small-size *w* at *t*
c^{a}_{iwt}	Emission coefficient for the choice of small/medium/large warehouses for holding *i* in *w* at *t*
cm^{a}_{iwt}	Emission generation coefficient for holding *i* in medium-size *w* at *t*
cl^{a}_{iwt}	Emission generation coefficient for holding *i* in large-size *w* at *t*
a^{maxm}_{mt}	Maximum allowed carbon emission in *m* at *t*
a^{maxw}_{wt}	Maximum allowed carbon emission in *w* at *t*
a^{maxa}_{t}	Maximum allowed transport emission at *t*
b_{igmt}	Energy use per hour for processing *i* on *g* in *m* at *t*
b^{m}_{imt}	Energy use for holding one inventory unit of *i* in *m* at *t*
b^{w}_{iwt}	Energy use for holding one inventory unit of *i* in small-size *w* at *t*
c^{b}_{iwt}	Energy coefficient for the choice of small/medium/large warehouses for holding *i* in *w* at *t*
cm^{b}_{iwt}	Energy use coefficient for holding *i* in medium-size *w* at *t*
cl^{b}_{iwt}	Energy use coefficient for holding *i* in large-size *w* at *t*
b^{maxm}_{mt}	Maximum allowed energy use in *m* at *t*
b^{maxw}_{wt}	Maximum allowed energy use in *w* at *t*
u_{igmt}	Average waste generated for processing *i* on *g* in *m* at *t*
u^{m}_{imt}	Average waste generated for holding one inventory unit of *i* in *m* at *t*
u^{w}_{iwt}	Average waste generated for holding one inventory unit of *i* in small-size *w* at *t*
c^{u}_{iwt}	Waste coefficient for the choice of small/medium/large warehouses for holding *i* in *w* at *t*
cm^{u}_{iwt}	Waste generation coefficient for holding *i* in medium-size *w* at *t*
cl^{u}_{iwt}	Waste generation coefficient for holding *i* in large-size *w* at *t*
u^{max}_{it}	Maximum allowed waste generation for *i* at *t*
M	"Big M" method: "M" stands for a large number - an artificial variable
ρ_1	Cost function coefficient
ρ_2	Emission function coefficient
ρ_3	Energy function coefficient
ρ_4	Waste function coefficient

Appendix B Detailed numerical results for three WTSs

Table B1 Numerical result for warehouse-transport scenario 1 (WTS1)

					Objective Function 1 ($) Cost Function				Objective Function 2 (kg) Emission Function			Objective Function 3 (kW-h) Energy Function			Objective Function 4 (units) Waste Function		
Iter	No of Feas Sol	Overal Cost	Best Sol Found	Best Sol Found in Iter	Obj Val 1	Prod Cost	Dist Cost	Backl Cost	Obj Val 2	Prod Em	Dist Em	Obj Val 3	Prod En	Dist En	Obj Val 4	Prod Wa	Dist Wa
1	100	34812559	34812559	1	32748444	20875015	11278184	595245	26410420	12556568	13853852	2715783	2204776	511007	704	580	124
2	100	34612611	34612611	2	32548493	20675029	11278219	595245	26410486	12556567	13853919	2715788	2204776	511012	704	580	124
3	100	34429426	34429426	3	32357388	20464658	11316676	576054	26615111	12641334	13973777	2716667	2205658	511009	707	583	124
4	100	34314091	34314091	4	32240989	20391977	11253767	595245	26879649	12722987	14156662	2712867	2201840	511027	703	579	124
5	100	34304561	34304561	5	32200994	20512860	11108482	579652	26697407	12690494	14006913	2762465	2209405	553060	724	590	134
6	96	34118258	34118258	6	32029731	20262601	11187476	579654	26949616	12785853	14163763	2719824	2208756	511068	715	591	124
7	100	34118188	34118188	7	32029946	20352192	11085725	592029	26937358	12780786	14156572	2719813	2208798	511015	715	591	124
8	100	33932012	33932012	8	31805268	20160942	11068273	576053	26776818	12713248	14063570	2803395	2208387	595008	734	589	145
9	100	33822652	33822652	9	31627812	19738967	11319176	569669	27891996	13065908	14826088	2898478	2198382	700096	750	580	170
10	98	33667145	33667145	10	31545860	20133206	10817409	595245	26578982	12636176	13942806	2803681	2208669	595012	733	588	145
11	84	33950937	33667145	10	31790044	20639246	10574670	576128	26286153	12533138	13753015	2845567	2229535	616032	768	618	150
12	80	33359932	33359932	12	31235145	19650360	11009989	574796	27392148	13015254	14376894	2731733	2220512	511221	738	614	124
13	84	33427046	33359932	12	31311680	20144364	10575288	592028	27085886	12837811	14248075	2762097	2209084	553013	727	593	134
14	86	33552114	33359932	12	31410579	20072076	10748390	590113	26538168	12561815	13976353	2815778	2220690	595088	751	606	145
15	80	33195236	33195236	15	30951742	19326895	11032817	592030	27795706	13042113	14753593	2981252	2204215	777037	778	589	189
16	72	33276865	33195236	15	31081192	19905430	10579317	596445	27023355	12811741	14211614	2912759	2212759	700000	767	597	170
17	44	33343010	33195236	15	31080475	20116462	10386405	577608	27185224	12904517	14280707	3000502	2223460	777042	806	617	189
18	64	33971552	33195236	15	31498638	20487028	10480507	531103	26847118	12767307	14079811	3309852	2263830	1046022	939	677	262
19	44	32772278	32772278	19	30534143	19315916	10648981	569246	27636681	13015624	14621057	2950451	2215427	735024	785	606	179
20	60	33586781	32772278	19	31046092	19500749	11040354	504989	29694409	13735357	15959052	3310956	2223984	1086972	941	633	308
21	54	32835500	32772278	19	30590142	19916363	10081751	592028	27697686	12968306	14729380	2946508	2208006	738502	792	593	199
22	42	33842469	32772278	19	31461599	21151877	9808674	501048	25619627	12320510	13299117	3170258	2274310	895948	914	685	229
23	36	33624328	32772278	19	31131646	20086703	10522207	522736	28538237	13753203	14785034	3177961	2292420	885541	957	742	215
24	30	32488231	32488231	24	30224800	19517140	10122986	584674	26358552	12463336	13895216	2930322	2247811	682511	846	666	180
25	28	34305626	32488231	24	31611680	20819682	10310242	481756	27189312	13119028	14070284	3562514	2295372	1267142	1083	743	340
26	14	34137264	32488231	24	31131756	21080252	9489334	562170	27433128	12715791	14717337	4178369	2232366	1946003	1218	628	590
27	14	34382672	32488231	24	31280594	20768575	10066031	445988	27022566	12714649	14307917	4362721	2298024	2064697	1273	729	544
28	18	36640249	32488231	24	32788107	22641253	9860717	286137	26311997	12373057	13938940	5598726	2378065	3220661	1698	845	853
29	16	35925371	32488231	24	31734404	21078670	10167238	488496	28224105	12914480	15309625	6390372	2285913	4104459	1772	713	1059
30	12	36300646	32488231	24	32148745	21348868	10528533	271344	28780292	13243397	15536895	6095667	2326675	3768992	1803	784	1019
31	18	34217680	32488231	24	31195132	20928517	9844261	422354	27135453	13044454	14090999	4182440	2334246	1848194	1241	792	449
32	8	35490054	32488231	24	31819361	21154733	10290542	374086	28546112	13410396	15135716	5328788	2329580	2999208	1539	790	749

Table B2 Numerical result for warehouse-transport scenario 2 (WTS2)

					Objective Function 1 ($) Cost Function				Objective Function 2 (kg) Emission Function			Objective Function 3 (kW-h) Energy Function			Objective Function 4 (units) Waste Function		
Iter	**No of Feas Sol**	**Overal Cost**	**Best Sol Found**	**Best Sol Found in Iter**	Obj Val 1	Prod Cost	Dist Cost	Backl Cost	Obj Val 2	Prod Em	Dist Em	Obj Val 3	Prod En	Dist En	Obj Val 4	Prod Wa	Dist Wa
1	100	34633251	34633251	1	32689660	20876065	11218346	595249	22284990	12558183	9726807	2606554	2205029	401525	709	581	128
2	100	34427481	34427481	2	32479230	20580973	11303009	595248	22666982	12715010	9951972	2602415	2200891	401524	706	578	128
3	100	34271407	34271407	3	32321101	20504237	11221615	595249	22325613	12587815	9737798	2609537	2208008	401529	714	586	128
4	100	34119554	34119554	4	32168769	20592946	10980575	595248	22676379	12725376	9951003	2603628	2202105	401523	708	580	128
5	100	34002556	34002556	5	32040190	20350109	11119500	570581	22560343	12717865	9842478	2612136	2210525	401611	720	592	128
6	96	33859611	33859611	6	31908821	20592966	10720606	595249	22676446	12725382	9951064	2603640	2202106	401534	708	580	128
7	98	33703308	33703308	7	31741267	20254808	10893223	593236	22335024	12644481	9690543	2615352	2213820	401532	724	596	128
8	92	33524298	33524298	8	31528535	20198524	10734765	595246	22942421	12876463	10065958	2668236	2200722	467514	729	580	149
9	96	33547244	33547244	8	31482921	20198559	10689117	595245	22481045	12705936	9775109	2746126	2212621	533505	787	596	191
10	92	33337752	33337752	10	31329102	20140131	10593714	595257	22725978	12766289	9959689	2661395	2206913	454482	749	588	161
11	96	33205078	33205078	11	31201039	20157827	10447966	595246	22632971	12784021	9848950	2677293	2209765	467528	742	593	149
12	92	33138690	33138690	12	31115005	20496476	10023282	595247	22589936	12719768	9870168	2722734	2205723	517011	750	585	165
13	80	33072841	33072841	13	30958269	20007577	10373713	576979	22610637	12718733	9891904	2869025	2208842	660183	800	590	210
14	80	32807337	32807337	14	30773323	19721632	10480552	571139	23426913	13205827	10221086	2659083	2221766	437317	759	620	139
15	82	32800292	32800292	15	30736372	19961623	10198778	575971	22950424	12960046	9990378	2737919	2220913	517006	778	613	165
16	76	32784237	32784237	16	30722212	20367606	9762569	592037	23016254	13035202	9981052	2718680	2226304	492376	780	623	157
17	74	32577076	32577076	17	30471210	19767531	10126084	577595	22540550	12822963	9717587	2808366	2230732	577634	810	626	184
18	72	32546688	32546688	18	30310281	19833959	9883094	593228	22989990	12893068	10096922	2951565	2209020	742545	891	593	298
19	50	32473515	32473515	19	30214559	19358806	10284840	570913	22964494	12849642	10114852	2974143	2222678	751465	908	614	294
20	50	33131866	32473515	19	30585011	20201693	9805989	577329	23690909	13290169	10400740	3458782	2245946	1212836	1045	659	386
21	38	32533300	32473515	19	30104304	19792433	9750772	561099	23002156	12812262	10189894	3306361	2226363	1079998	985	619	366
22	60	31997512	31997512	22	29841333	19605431	9661471	574431	22883336	13032111	9851225	2829210	2251479	577731	847	663	184
23	32	31600746	31600746	23	29450924	19039517	9861032	550375	23491646	13298402	10193244	2837776	2227243	610533	824	630	194
24	24	33391989	31600746	23	30414579	20402453	9562834	449292	23444287	12946341	10497946	4133698	2265684	1868014	1295	681	614
25	24	32960672	31600746	23	30146528	20207847	9407003	531678	23292460	12687707	10604753	3969275	2232884	1736391	1180	628	552
26	22	35490561	31600746	23	31913289	22067353	9461268	384668	24644009	13631460	11012549	4817639	2347404	2470235	1680	824	856
27	24	32179439	31600746	23	29919598	20331758	9075078	512762	22404376	12898422	9505954	2949140	2289091	660049	929	719	210
28	18	32649833	31600746	23	29858648	20446687	8915245	496716	22202539	12377627	9824912	3800199	2279796	1520403	1230	694	536
29	16	31752737	31600746	23	29359206	19546103	9275375	537728	22278808	12547148	9731660	3161412	2250605	910807	1007	652	355
30	8	34320985	31600746	23	30840447	21511812	8993754	334881	23565128	13105476	10459652	4776245	2330964	2445281	1619	787	832
31	6	34521899	31600746	23	30929231	21418150	9251442	259639	24947746	13908795	11038951	4833547	2363103	2470444	1684	855	829

Table B3 Numerical result for warehouse-transport scenario 3 (WTS3)

					Objective Function 1 ($) Cost Function				Objective Function 2 (kg) Emission Function			Objective Function 3 (kW-h) Energy Function			Objective Function 4 (units) Waste Function		
Iter	**No of Feas Sol**	**Overal Cost**	**Best Sol Found**	**Best Sol Found in Iter**	Obj Val 1	Prod Cost	Dist Cost	Backl Cost	Obj Val 2	Prod Em	Dist Em	Obj Val 3	Prod En	Dist En	Obj Val 4	Prod Wa	Dist Wa
1	100	34439014	34439014	1	32513162	20875011	11042906	595245	22441548	12556570	9884978	2551529	2204775	346754	703	580	123
2	100	34241231	34241231	2	32315364	20675007	11045112	595245	22442199	12556576	9885623	2551530	2204776	346754	703	580	123
3	100	34131923	34131923	3	32206048	20675065	10935738	595245	22442333	12556560	9885773	2551550	2204778	346772	703	580	123
4	96	33970530	33970530	4	32037035	20503174	10938616	595245	22479647	12586201	9893446	2554507	2207753	346754	709	586	123
5	100	33863906	33863906	5	31930127	20416198	10918682	595247	22867881	12738927	10128954	2548354	2201576	346778	702	579	123
6	100	33697278	33697278	6	31762830	20360635	10805750	596445	22467798	12588574	9879224	2555352	2208600	346752	710	587	123
7	98	33712614	33712614	7	31772729	20582965	10594519	595245	22505540	12612119	9893421	2557542	2210790	346752	714	591	123
8	98	33458860	33458860	8	31508358	19992248	10922882	593228	22839698	12770290	10069408	2557410	2210656	346754	717	594	123
9	98	33410317	33410317	9	31468422	20317017	10556160	595245	22762093	12717992	10044101	2554242	2207474	346768	711	588	123
10	98	33306095	33306095	10	31286457	20103989	10612805	569663	23039919	12842959	10196960	2657188	2210677	446511	754	595	159
11	98	33319076	33306095	10	31273145	20068538	10639937	564670	22870309	12784367	10085942	2659063	2215656	443407	784	602	182
12	82	33051063	33051063	12	31021645	19950175	10479441	592029	22984375	12806117	10178258	2682553	2207521	475032	758	589	169
13	66	33642618	33051063	12	31492099	20294094	10632763	565242	24005489	13378224	10627265	2769800	2232958	536842	832	641	191
14	76	32864311	32864311	14	30815754	19679629	10540880	595245	23068514	12861968	10206546	2691014	2216012	475002	773	604	169
15	78	33094101	32864311	14	30954594	20146757	10213010	594827	22997620	12807685	10189935	2774407	2218629	555778	843	607	236
16	60	32565048	32565048	16	30509791	19322287	10631043	556461	23770761	13145686	10625075	2689049	2204859	484190	764	591	173
17	66	32866344	32565048	16	30857885	20076311	10191464	590110	22357659	12506050	9851609	2634455	2230415	404040	765	621	144
18	58	34299087	32565048	16	31404719	20784447	10141394	478878	23411464	12885185	10526279	3861012	2259495	1601517	1289	671	618
19	54	31765593	31765593	19	29718749	19131642	9990661	596446	23037391	12868136	10169255	2690983	2215919	475064	772	603	169
20	48	33789673	31765593	19	31160299	20162163	10551000	447136	24733513	13606347	11127166	3477115	2243711	1233404	1099	661	438
21	36	33132532	31765593	19	30991055	20617894	9829171	543990	22977941	12868538	10109403	2775998	2250638	525360	845	658	187
22	50	31482940	31482940	22	29447426	19204510	9750888	492028	23185519	12942905	10242614	2663075	2216566	446509	765	606	159
23	60	32381409	31762940	22	29981091	19200864	10223287	556940	22730549	12569986	10160563	3113218	2234581	878637	1017	628	389
24	20	33323491	31762940	22	30880923	20454915	9879807	546201	23041312	12969449	10071863	3065511	2281202	784309	1066	709	357
25	36	32402691	31762940	22	29882724	19317854	10077582	487288	24545490	13601960	10943530	3228977	2247070	981907	1063	667	396
26	32	33497966	31762940	22	30720030	20577391	9618252	524387	23388266	12947074	10441192	3641355	2268585	1372770	1234	688	546
27	10	34255830	31762940	22	31291660	20675566	10155556	460538	25136252	13903042	11233210	3717840	2324890	1392950	1360	795	565
28	12	35454519	31762940	22	31411401	21562100	9335048	514253	23098760	12277835	10820925	5675823	2270993	3404830	1944	679	1265
29	16	33388466	31762940	22	30357850	20247530	9565767	544553	24892039	13808957	11083082	3950484	2287023	1663461	1367	735	632
30	12	34531772	31762940	22	30889815	21105693	9359524	424598	23944672	13039546	10905126	4986009	2289672	2696337	1714	722	992
31	10	37627863	31762940	22	32599607	22619429	9709905	270273	24396724	12879152	11517572	6908219	2356026	4552193	2561	819	1742
32	6	36252350	31762940	22	31840783	21855559	9790342	194882	24718546	13266682	11451864	6007412	2355776	3651636	2185	828	1357
33	8	41269151	31762940	22	33317862	21978485	11186458	152919	27581904	13679730	13902174	11049554	2402316	8647238	4270	910	3360
34	2	39620639	31762940	22	32529671	21008780	11406697	114194	28024012	14145245	13878767	9865677	2377495	7488182	3725	878	2847