Decision Support Systems 51 (2011) 262–269

Contents lists available at ScienceDirect

Decision Support Systems

journal homepage: www.elsevier.com/locate/dss

A multi-objective optimization for green supply chain network design

Fan Wang [a], Xiaofan Lai [b], Ning Shi [a,*]

[a] Sun Yat-sen Business School, Sun Yat-sen University, Guangzhou 510275, PR China
[b] School of Business, The Hong Kong Polytechnic University, Hong Kong, PR China

ARTICLE INFO

Available online 26 November 2010

Keywords:
Green supply chain management
Network design
Multi-objective optimization

ABSTRACT

In this paper, we study a supply chain network design problem with environmental concerns. We are interested in the environmental investments decisions in the design phase and propose a multi-objective optimization model that captures the trade-off between the total cost and the environment influence. We conduct a comprehensive set of numerical experiments. The results show that our model can be applied as an effective tool in the strategic planning for green supply chain. Meanwhile, the sensitivity analysis provides some interesting managerial insights for firms.

1. Introduction

The operations in supply chain and logistics are part of today's most important economic activities as they remain to be vital tools for businesses to remain competitive. The ever growing volume of activity generated by both passenger and freight transportation not only benefits the growth and sustainability of international economy and globalization but also has its own consequences, particularly those pertaining to the environment. Transportation activities are significant sources of air pollution and greenhouse gas emissions, with the former known to have harmful effects on human health and the latter, responsible for global warming. These issues have raised concerns on reducing the amount of emissions worldwide. In this respect, many countries, including both developed countries and developing countries, have set strict targets on reducing their carbon emissions in the near future. For example, China, in its 11th five year developing plan, sets a clear objective to “reduce the carbon emission by 10%.” The central government is studying and ready to publish regulatory policies for protecting environments, which are expected to play positive effects on resolving current environment problems. Billions of dollars are spent each year by government and private enterprise on the environmental pollution control.

Some leading companies are now proactively implementing “green” initiatives. For example, the largest furniture manufacturer, IEKA, built a train transportation network with an emphasis on the “greenness” of train operations. HP, IBM, and GE are all taking “green” as an important merit in their enterprise's value system in order to maintain good public images. They are designing greener products by adopting new energy saving technology. Besides product design, they are also thinking of enhancing their supply chain management capability to release environmental concerns. For example, the global procurement center of IBM, located in Shenzhen, China, adds “CO_2 Emission, Solid Waste Produced” and other environment related indicators in the logistics management KPIs. We are motivated to study a “green” supply chain network design problem where an initial investment on environmental protection equipment or techniques should be determined in the design phase. This investment can influence the environmental indicators in the operations phase. Therefore, a trade-off exists between the initial investment and its long-term benefit to environment. With such a concern, the decisions on facility location and capacity allocation have to be integrated with the decision on environmental investment.

There is a large amount of literature on supply chain management concerned with environmental issues through the emerging concept “green supply chain management” (GrSCM). According to the most recent comprehensive review on GrSCM by Srivastava [34], two types of “greenness” are considered by researchers: green design for products [18] and green operations. Our research falls in the second category which is mainly composed of green manufacturing and remanufacturing [32], reverse logistics and network design [10,38], and waste management [4,5]. Among them, the most relevant work is the reverse logistics network design problem which focuses on setting up some special facilities (i.e., recovery center) to enable the recycling initiatives [10] or optimizing the network configurations in a close-loop network [31]. However, our research has a different perspective on the “greenness.” More specifically, we are interested in the environmental investment decision making in the network design phase and taking precautions against environmental pollution.

Another relevant research is the classical supply chain network design problem which receives a lot of researchers' attentions. The network design problem is one of the most comprehensive strategic decision problems that needs to be optimized for long-term efficient operations of the whole supply chain. It determines a portfolio of configuration parameters including the number, location, capacity,

* Corresponding author. Tel.: +86 20 84112672; fax: +86 20 84036924.
E-mail address: shiningchina08@gmail.com (N. Shi).

0167-9236/$ – see front matter © 2010 Elsevier B.V. All rights reserved.
doi:10.1016/j.dss.2010.11.020

and type of various facilities in the network. The problem covers a wide range of formulations ranged from linear deterministic models [20,24,28] to complex non-linear stochastic ones [30,33]. In literature, there are different studies dealing with the design problem of supply networks and these studies have been surveyed by Vidal and Goetschalckx [36], Beamon [3], Erenguc et al. [9], and Pontrandolfo and Okogbaa [27]. Researchers have attempted to extend the classical model by incorporating various factors such as transportation modes [37,6], tax issue [18], risk management [1,13], etc. However, we do not find any one that explicitly considers the environmental investment decision in the design phase. On the other hand, the supply chain network design problem is usually modeled as a single objective problem [20,30]. However, any “design” in nature is usually involving trade-offs among different incompatible objectives. Therefore, considering supply network design with multi-objective optimization is another influential trend worthy of study. Comparing that with single objective, it is more reasonable and more practical in terms of actual applications. As we know, multi-objective optimization is widely used in a variety of areas [14,16,19,25,29] and is also used to embed into a multitude of decision support system [8,12,35]. Recently, multi-objective optimization of supply chain network design has been considered by different researchers in literature. For example, a multi-objective programming model is proposed by Mincirardi et al. [23] to analyze solid waste management. Gabriel et al. [11] propose a model for simultaneously optimizing the operations of both integrated logistics and its corresponding used-product reverse logistics in a close-looped supply chain. Alçada-Almeida et al.[2] propose a multi-objective programming approach to identify the locations and capacities of hazardous material incineration facilities and balance the society, economic, and environmental impacts. However, their study was limited in a special situation. It cannot be extended to common scenarios. Another related study is conducted by Paksoy et al. [26], who considered the green impact on a close-looped supply chain network and tried to prevent more CO_2 gas emissions and encourage the customers to use recyclable products via giving a small profit. They have presented different transportation choices between echelons according to CO_2 emissions. They also considered recyclable ratio of raw material. However, it always needs to set up some special recycle facilities in a close-looped supply chain network, which limits its applications to a certain extent.

In this paper, we make the following contributions:

1) We provide a multi-objective mixed-integer formulation for the supply chain network design problem. To our knowledge, it is the first model that considers the environmental investment decision in the supply network design phase. The multi-objective model explicitly considers the environmental issues by introducing a new category of decision variables: the environmental protection level (we will explain this concept later). This new type of variables links the decision of environmental investment in the planning phase as well as its environment influence in the operation phase.
2) We apply a normalized normal constraint method, which is a posteriori articulation of preference method and can find a set of even distributed Pareto optimal solutions so that the result obtained can be easily applied to the decision support systems which the industry needs.
3) We conduct a comprehensive set of numerical studies and characterize the Pareto solutions especially their sensitivities to various parameters. Consequently, we reach some useful managerial insights. For example, we find that, if we install more capacities in the network, not only the total cost but also the total environmental influence can be reduced.

The rest of the paper is organized as follows. In the next section, we detail our problem and present our general model. In Section 3, we optimize the given model by a linearization step and summarize the solving method. In Section 4, we conduct numerical experiments to characterize the optimal solutions and their sensitivities to various input parameters. Some interesting managerial insights are also introduced. Finally, conclusions are given in Section 5.

2. Problem definition and modeling

Consider a supply chain network, $G=(N,A)$, where N is the set of nodes and A is the set of arcs. Here, N is composed by the set of suppliers, S, facilities, F, and customers, C, i.e., $N=S\cup F\cup C$. When given demand forecasting, we not only aim to choose the potential suppliers from the suppliers set and decide which facility to open and finally consider how to distribute the product but also consider the CO_2 emission in each process of the whole network. Let us define:

Parameters

P	the set of products
d_i^{p}	the demand of customer for product
s_i^{p}	the supply of supplier for product
c_{ij}^{p}	transportation cost for product from facility to facility
f_j	setup cost for facility j
u_j	the handling capacity in facility j
r_j^{p}	capacities consumed by handling a unit of product in facility j
ℓ_j^{p}	handling cost of product p in facility j

Decision variables

$$y_j \quad = \begin{cases} 1, \text{if facility } j \text{ is open;} \\ 0, \text{if otherwise.} \end{cases}$$

x_{ij}^{p}	the flow of product p from node i to node j
z_{jz}	the environment protection level in facility j

In our paper, a “product” can either represent a specific product or a product category; for simplicity, we assume that suppliers and facilities do not need to consider tariff and directly use the transportation cost and each product do not consider the bill of material. For convenience to express, we only consider CO_2 emission as the only environmental influence which is a very popular environment index and can be measured easily. Besides, note that we introduce a new type of decision variable, z_j, that has not been considered in classical supply chain network design literature. This variable is associated with facility j and represents the “level” of environmental protection. More specifically, higher value of z_j corresponds to a heavier environmental investment but leads to a lower CO_2 emission. We define a monotonic increasing function $g_j(z_j)$ to denote the environmental investment in facility j. The environmental investment can be used to purchase equipment or technology for environmental protection. A higher $g_j(z_j)$ means that a more sophisticated equipment or technology is installed. Consequently, in long-term, the CO_2 emission in facility j for handling product p, denoted by $w_j^{\mathrm{p}}(z_j)$, should be lower. In this paper, we assume that z_j is a discrete number and that $z_j \in\{0,1,2,...,L\}$. Having said that, we can define the objective functions below:

Objective functions

$$\text{OBJ1}: min \sum_{j\in F} f_j y_j + \sum_{j\in F} g_j\left(z_j\right) + \sum_{\mathrm{p}\in \mathrm{P}} \sum_{(ij)\in A} c_{ij}^{\mathrm{p}} x_{ij}^{\mathrm{p}} + \sum_{\mathrm{p}\in \mathrm{P}} \sum_{j\in F} \ell_j^{\mathrm{p}} \sum_{i\in S} x_{ij}^{\mathrm{p}} \quad (1)$$

$$\text{OBJ2}: min \sum_{j\in F} \sum_{\mathrm{p}\in \mathrm{P}} w_j^{\mathrm{p}}\left(z_j\right) \sum_{i\in S} x_{ij}^{\mathrm{p}} + \sum_{\mathrm{p}\in \mathrm{P}} \sum_{(ij)\in A} e_{ij}^{\mathrm{p}} x_{ij}^{\mathrm{p}} \quad (2)$$

We explicitly consider two objective functions. OBJ1 measures the total cost. The first part is the fixed setup cost, the second part is the environmental protection investment, the third part is the total transportation cost, and the last part is the total handling cost. OBJ2 measures the total CO_2 emission in all the supply chain. The first part is the total CO_2 emission in all facilities. For each product p, facility j, and each unit of flow in the facility, an amount of $w_j^p(z_j)$ of CO_2 is generated. Besides the facility-dependent CO_2 emission, we also take the arc-dependent CO_2 emission into account, which is the second part of OBJ2 and is decided by the choice of suppliers, and how to transport the final product. For each arc and each flow in the arc, an amount of CO_2 emission e_{ij}^p is generated.

Constraints

$$\sum_{i\in S} x_{ij}^p - \sum_{i\in C} x_{ji}^p = 0 \quad \forall j\in F \quad \forall p\in P \tag{3}$$

$$\sum_{i\in F} x_{ij}^p = d_j^p \quad \forall j\in C \quad \forall p\in P \tag{4}$$

$$\sum_{i\in F} x_{ij}^p \le s_i^p \quad \forall i\in S \quad \forall p\in P \tag{5}$$

$$\sum_{p\in P} r_j^p \sum_{i\in S} x_{ij}^p \le u_j y_j \quad \forall j\in F \tag{6}$$

$$z_j \le y_j L \quad \forall j\in F \tag{7}$$

$$x_{ij}^p \ge 0 \quad \forall (i,j)\in A \quad \forall p\in P \tag{8}$$

$$y_j\in\{0,1\} \quad \forall j\in F \tag{9}$$

$$z_j\in\mathbb{Z} \text{ and } z_j\in[0,L] \quad \forall j\in F \tag{10}$$

Constraint (3) is the flow conservation constraint. Note that our model is a single period model and there is no inventory stored in each facility. Constraint (4) requires that the demands should be satisfied while constraint (5) ensures that each product p flowing out of supplier i should not exceed the total supply amount of suppliers. Constraint (6) states that the total processing requirement of all products handling in facility j should not exceed the capacity of the facility u_j when it is opened ($y_j = 1$) and ensures that $x_{ij}^p = 0$ when $y_j = 0$. Constraint (7) requires that decision makers can only choose an environmental level less than L for opening facility j. Constraints (8), (9), and (10) restrict that x_{ij}^p are non-negative, y_j are binary integer variables, and z_j are integers in interval $[0,L]$.

We call the above model as a general model (GM). This model is a two objective non-linear model and, therefore, is not easy to solve even when the network is small. In the following section, we reformulate this model as a mixed-integer programming model.

3. Solving approach

In this section, we first introduce a modified model that transfers the GM as a linear program. Then, we introduce the solving approach.

First, due to the discrete and bounded property of z_j, let us introduce a series of binary variables:

$$z_{jl} = \begin{cases} 1, \text{if the environment protection level } l \text{ is selected;} \\ 0, \text{if otherwise.} \end{cases}$$

Note that the decision maker selects one and only one environmental protection level. Hence, we can reach the following property:

Property 1. We can rewrite $z_j = \sum_{l\in L} z_{jl} l$, where

$$\sum_{l\in L} z_{jl} = y_j, \forall j\in F \tag{11}$$

Proof. We consider two cases. In the first case, the facility j is opened, that is, $y_j = 1$. As one and only one environmental protection level is selected, therefore:

$$\sum_{l\in L} z_{jl} = 1.$$

Suppose that ℓ is selected, we can easily verify that

$$z_j = \ell = z_{j\ell}\ell = \sum_{l\in L} z_{jl} l.$$

Suppose that the facility is close, that is, $y_j = 0$. It is followed that $z_{jl} = 0$ for all l, and then

$$z_j = 0 = \sum_{l\in L} z_{jl} l.$$

As a summary of these two cases, we can reach that the property is correct.

Then, we can define a sequence of g_{jl} and w_{jl}^p such that

$$g_{jl} = g_j(l) \quad \forall l\in L \tag{12}$$

$$w_{jl}^p = w_j^p(l) \quad \forall l\in L \tag{13}$$

Here, g_{jl} and w_{jl}^p represent fixed environmental investment and per-unit environmental influence in facility j under l environmental level, respectively.

Based on the relationship between z_{jl} and y_j, we can redefine a new variable, f_{jl}, such that $f_{jl} = g_{jl} + f_j(\forall j\in F \forall l\in L)$. In this way, we can eliminate all y_j. By these transformations, we can obtain a mixed-integer program where the number of continuous variables is $|F|^2|P|$ and the number of binary variables is $|F||L|$. Note that we introduce a new type of decision variable x_{jl}^p which measures the amount of product p handling in facility j under l environmental protection level. Note that they satisfy the constraints that $\sum_{l\in L} x_{jl}^p = \sum_{i\in S} x_{ij}^p$.

The modified model (MM) is shown as follows:

$$\min \sum_{p\in P} \sum_{(ij)\in A} c_{ij}^p x_{ij}^p + \sum_{j\in F} \sum_{l\in L} f_{jl} z_{jl} + \sum_{p\in P} \sum_{j\in F} \ell_j^p \sum_{i\in S} x_{ij}^p \tag{14}$$

$$\min \sum_{j\in F} \sum_{p\in P} \sum_{l\in L} w_{jl}^p x_{jl}^p + \sum_{p\in P} \sum_{(ij)\in A} e_{ij}^p x_{ij}^p \tag{15}$$

$$\sum_{i\in S} x_{ij}^p - \sum_{i\in C} x_{ji}^p = 0 \quad \forall j\in F \quad \forall p\in P \tag{16}$$

$$\sum_{i\in F} x_{ij}^p = d_j^p \quad \forall j\in C \quad \forall p\in P \tag{17}$$

$$\sum_{i\in F} x_{ij}^p \le s_i^p \quad \forall i\in S \quad \forall p\in P \tag{18}$$

$$\sum_{p\in P} r_j^p x_{jl}^p \le u_j z_{jl} \quad \forall j\in F \quad \forall l\in L \tag{19}$$

$$\sum_{l\in L} z_{jl} \le 1 \quad \forall j\in F \tag{20}$$

$$x_{ij}^p, x_{jl}^p \ge 0 \quad \forall (ij)\in A \quad \forall p\in P \quad \forall l\in L \quad \forall j\in F \tag{21}$$

$$z_{jl}\in\{0,1\} \quad \forall j\in F \quad \forall l\in L \tag{22}$$

In the above formulation, Constraints (16), (17), and (18) are the same as those in GM while Constraint (19) is the capacity constraint which results from Constraints (6) and (11). Constraint (20) restricts that only one environmental level can be set for any opening facility. Constraints (21) to (22) define the variables' types.

It is well-known that there exist multiple non-dominated solutions for a multi-objective optimization problem. Those solutions are called "Pareto optimal" solutions. In this paper, our objective is to obtain a "Pareto frontier" which provides evenly distributed Pareto solutions and it is convenient for the decision maker to select a suitable configuration. One of the typical approaches to generating these solutions is to use an aggregate objective function (AOF) by varying the numerical scalar weights. As each set of weights results in a corresponding Pareto solution, one may expect that using a number of evenly distributed scalar weights can yield a corresponding set of evenly distributed Pareto solutions. Those evenly distributed Pareto solutions are desirable because it is an indication that the design space is well represented in the Pareto set (i.e., Pareto frontier) and it can be easy for the decision maker to make decisions. Unfortunately, most methods do not yield a well-distributed set of Pareto solutions [7,15,21]. In this paper, it is important to obtain a well-distributed Pareto frontier as we are investigating how different parameters influence the decision making behavior and we are aiming to provide an effective decision support tool for the industry. Therefore, we apply the normalized normal constraint method in Messac et al. [22] to solve the multi-objective model. This method enjoys with a posteriori articulation of preference and can generate a palette of Pareto solutions for decision makers to choose. This method don't need an initial weight for each objective and can yield a well-distributed set of all available Pareto solutions. In the following, we combine MM to illustrate the algorithms for short. The basic idea is that we first normalized the objective and find the Pareto solution along a certain direction, say Utopia line, which will be illustrated in more detail in the following.

First of all, MM has two objective functions (OBJ1 and OBJ2); in the method, the objective value of these two functions are represented by u_1 and u_2, respectively. Then, we solve the MM with each objective function separately and get the objective value $\bar{\mu}^{1*}$ and $\bar{\mu}^{2*}$corresponding to OBJ2 and OBJ1, respectively. x^{1*} and x^{2*} is the solution vector corresponding to μ^{1*} and μ^{2*}, respectively. After that, we normalize the two objectives, map them to the normalized design objective space, and join the two objective values $\bar{\mu}^{1*}$ and $\bar{\mu}^{2*}$ with a line called Utopia line, as shown in Fig. 1. For each vector $\mu = [\mu_1(x) \quad \mu_2(x)]^T$, the normalization design metrics is

$$\bar{\mu} = \left\{ \frac{\mu_1(x)-\mu_1\left(x^{1*}\right)}{\mu_1\left(x^{2*}\right)-\mu_1\left(x^{1*}\right)} \quad \frac{\mu_2(x)-\mu_2\left(x^{2*}\right)}{\mu_2\left(x^{1*}\right)-\mu_2\left(x^{2*}\right)} \right\}^T.$$

Based on the following metrics, the normalized constraint method [22] attempts to obtain the Pareto points along the direction given by the Utopia line:

$$\overline{N} = \bar{\mu}^{2*}-\bar{\mu}^{1*} = [1,0]-[0,1] = [1,-1].$$

According to the prescribed number of solution, m, we can further decide the step $\delta = 1/(m-1)$ along the direction $\overline{N}$. Here, the choice of the solution number is a trade-off between the speed in solving the problem and the accuracy of the Pareto frontier, where the more solution number, the more accurate is the frontier shown.

Hence, we take $m = 30$ and $\delta = 1/29$ which is a proper number of the point in the Pareto frontier, and the problem can be solved in a reasonable time. Given two weights, $0 \le \alpha_{1j}, \alpha_{2j} \le 1, \quad \alpha_{1j} + \alpha_{2j} = 1$, it evaluates a set of evenly distributed points on the Utopia line:

$$\overline{X}_j = \alpha_{1j}\bar{\mu}^{1*} + \alpha_{2j}\bar{\mu}^{2*}.$$

Note that for each $j \in \{1,2,\cdots,m\}$, α_{1j} is incremented by the step δ while α_{2j} is decremented by the same step. Using the distributed point set $\overline{X}_j$, we can generate the corresponding Pareto point set through solving the following sub-problem.

Sub-problem (for th point):

$$\min_x \bar{\mu}_2$$

subject to (16)–(22) and $\overline{N}\left(\bar{\mu}-\overline{X}_j\right)^T \le 0 \bar{\mu} = \left[\bar{\mu}_1(x)\ \bar{\mu}_2(x)\right]^T$.

Note that solving each sub-problem can get a Pareto point, which is a component of the well-distributed set. Although there exists a new constraint to the sub-problem, our experiments have shown that

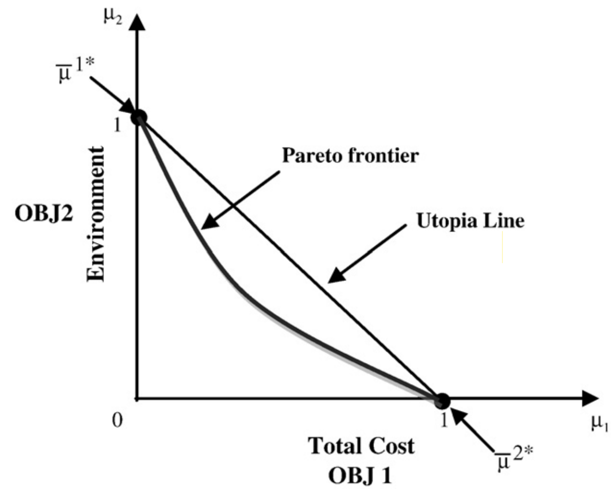

Fig. 1. The Pareto frontier and the Utopia line for MM with two objectives.

it has little effect on solving the sub-problems of our practical instances and all the sub-problems can be solved in a reasonable time. More importantly, the solution it has obtained is well-distributed.

4. Computational experiments

In this section, in order to evaluate the model, we create two examples: a six-node problem and a mid-size network. By the first example, we want to portrait a real scenario for demonstrating the solutions. In the second example, we focus on the sensitivity analysis and its managerial insights. The problem is solved by the normalized normal constraint method and it is implemented by Microsoft Visual C++ 6.0, and each sub-problem is solved by ILOG CPLEX 9.0 solver subroutine. All the experiments are conducted on a PC with Intel Core 2 Duo 2.19 GHz and 1 GB RAM. We start from the small six-node problem.

4.1. A six-node example

Consider the six-node network shown in Fig. 2, which modifies the one from Melkote and Daskin [20]. We give a minimum road infrastructure connecting all the nodes in this network. Customers, suppliers, and facilities can be located at every node. There are, in total, three suppliers and two products in this network. Each arc is associated with a transportation cost and an amount of CO_2 emission. The parameters are all shown in Fig. 2. The decision maker should determine (1) where to set up the facility, (2) how to set environmental protection level, (3) which suppliers should be selected for each facility, and (4) how products are transported. We consider two scenarios. In the first scenario, we set the maximum CO_2

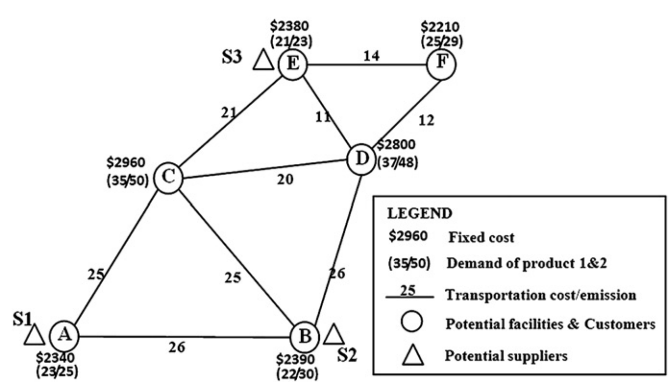

Fig. 2. Modified six-node network [20].

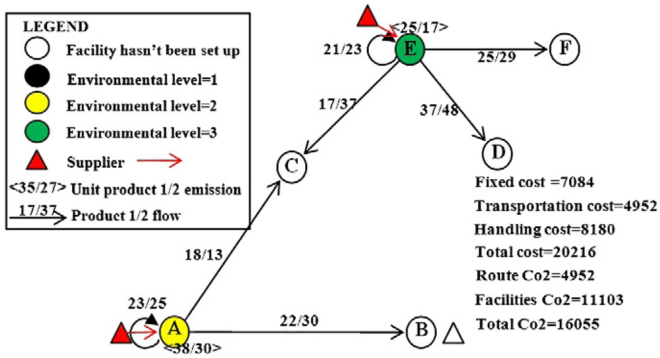

Fig. 3. Optimal configuration for CO_2 emission = 16,500.

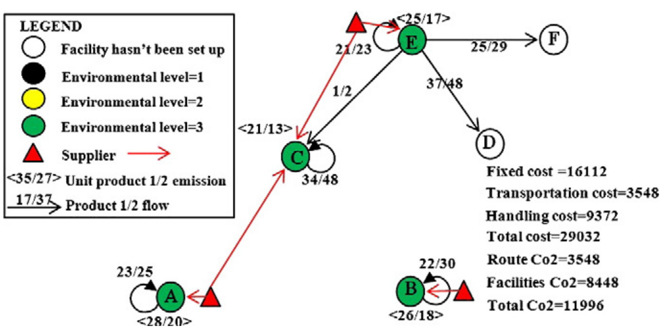

Fig. 4. Optimal configuration for CO_2 emission = 12,000.

emission as 16,500. Therefore, obtaining the corresponding OBJ2 in MM can be treated as a constraint and the problem becomes a single objective problem which can be solved by the CPLEX solver. In the second scenario, we set the maximum CO_2 emission as 12,000.

The optimal configuration for the first scenario is illustrated in Fig. 3. In the optimal configuration, there are two facilities set up. One is located at node A and its environmental protection level is set as 2. The other is located at node E and its environmental protection level is set as 3. The total cost is 20,216.

The optimal configuration of the second scenario is illustrated in Fig. 4. It is found that 4 facilities are built up. They are located at nodes A, B, C, and E, respectively, and their environmental protection levels are all set to 3. The number of suppliers is also increased to 3. It is reasonable because a stricter requirement on CO_2 emission demands more capacities on environmental protection. For example, a facility is built in node C. The facility has the highest environmental investment but its CO_2 emission is the lowest. As more facilities are built up, the total fixed cost including the fixed environmental investment and setup cost is dramatically increased while the transportation cost is reduced as the increasing number of facilities provides more alternatives for shipping products. Moreover, the total handling cost increases due to the high unit handling cost of nodes C and B. From the analysis of this example, we can clearly observe the trade-off between the total cost and the CO_2 emission. In general, either higher environmental protection levels should be set or more facilities should be built up (and equip them with sufficient environmental protection levels). This observation provides a managerial insight that, when the environmental protection is considered in the network design phase, the facility layout could be very different. This coincides with our intuition. However, it is not clear how the handling capacity of each facility can impact the design. In the latter, we will use a real case for a demonstration.

4.2. Case study

In this section, we conduct a case study. This case is motivated by the global procurement center of a world-class company in Shenzhen, China. In this case, we are required to provide some strategic guidance on the supply chain network design if the environmental issue is concerned. We then set up the bi-objective optimization model and conducted a case analysis based on a network consisting of 8 facilities, 6 suppliers, 12 final customers with 3 products (P1, P2, and P3), and 4 environment levels. These facilities represent its major manufacturing and distribution sites. The suppliers and customers are in an aggregative sense, say, each customer represents all customers in a region. The network is illustrated in Fig. 5. The formulation of this case contains 32 binary variables, 432 continuous variables, and 620 constraints. As the objective of this study is to discover potential strategic managerial insights, we choose a mid-size sample because it

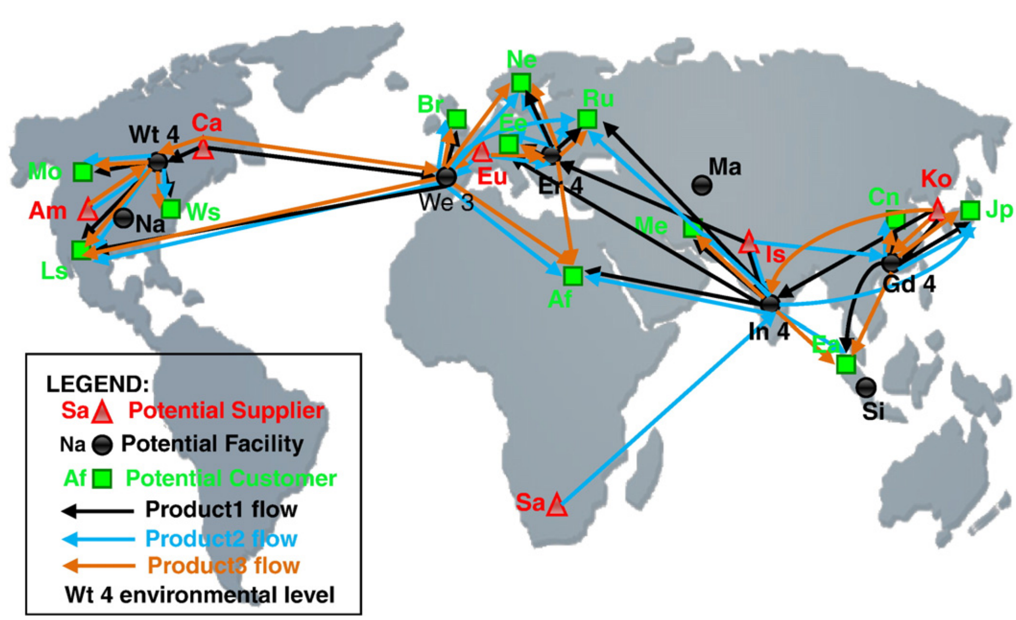

Fig. 5. The network consists of 8 facilities, 6 suppliers, 12 customers, 4 environmental protection levels, and 3 products.

Table 1
Design of input for MM.

Parameter	Setting
Demand of product p in facility j	d_j^p: uniform(d, 1.5d)units; here, d is the demand ratio
Supply for each products from suppliers with a probability	s_i^p: uniform$(\alpha,\beta)\cdot\overline{d}^p$ units; here (α,β) is the supply range and $\overline{d}^p$ is the average product demand
Capacity for each facility	$u_j = c^* U$; here, c is the capacity ratio; U is a constant
Transportation cost for each arc in network	$c_{ij}^p = a^p *$geographic distance of this arc. Here, a^p: uniform(0.8, 1.2).
Carbon emission in the route for each kind of product	$e_{ij}^p = b_{ij} \times$ geographic distance of arc (i,j); here, $b_{ij} \sim U(0.9, 1.2)$
Carbon emission for different environmental levels	$w_j^p(z_j) \sim$ uniform$(48/2^{z_j-1}, 72/2^{z_j-1})$
Fixed setup cost for each facility	f_j: uniform(50, 80)$^* r_{cost}$; here, r_{cost} is a cost ratio
Environmental investment cost for different environmental levels in each facility	g_{jl}: $f_j^* r_{cost}(l)$; here, $r_{cost}(l)$ — characteristic of level l
Handling cost for different products in different facilities	ℓ_j^p : uniform(50, 100)
Per-unit processing requirement for each kind of product	$r_j^p = 7$, 8, 9 for products 1, 2, and 3, respectively.

is sufficient to represent its real supply chain network and it is computationally manageable.

Although the data for the case was randomly generated, they nearly fit a small scale environment. The design of input parameters for our new model is shown in Table 1.

In this case, we set the demand ratio d equals to 1000 (represented with 1 K). In the sensitivity analysis, we will increase this ratio from 1 K to 3 K. We assume that each facility has the same total capacity, so all u_j are equal to a constant U and $U = 45{,}000$ units. Under this setting, the capacity is just enough for handling all demands.

First, we generate the Pareto frontier which can provide the decision maker a portfolio of alternative “optimal solutions.” The Pareto frontier is illustrated in Fig. 6. It clearly demonstrates the trade-off between the total cost and the total CO_2 emission. It coincides with our intuition that a lower CO_2 emission can only be reached by putting more investment. Also, we can find that the absolute value of the curve's slope decreases and curves became more flat when the total cost increases, that is, the curve exhibits a seemingly convex property.

We are interested on how capacity impacts the decision making. We define a “capacity ratio” that is the total network capacity over the total demands. We vary this ratio from 1 to 1.2 and obtain a series of Pareto frontiers which are shown in Fig. 6. It clearly shows that the Pareto optimal curves move from right to left as the ratio increases from 1 to 1.2.

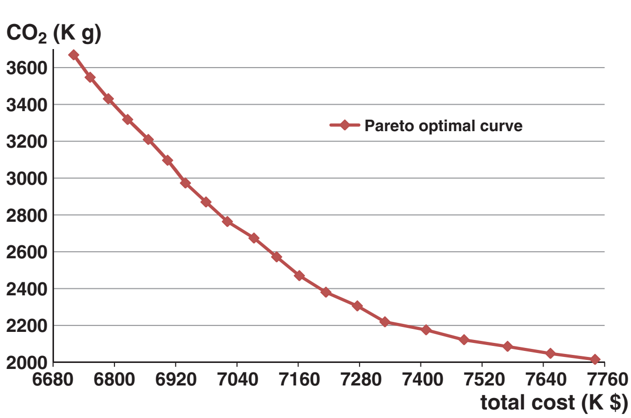

Fig. 6. Pareto optimal curve of the model: CO_2 vs. total cost.

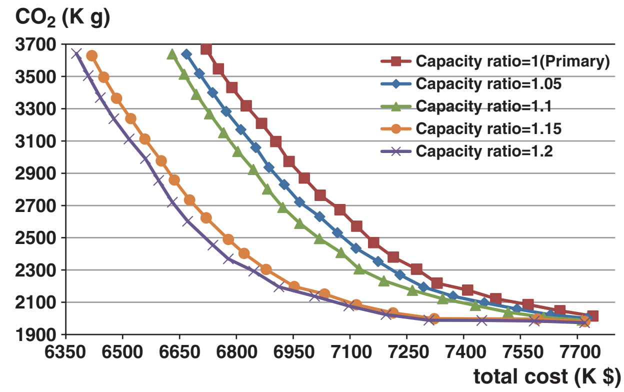

Fig. 7. Pareto optimal curve of different capacity ratio.

It implies that, at the same CO_2 emission level, larger capacity ratio leads to less total cost. While at the same total cost, CO_2 emission will monotonically decrease with capacity ratio, as expected. In other words, supply chain network with larger capacity exhibits lower total cost and lower CO_2 emission. That is mainly because when the surplus capacity is installed, the network provides more flexibility to conduct the logistics such that the cost and the CO_2 emission in the transportation process can be reduced simultaneously. The higher capacity may also provide possibilities that fewer facilities can be built without scarifying any objective. For example, when the capacity ratio increases from 1.1 to 1.15, it results in a large drop both in CO_2 emission and total cost. In the optimal solutions, we found that the number of facilities to be built up is dropped. This can be explained by the economies of scale in the operation stage. Note that we assume that the capacity is assumed external and given. In fact, it is possible that installing more capacity needs more money. Therefore, the decision maker can decide whether to improve the capacity of the network by examining this series of Pareto frontiers. More specifically, given a CO_2 emission goal, we can get the cost difference between different capacity ratio curves (Fig. 7). If the cost difference is enough to improve the corresponding capacity, it is better for decision makers to improve it; otherwise, we should go on to find a trade-off between capacity and capacity investment cost through decreasing the capacity ratio. This does provide a new reason for operations managers to reserve more capacities. Through Zara's case (Ghemawat and Nueno, 2003), we know that the reserved capacity is necessary to maintain high flexibility in delivery. In this paper, we show that reserving more capacity might also be beneficial for the environmental protection.

We are also interested on how supply impacts the decision making. We first set that the total supply is equal to the total demand

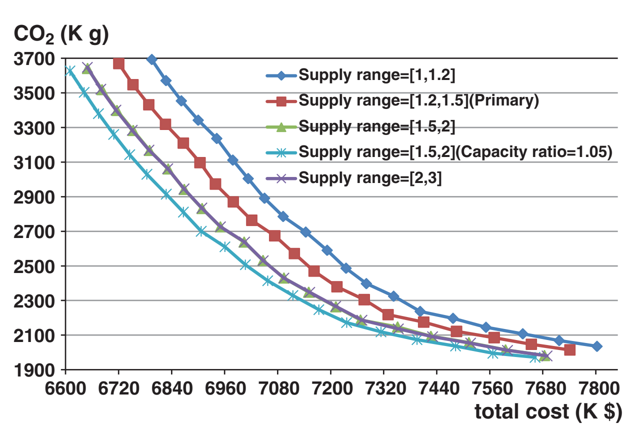

Fig. 8. Pareto curve of different supply range.

Table 2
Minimum, maximum, and gap of CO_2 emission and total cost.

Demand ratio	Minimum CO_2	Maximum CO_2	CO_2 gap	Minimum cost	Maximum cost	Cost gap
1 K(primary)	2,014,530	3,669,580	82.16%	6,720,380	7,741,320	15.19%
1.5 K	2,794,670	5,138,980	83.89%	8,680,330	9,719,350	11.97%
2 K	3,811,780	7,026,370	84.33%	11,220,000	12,260,800	9.28%
3 K	5,893,110	10,803,600	83.33%	16,417,800	17,446,500	6.27%

Gap = (max − min) / min

and then multiply the origin supply at each facility by a factor in a range, say, [1,1.2]. This gives a sense of whether the total supply is tight or rich. It shows that when the supply range becomes larger, both CO_2 emission and total cost will monotonically decrease. This tells us that increasing the supply can reduce both the CO_2 emission and transportation cost for the reason that it would not need to get the products from a far supplier. Fig. 8 illustrates the Pareto frontiers corresponding to various supply range. As a result, if possible, it is best for the decision maker to let the supply closer and richer to facilities in order to reduce the transportation CO_2 emission and transportation cost. However, in fact, when the capacity of facilities are always limited, it will come to an utmost for supply range which can be seen from the two plots whose supply ranges are [1.5,2] and [2,3]. The two plots are almost coincidental for the aforementioned reason. It is worth noting that increasing the capacity and the amount of supply will lead to a significant decrease in CO_2 emission and total cost of supply chain network. This can be seen from the sky blue Pareto optimal curve whose supply range is [1.5,2] and capacity ratio is equals to 1.05. That verified our observation about capacity again.

Finally, we conduct a sensitivity analysis of the model with changes in the different demand. The results are listed in Table 2. We record the “minimum” of CO_2 emission, that is, the lowest value of CO_2 emission in the Pareto frontier. We also record the “maximum” of CO_2 emission which is the highest value of CO_2 emission in the Pareto frontier. The “CO_2 gap” records the difference between “minimum” and “maximum” measured by percentage. Similar concepts are defined for the total cost. We observed that, for various values of demand, the CO_2 gaps are similar. However, it seems that the cost gap is decreasing when the demand is increasing. When the demand becomes larger, the cost gap becomes smaller while the CO_2 gap has little change. It means that, when the demand is large, it will be of greater benefit to consider investing more in environmental protection.

5. Conclusions

In this paper, we introduce a green supply chain network design model based on the classical facility location problem for the firm's strategic planning. The distinguishing feature of our model is its consideration of environmental element which includes environmental level of facility and environmental influence in the handling and transportation process. This model will have an important application in the regional or global supply chain network design with green consideration.

The model is a multi-objective model which consists of minimizing total cost and environmental influence. We use normalized normal constraint method to solve the model by general MIP solver CPLEX 9.0 to get the Pareto optimal set. After that, we test the model by a six-node example and a case study. The Pareto optimal curve by the model provides a portfolio of configurations for decision makers and further computation experiments show that our model can serve as an effective tool in designing a green supply chain network. Finally, sensitivity analysis for the case study is conducted and we observe that improving the capacity of the network and increasing the supply to the facilities can decrease CO_2 emission of the whole network and total cost. On the other hand, considering the environmental emission of supply chain network is more effective and necessary at a higher demand level.

Our further research direction is to consider more factors in supply chain, such as the transportation modes, demand uncertainty, and so on, so that it can enhance its applicability to real-life scenarios. On the other hand, we can also extend our research through designing new solution methods to solve this multi-objective model.

Acknowledgements

This paper is supported by the National Natural Science Foundation of China (NSFC) under Project Nos. 70971142 and 70802063.

References

[1] E. Aghezzaf, Capacity planning and warehouse location in supply chains with uncertain demands, The Journal of the Operational Research Society 56 (2005) 453–462.
[2] L. Alçada-Almeida, J. Coutinho-Rodrigues, J. Current, A multiobjective modeling approach to locating incinerators, Socio-Economic Planning Sciences 43 (2009) 111–120.
[3] B.M. Beamon, Supply chain design and analysis: models and methods, International Journal of Production Economics 55 (1998) 281–294.
[4] J.M. Bloemhof-Ruwaard, L.N. Van Wassenhove, H.L. Gabel, P.M. Weaver, An environmental life cycle optimization model for the European pulp and paper industry, Omega 20 (1996) 615–629.
[5] S. Cheng, C.W. Chan, G.H. Huang, An integrated multi-criteria decision analysis and inexact mixed integer linear programming approach for solid waste management, Engineering Application of Artificial Intelligence 16 (2003) 543–554.
[6] J.F. Cordeau, F. Pasin, M.M. Solomon, An integrated model for logistics network design, Annals of Operations Research 144 (2006) 59–82.
[7] I. Das, J.E. Dennis, Normal-boundary intersection: a new method for generating the Pareto surface in nonlinear multicriteria optimization problems, SIAM Journal on Optimization 8 (1998) 631–657.
[8] D.K. Despotis, D. Derpanis, A Min–Max goal programming approach to priority derivation in AHP with interval judgements, International Journal of Information Technology & Decision Making 7 (1) (2008) 175–182.
[9] S.S. Erenguc, N.C. Simpson, A.J. Vakharia, Integrated production/distribution planning in supply chains: an invited review, European Journal of Operational Research 115 (1999) 219–236.
[10] M. Fleischmann, P. Beullens, J.M. Bloemhof-Ruwaard, L.N. Van Wassenhove, The impact of product recovery on logistics network design, Production & Operations Management 10 (2001) 156–173.
[11] S.A. Gabriel, P. Sahakij, M. Ramirez, C. Peot, A multiobjective optimization model for processing and distributing biosolids to reuse fields, The Journal of the Operational Research Society 58 (2007) 850–864.
[12] Y. Gao, G. Zhang, J. Lu, A fuzzy multi-objective bilevel decision support system, International Journal of Information Technology & Decision Making 8 (1) (2009) 93–108.
[13] M. Goh, J.I.S. Lim, F. Meng, A stochastic model for risk management in global supply chain networks, European Journal of Operational Research 182 (2007) 164–173, P. Ghemawat and J.L. Nueno. ZARA: Fast Fashion. Harvard Business Case. No. 9–703–497. (2003).
[14] C.F. Hu, S.Y. Li, Two-phase interactive satisfying method of fuzzy multiple objective optimization with linguistic preference, International Journal of Information Technology & Decision Making 8 (3) (2009) 427–443.
[15] A. Ismail-Yahaya, A. Messac, Effective generation of the Pareto frontier using the normal constraint method, 40th Aerospace Sciences Meeting and Exhibit (held in Reno, Nevada), Paper No. AIAA 2002–0178, 2002.
[16] M. Koksalan, C. Tuncer, A DEA-based approach to ranking multi-criteria alternatives, International Journal of Information Technology & Decision Making 8 (1) (2009) 29–54.
[17] P. Kouvelis, M.J. Rosenblatt, A mathematical programming model for global supply chain management: conceptual approach and managerial insights, in: J. Geunes, P.M. Pardalos, H.E. Romeijn (Eds.), Supply Chain Management: Models, Applications, and Research Directions, Applied Optimization, Kluwer, Dordrecht, 2002, pp. 245–277.

[18] T.C. Kuo, S. Huang, H. Zhang, Design for manufacture and design for "X": concepts, applications and perspectives, Computers & Industrial Engineering 41 (2001) 241–260.
[19] Z.J. Max Shen, M.S. Daskin, Trade-offs between customer service and cost in integrated supply chain design, Manufacturing & service operations management 7 (3) (2005) 188–207.
[20] S. Melkote, M.S. Daskin, Capacitated facility location/network design problems, European Journal of Operational Research 129 (2001) 481–495.
[21] A. Messac, C.A. Mattson, Generating well-distributed sets of Pareto points for engineering design using physical programming, Optimization Engineering 3 (2002) 431–450.
[22] A. Messac, A. Ismail-Yahaya, C.A. Mattson, The normalized normal constraint method for generating the Pareto frontier, Structural and Multidisciplinary Optimization 25 (2) (2003) 86–98.
[23] R. Mincirardi, M. Paolucci, M. Robba, A multiobjective approach for solid waste management, in: Andrea E. Rizzoli, Anthony J. Jakeman (Eds.), Proceedings of the 1st Biennial Meeting of the iEMSs, 2002, pp. 205–210, Integrated Assessment and Decision Support.
[24] P.B. Mirchandani, R.L. Francis, Discrete Location Theory, Wiley, New York, 1990.
[25] Y.P. Ou Yang, H.W. Shieh, J.D. Leu, G.H. Tzeng, A Vikor-based multiple criteria decision method for improving information security risk, International Journal of Information Technology & Decision Making 8 (2) (2009) 267–287.
[26] T. Paksoy, E. Ozceylan, G.W. Weber, A multi-objective model for optimization of a green supply chain network, Proceedings of PCO 2010, 3rd Global Conference on Power Control and Optimization, February 2–4, 2010, Gold Coast, Queensland, Australia, 2010.
[27] P. Pontrandolfo, O.G. Okogbaa, Global manufacturing: a review and a framework for planning in a global corporation, International Journal of Production Economics 37 (1) (1999) 1–19.
[28] H.E. Romeijn, J. Shu, C.P. Teo, Designing two-echelon supply networks, European Journal of Operational Research 178 (2007) 449–462.
[29] E.H. Sabri, B.M. Beamon, A multi-objective approach to simultaneous strategic and operational planning in supply chain design, Omega 28 (2000) 581–598.
[30] T. Santoso, S. Ahmed, M. Goetschalckx, A. Shapiro, A stochastic programming approach for supply chain network design under uncertainty, European Journal of Operational Research 167 (2005) 96–115.
[31] R.C. Savaskan, S. Bhattacharya, L.N. Van Wassenhove, Closed loop supply chain models with product remanufacturing, Management Science 50 (2) (2004) 239–252.
[32] J.B. Sheu, Y.H. Chou, C. Hu, An integrated logistic operational model for green-supply chain management, Transportation Research. Part E 41 (2005) 287–313.
[33] J. Shu, C.P. Teo, Z.J. Shen, Stochastic transportation–inventory network design problem, Operations Research 53 (2004) 48–60.
[34] S.K. Srivastava, Green supply chain management: a state-of-the-art literature review, International Journal of Management Reviews 9 (1) (2007) 53–80.
[35] C. Stummer, E. Kiesling, W.J. Gutjahr, A multicriteria decision support system for competence-driven project portfolio selection, International Journal of Information Technology & Decision Making 8 (2) (2009) 379–401.
[36] C.J. Vidal, M. Goetschalckx, Strategic production–distribution models: a critical review with emphasis on global supply chain models, European Journal of Operational Research 98 (1997) 1–18.
[37] W. Wilhelm, D. Liang, B. Rao, D. Warrier, X. Zhu, S. Bulusu, Design of international assembly systems and their supply chains under NAFTA, Transportation Research Part E: Logistics and Transportation Review 41 (2005) 467–493.
[38] Q. Zhu, J. Sarkis, K.H. Lai, Green supply chain management implications for closing the loop, Transportation Research. Part E 44 (1) (2008) 1–18.

Fan Wang is a professor of operations and information management in Sun Yat-sen Business School, Sun Yat-sen University (China), and senior visiting professor in Grenoble de Management (France). His research interests include service operations management, E-service, and business analysis and optimization.

Xiaofan Lai is currently a PhD student in The Hong Kong Polytechnic University. His research interests include operations management and optimization.

Ning Shi is an associate professor in Sun Yat-sen Business School, Sun Yat-sen University. His primary research interests include supply chain and logistics management and financial engineering.