

Design and Analysis of Supply Chain Networks with Low Carbon Emissions

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Abstract Low carbon supply chain network design is a multi-objective decision-making problem that involves a trade-off between low carbon emissions and cost. This study calculates the carbon footprint, wherein the greenhouse gases (GHGs) emissions data are based on carbon footprint standards. Many firms have redesigned their supply chain networks to reduce their GHG emissions. Furthermore, the production capacities and costs are collected and evaluated by using Pareto optimal solutions. In order to achieve the optimal solutions, a normal constraint method is used to formulate a mathematical model to meet two objectives: low carbon emissions and low cost. A case study is also presented to demonstrate the predictive ability of this model. The result shows that it is possible to reduce carbon emissions and lower cost simultaneously.

Keywords Greenhouse gas emission · Low carbon supply chain networks · Normal constraint method

1 Introduction

The introduction of the Kyoto Protocol (Kyoto 1997) and Paris agreement (Paris 2015) has caused firms to reduce carbon emissions from their operations. Following the legal drivers and commercial pressure of carbon reduction (Hitchcock 2012), many firms have redesigned their products and supply chain networks (SCNs) to reduce environ-

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mental impacts, through green supply chain network. Green supply chain network design needs to adjust production plants, distribution centers, and supplier and customer links around the globe (Melo et al. 2009). In this regard, some researchers have highlighted and solved the problem of green supply chain network design (Dubey et al. 2015; Zhu and Sarkis 2007). A significant amount of new research addresses issues associated with green supply chain network design: challenges and framework (Kauppi 2013; Melnyk et al. 2014), supplier management (Pagell and Wu 2009), and resource allocation (Du et al. 2016; Wu et al. 2015).

As sustainability is more emphasized, the green supply chain is further developed as a sustainable supply chain network design based on the triple bottom line (TBL) (Wang et al. 2016; Baud-Lavigne et al. 2014; Jin et al. 2014; Pagell and Wu 2009) framework. Sustainable supply chain network design considers both sustainability and supply chain network design, which is broader than traditional supply chain network design. Seuring and Müller (2008) distinguished between traditional and sustainable supply chain network design, wherein the former focuses on the management of materials, information, and capital flows in the supply chain. Furthermore, sustainable supply chain network design meets the needs of the present generation without compromising the needs of future generations (Du et al. 2016). Therefore, for the reduction of greenhouse gases (GHGs) emissions, a sustainable supply chain network design must be planned before a product is launched in the marketplace (Amini and Li 2011).

An increasing number of leading firms are proactively performing GHG emissions reductions through adopting supply chain network and supplier management. Hua et al. (2011) investigate how firms manage their carbon footprints in inventory management under a carbon emission trading mechanism. Among enterprises, the Taiwan Semiconductor Manufacturing Company (TSMC 2013) collaborates with its suppliers to manage global environment, safety, and health (ESH) risks toward supply chain sustainability. Lee and Cheong (2011) investigate the measurement of a carbon footprint and environmental program in supply chain management. From the GHG reduction of the supply chain, 75–90% of a typical product's carbon footprint could be found in the supply chain upstream. Therefore, it is important to redesign the supply chain network to reduce the GHG emissions.

When considering sustainable supply chain network design, most research highlights two objectives that must be solved simultaneously: lowered cost (the economic aspect) and reduced carbon emissions (the environmental aspect). However, sometimes, there exists a trade-off between the initial investment and its long-term benefit to the environment. In order to solve the above trade-off problem, a bi-objective optimization problem of supply chain network design is investigated in this research. Then, the suppliers' carbon emissions, cost, and production capacities are formulated as the constraints. Through solving the bi-objective problem, the supply chain network design could be determined. Also, the appropriate suppliers could be selected for the low carbon emission and cost.

In summary, the factors of carbon emissions, costs, and supplier's production capacities are considered in low carbon product design and sustainable supply chain network design. The remainder of this paper is organized as follows: Sect. 2 provides the conceptual background of the supply chain network design and GHG calculations. Sect. 3 presents the Pareto-based approach, a mathematical model with two objectives: low

carbon emissions and low cost. Section 4 provides the empirical evidence for the case study. Section 5 summarizes the implications and main findings of this study. Section 6 provides a conclusion and direction for future research.

2 Literature Review

This section reviews the literature on sustainable supply chain network design optimization and presents the methods typically used to calculate GHG emissions.

2.1 Sustainable Supply Chain Network Design Optimization

Sustainable supply chain network could be seen as a problem of resource reallocation (Dubey and Gunasekaran 2016; Pagell and Wu 2009; Seuring 2013) since the challenges involved future uncertainty about resources (Melnik et al. 2014). Normally, the supplier indices include cost/price, quality, technology capability, production facilities and capacity, delivery, service, relationship, flexibility, environmental competencies, pollution control, energy using design, and innovation, among others. The method here uses the analytical hierarchy process (AHP), analytical network process (ANP), data envelopment analysis (DEA), mathematical programming, and fuzzy inference (Amindoust et al. 2012; Shaw et al. 2012; Azadi et al. 2015; Sarkis and Dhavale 2015).

With rational hypotheses and parameter design, several studies focused on minimizing fixed and operating costs by considering carbon emissions or other environmental impacts. For example, Lee (2011) showed how the carbon footprint of components from key suppliers may be measured, thus allowing auto makers to improve measurements of total emissions. In addition to carbon emissions, Sundarakani et al. (2010) investigated the carbon footprint across supply chains. Some studies in the supply chain literature have also proposed optimization models for supply chain network design based on the metrics of cost, service, and quality (Chopra and Meindl 2012; Su et al. 2012a). Garg et al. (2015) found a firm could create a green image of its products to reduce its usage of transportation. Additionally, the company met the objectives of low carbon output and reducing operating costs. Tang et al. (2012) constructed a hierarchy analysis for the development of a low carbon economy in China. Su et al. (2012b) developed the environmental impacts at the product's conceptual design phase and underscored the importance of the quantitative assessments of its environmental impact and cost in the design phase itself.

For the CO₂ emissions and costs, Yang et al. (2016) used the bilinear non-convex mixed integer programming that was reduced to a pure linear mixed integer model for low-carbon city logistics distribution network design. Kawasaki et al. (2015) constructed a simulation model to simulate the relationship of CO₂ emissions, cost, and lead time. Kawasaki et al. (2015) built a discrete event simulation model for lead time, costs, and CO₂ emissions. The supply chain network includes Malaysia, China, and Japan. Tseng and Hung (2014) developed an objective function that considered the operations costs and social costs of CO₂ emissions. The carbon emissions could be evaluated in more detail through the life cycle stages. Kuo (2013) further constructed a collaborative design framework to help firms collect data on and calculate product

carbon footprints in a simple and timely manner throughout the supply chain. Based on the model of [Kuo et al. \(2014a\)](#), the low carbon supply chain network was optimized based on the carbon emissions, cost, and supplier's manufacturing capacities. Although some research documents the supply chain optimization operations under carbon emissions constraints, as shown in [Table 1](#), few studies used the Pareto-optimal solutions. For multi-objective supply chain network design ([Table 1](#)), [Chaabane et al. \(2011\)](#) and [Zhang et al. \(2014\)](#) formulated the multi-objective supply chain network and used ε -constraint algorithm to solve the proposed mathematical model. [Brandenburg \(2015\)](#) also formulated the multi-objective supply chain network and used the goal programming method to obtain optimal solutions. The ε -constraint algorithm was to adopt one objective as the objective function and transform the other objectives into constraints. In addition, the goal programming method used the same concept of the ε -constraint algorithm to obtain optimal solutions. This research formulated a bi-objective supply chain network and used the normal constraint method to obtain the Pareto frontier. The advantage of the normal constraint method was to have a greater opportunity to obtain uniform non-dominated points on the Pareto frontier than the ε -constraint algorithm and goal programming method.

2.2 The Proposed Method in Calculating GHG Emissions

The most accepted measure of GHG emissions is carbon footprint. A carbon footprint inventory contains the amount of GHGs emitted of a product ([Kuo et al. 2014b](#)) during its life cycle stages. Most firms follow the ISO 14064, ISO 14067, and PAS 2050 standards for calculating the carbon footprint of a product or service. The carbon footprint evaluation method involves the following steps: (1) scoping, (2) data collection, (3) footprint calculation, and (4) interpretation of results and suggesting reductions ([BSI 2008](#)). The details could be summarized as follows ([Kuo et al. 2016](#)).

- (1) Company data: company products, characteristics.
- (2) Product production data: weight and number of units.
- (3) Manufacturing process data: flow chart, inputs, manufacturing system, and outputs (including recycling, hazardous substance, energy consumption, carbon dioxide emissions, and other environmental impact data).
- (4) Direct and indirect materials data: all direct materials listed in the bill of materials for the product, and other indirect materials used to produce the product.
- (5) Energy consumption data: all energy resources, electricity, and other energy resources used to produce the product.
- (6) Transportation resources data: all transportation resources used to produce the product.

Among the above steps, the most difficult part of carbon footprint measurement is to conduct the life cycle inventory. [Song and Lee \(2010\)](#) developed a low carbon product design system. In Song and Lee's model, the evaluation of carbon emissions is based on products' life cycle stage. [Yung et al. \(2011\)](#) described an approach for using the GHG emissions data by Song and Lee's (2010) research to revise and improve the life cycle assessment (LCA) results. [Kuo et al. \(2016\)](#) conducted a multi-attribute

Table 1 Supply chain optimization operations under carbon emissions constraints

Author	Measure	Methodology	Description
Sundarakani et al. (2010)	Carbon emissions	Finite difference methods	The knowledge and practice of green supply chain management are studied
Chaabane et al. (2011)	Total logistics costs and total CO ₂ emissions	ϵ -constraint algorithm	A multi-objective mixed-integer linear programming model is used to consider economic and environmental factors
Jin et al. (2014)	Four models with associated total costs	Linear programming	Optimization models for major retailers are proposed to design supply chains under various carbon policies
Tseng and Hung (2014)	Total costs (operational costs and social costs of CO ₂ emissions)	Mixed integer programming	The operational cost is significantly influence the CO ₂ emissions
Zhang et al. (2014)	Total costs, total GHG emissions, and total lead time	ϵ -constraint algorithm	A multi-objective optimization framework is considered
Urata et al. (2015)	Total costs	Mixed integer programming	The carbon emissions could be reduced if the supplier and factory locations are changed
Brandenburg (2015)	Net present value, achieved average service level, and total carbon emissions	Goal programming	The trade-offs between the ecological factors of carbon emissions, financial value creation, and customer service levels are studied

Table 1 continued

Author	Measure	Methodology	Description
Ni and Shu (2015)	Safety stock cost and carbon tax cost across all the stages in the supply chain	Mixed integer programming	It studied the trade-off between service time and carbon emissions for safety stock placement in multi-echelon supply chains
Garg et al. (2015)	Total profit and carbon footprint of the company	Interactive multi-objective programming approach algorithm	An interactive algorithm is constructed to determine the optimal flow of parts and trucks hired by facilities
Kawasaki et al. (2015)	Lead time, total costs, and CO ₂ emissions	Discrete event simulation	The result shows it is proportional for the increase of CO ₂ emissions growth and lead time, while the cost is on the opposite
Ren et al. (2015)	Carbon emissions and total profits	Stackelberg game model	An allocation problem of carbon emission abatement target (PCEAT) in a decentralized made-to-order supply chain is studied
This research	Total costs and total CO ₂ emissions	Normal constraint method	A number of Pareto-optimal solutions should be achieved instead of one single solution

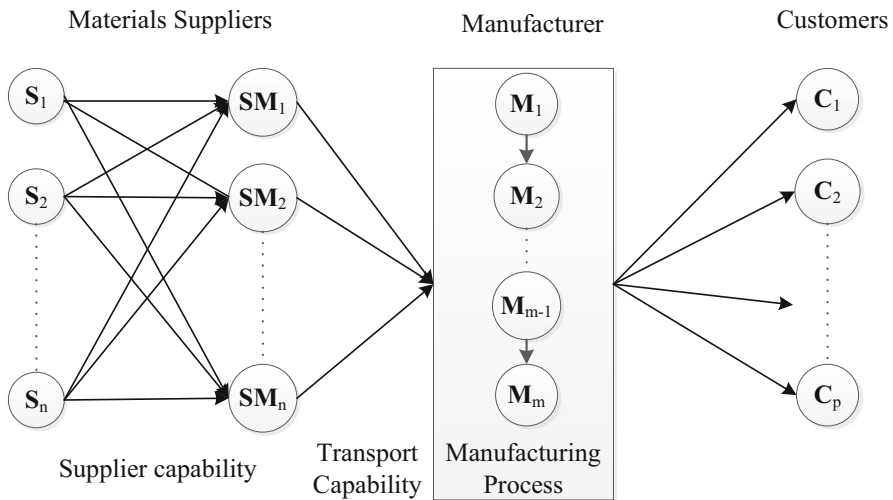


Fig. 1 The supply chain network design

function, a similarity threshold, and depth-first-search (DFS) graph searching techniques to match new designs to previous designs, search the similarity graph, and separate designs into groups to find the new product's GHGs. Nabavi-Pelesaraei et al. (2016) presented a non-parametric method of data envelopment analysis, and used a multi-objective genetic algorithm to estimate gains from energy efficiency and GHG emissions reduction.

3 Methodology

This study proposes a model for low carbon product design in a sustainable supply chain network. This model evaluates a supplier's capacity, manufacturing cost, transportation method, and carbon emissions. An illustration of this model is shown in Fig. 1. Figure 1 represents a multi-tier supply chain network, which consists of suppliers, manufacturers, and customers.

3.1 Calculating GHG Emissions

The carbon footprint inventory contains the amount of GHGs emitted from the exploitation and processing of raw materials, as well as the production, assembly, use, disposal, and recovery of products. Basically, the GHG data could be calculated based on the following standards: ISO (2006), PAS 2050:2008 (BSI 2008), and ISO (2012). The scope of carbon emissions could be cradle-to-gate or cradle-to-cradle. Calculating the GHG emissions requires three types of data: (1) national or regional energy usage and emissions, (2) emissions from firms, and (3) GHGs emitted during the life cycle of each individual product (Kuo et al. 2015).

3.2 Pareto-Optimal Solutions

Normally, a multi-objective optimization problem can be formally defined as Eq. (1),

$$\begin{aligned} \min_{x \in X^{n_x}} \quad & f(x) = \{f_1(x), f_2(x), \dots, f_M(x)\} \\ \text{s.t.} \quad & \\ & g(x) \leq 0, \\ \text{and} \quad & h(x) = 0. \end{aligned} \tag{1}$$

where x is the vector of decision variables bounded by the decision space, X^{n_x} , and f is the set of the objectives to be minimized. The terms “solution space” and “search space” are normally used to denote the decision space. The functions $g(x)$ and $h(x)$ respectively represent the sets of inequality and equality constraints that define the feasible region of the n_x -dimensional continuous or discrete space. The relationships between the decision variables and the objectives are controlled by the objective function $f : X^{n_x} \rightarrow F^M$. Figure 2 shows the Pareto-optimal frontier, denoted as PF^* , which is a set of non-dominated solutions (or black points) with respect to the objective space such that $PF^* = \{f_i^* | \nexists f_j \leq f_i^*, f_j \in F^M\}$. Typically, there are infinitely many Pareto optimal points for a problem, and to settle on one point requires the decision maker to articulate preferences in terms of the relative importance of the objectives or in terms of goals, before the optimization algorithm is run. These approaches could be considered as belonging to one of two classes: first class and second class. The first class involves defining an objective/constraint function. The second class of methods for obtaining a Pareto optimal design involves generating a set of solutions and determining which one would be selected.

This study uses the second class of the normal constraint method for the following reasons: (1) The method should generate an even set of Pareto points in the design space and not neglect any region, (2) the method should have the ability to generate all available Pareto solutions, (3) the method should generate only Pareto solutions, and finally, (4) the method should be relatively easy to apply. Table 2 shows the generic and original mathematical representation as well as the normal constraint method. For more details about *Utopia line* and *Utopia hyperplane*, please see Messac et al. (2003). *Utopia line* refers to the line joining two anchor points in bi-objective cases. *Utopia hyperplane* refers to the plane that comprises all the anchor points in the multi-objective case. *Utopia point* is the point defined by a vector where the generic i th component is the value of the design objective function obtained by minimizing only the corresponding i th design objective. Table 2 shows the generic formulation [Eqs. (2) to (5)] and normal constraint method [Eqs. (6) to (11)]. Equations (2) and (6) represent the objective functions. Equations (3), (4), (7), and (8) represent different types of constraints. Equations (5) and (9) represent lower- and upper-bound constraints of decision variables. Equations (10) and (11) represent the required constraints of the normal constraint method. For the generic formulation of the optimization problem, the vector x denotes the design variables and μ_i

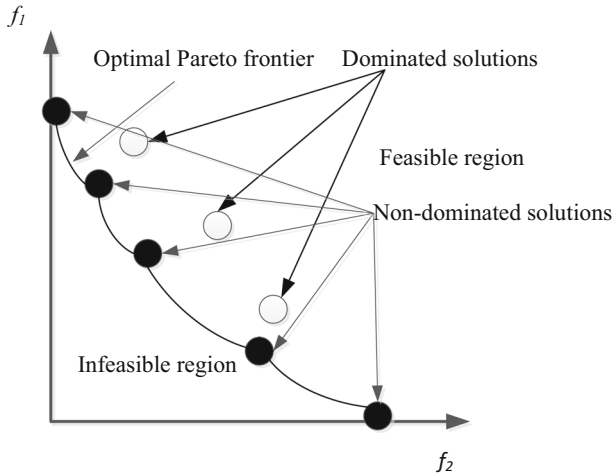


Fig. 2 The relationship between the approximation sets

Table 2 The generic and original mathematical representation and the normal constraint method

Generic formulation		Normal constraint method	
Problem 1		Problem 2 (for the j th point)	
$\min_x \mu_i(x), (1 \leq i \leq n)$,	(2)	$\min_x \bar{\mu}_2$,	(6)
subject to		subject to	
$g_j(x) \leq 0, (1 \leq j \leq r)$	(3)	$g_j(x) \leq 0, (1 \leq j \leq r)$	(7)
$h_k(x) = 0, (1 \leq k \leq s)$	(4)	$h_k(x) = 0, (1 \leq k \leq s)$	(8)
$x_{li} \leq x_i \leq x_{\mu i}, (1 \leq i \leq n_x)$	(5)	$x_{li} \leq x_i \leq x_{\mu i}, (1 \leq i \leq n_x)$	(9)
		$\bar{N}_1(\bar{\mu} - \bar{X}_{pj})^T \leq 0$	(10)
		$\bar{\mu} = [\bar{\mu}_1(x) \bar{\mu}_2(x)]^T$	(11)

denotes the i th generic design metric (i.e., objective). In this study, the objective function is a bi-objective goal. For the normal constraint method, the objective is to find a better solution on the Pareto frontier. The steps are as follows: obtaining anchor points, performing the objective mapping, defining the *Utopia line* vector, performing normalized increments, generating *Utopia line* points, generating Pareto frontier points, and finding the corresponding value of Pareto design metrics (Messac et al. 2003).

3.3 Notations

The indices, parameters, and decision variables used in the mathematical model are described as follows:

Index	Description
i	i th supplier, and $S = \{1, \dots, i\}$
j	j th transportation method, and $T = \{1, \dots, j\}$
k	k th raw material/component, and $K = \{1, \dots, k\}$
m	m th manufacturing process, and $M = \{1, \dots, m\}$
n	n th workstation, and $WS = \{1, \dots, n\}$
Parameter	
GHG_{ijk}	GHG emissions for the k th raw material/component of the i th supplier in the j th transportation method (gCO ₂)
$Cost_{ijk}$	Cost for the k th raw material/component of the i th supplier in the j th transportation method
GM	Unit GHG emissions of the manufacturing process (gCO ₂)
CM	Unit cost of the manufacturing process
GR_{ik}	GHG emissions from manufacturing using the k th raw material/component of the i th supplier (gCO ₂)
CR_{ik}	Cost of the k th raw material/component of the i th supplier
GT_j	GHG emissions of the j th transportation method (gCO ₂)
CT_j	Cost of the j th transportation method
D_i	Distance from the i th supplier to the manufacturer
W_k	Weight of the k th raw material/component
U_{mn}	Power rate of process m at workstation n
T_{mn}	Manufacturing time of process m at workstation n
GE	Carbon emission factor of electricity in Taiwan's context (gCO ₂ /kWh)
CE	Cost of electricity in Taiwan
PN	Total production quantity
M'	A big positive real number
F_{ijk}	$= \begin{cases} 1, & \text{if supplier } i \text{ can use transportation method } j \text{ for} \\ & \text{material/component } k \\ 0, & \text{otherwise} \end{cases}$
μ_k	Total demand for raw material/component k
P_{ik}	Capacity of the i th supplier for producing raw material/component k
L	Order quantity
UPH_{mn}	Units per hour of process m at workstation n
Decision variables	
x_{ijk}	The amount of raw material/component k that is supplied by supplier i for transportation method j
Y_{imn}	$= \begin{cases} 1, & \text{if process } m \text{ is processed at workstation } n \text{ of supplier } i \\ 0, & \text{otherwise} \end{cases}$
T_{ijk}	$= \begin{cases} 1, & \text{if supplier } i \text{ provides transportation method } j \text{ for} \\ & \text{raw material/component } k \\ 0, & \text{otherwise} \end{cases}$

3.4 Mathematical Model for Sustainable Supply Chain Network Design

Two objective functions are considered. In Eq. (12), OBJ_1 measures total cost per unit, where the first part is the sum of all costs divided by the total demand quantity, and the second part is the unit manufacturing cost. In Eq. (13), OBJ_2 measures total carbon emissions per unit, where the first part refers to GHG emissions divided by total demand quantity, and the second part denotes the GHGs generated by the

manufacturing process of each unit.

$$OBJ_1 = \min Z_1 = \sum_{k \in C} \frac{\sum_{i \in S} \sum_{j \in T} Cost_{ijk} \times x_{ijk}}{\mu_k} + CM, \tag{12}$$

where

$$\begin{aligned}
 Cost_{ijk} &= CR_{ik} + W_k \times D_i \times CT_j, \forall i \in S, j \in T, k \in C, \\
 CM &= \frac{\sum_{i \in S} \sum_{m \in M} \sum_{n \in WS} Y_{imn} \times U_{mn} \times T_{mn} \times CE}{PN}. \\
 OBJ_2 = \min Z_2 &= \sum_{k \in C} \frac{\sum_{i \in S} \sum_{j \in T} GHG_{ijk} \times x_{ijk}}{\mu_k} + GM, \tag{13}
 \end{aligned}$$

where

$$\begin{aligned}
 GHG_{ijk} &= GR_{ik} + W_k \times D_i \times GT_j, \forall i \in S, j \in T, k \in C, \\
 GM &= \frac{\sum_{i \in S} \sum_{m \in M} \sum_{n \in WS} Y_{imn} \times U_{mn} \times T_{mn} \times GE}{PN}.
 \end{aligned}$$

Constraints:

$$\sum_{i \in S} \sum_{j \in T} x_{ijk} = \mu_k, \quad \forall k \in C, \tag{14}$$

$$\sum_{j \in T} x_{ijk} \leq P_{ik}, \quad \forall i \in S, \quad k \in C, \tag{15}$$

$$\sum_{j \in T} T_{ijk} \leq 1, \quad \forall i \in S, \quad k \in C, \tag{16}$$

$$x_{ijk} \leq M' \times T_{ijk}, \quad \forall i \in S, \quad j \in T, \quad k \in C, \tag{17}$$

$$x_{ijk} \leq M' \times F_{ijk}, \quad \forall i \in S, \quad j \in T, \quad k \in C, \tag{18}$$

$$\frac{x_{ijk}}{L} \in \text{an integer number}, \quad \forall i \in S, j \in T, k \in C, \tag{19}$$

$$\begin{aligned}
 \sum_{j \in T} x_{ijk} &\leq \sum_{n \in WS} Y_{imn} \times (T_{mn}/UPH_{mn}), \\
 \forall i \in S, \quad m \in M, \quad k \in C, &\tag{20}
 \end{aligned}$$

$$x_{ijk} \geq 0, \quad \text{but } Y_{ijk} \text{ and } T_{ijk} \text{ are integer variables.} \tag{21}$$

Constraint (14) is the flow conservation constraint. The quantity supplied by all suppliers is equal to the total demand. Constraint (15) requires that raw material/component k shipped be no more than the i th supplier’s capacity. Constraint (16) implies that at most one transportation method can be used to transport each raw material/component by each supplier. Constraint (17) implies that, if raw material/component k is shipped from supplier i by transportation method j , the value of transportation method j must be assigned to 1. Constraint (18) implies that, if supplier i cannot ship raw material/component k by transportation method j , the amount of raw material/component k shipped by supplier i must be 0 by transportation method

j . Constraint (19) ensures that the batch size is an integer. Constraint (20) means that the production quantity of each process by each supplier must be no less than the amount of each raw material/component shipped by each supplier. Finally, Constraint (21) refers to the nonnegative and integer constraints for decision variables.

4 Cases and Results

This section presents a case study of a bi-objective optimization model including cost and GHG emissions. Data used in this research are from Kuo et al. (2014a), which were collected from company in Taiwan. The case company is a world-leading company, which obtained the world's first "ISO 14006 Environmental management systems–Guidelines for incorporating ecodesign" certification for networking products and "ISO 50001–Energy management" certification. Moreover, in recent years, the case company also calculates the product's carbon footprint with low carbon supply chain network design. This company is also committed to fulfilling its responsibility toward society and the environment.

The suppliers of this case company are distributed across Taiwan and Mainland China. The illustration refers to optimization for a router with 13 components, namely the nameplate (C_1), transformer (C_2), resistor (C_3), antenna (C_4), LED (C_5), electrolytic capacitor (C_6), crystal resonator (C_7), MLCC (C_8), IC (C_9), connector (C_{10}), cover (C_{11}), screws (C_{12}), and PCB (C_{13}). Six main component suppliers are considered in this model. They are located in northern Taiwan (S_1), central Taiwan (S_2), southern Taiwan (S_3), Suzhou in China (S_4), Zhejiang in China (S_5), and Guangdong in China (S_6). The distances between each supplier and the manufacturer, measured using Google maps, are as follows: 16 KM (S_1), 188 KM (S_2), 394 KM (S_3), 695.508 (S_4), 459.819 (S_5), and 860.998 (S_6). The transportation fees are as follows: airline (0.407 NTD/kg km), ship (0.04 NTD/kg km), and truck (0.05 NTD/kg km). The weights of different components are 2.24g (C_1), 5.4g (C_2), 1.1g (C_3), 41.3g (C_4), 6.4g (C_5), 18.8g (C_6), 0.52g (C_7), 8.58g (C_8), 3.04g (C_9), 44.2g (C_{10}), 192g (C_{11}), 4g (C_{12}), and 78g (C_{13}). Based on the LCI database of Simpro 7.2.2, the carbon emissions of different transportation methods are 1.09 kg CO₂ (cargo), 0.01 kg CO₂ (ship), and 0.66 kg CO₂ (truck). The transportation fees are 407 NTD/tkm (cargo), 40 NTD/tkm (ship), and 50 NTD/tkm (truck). The manufacturing processes and usage of electricity power are shown in Table 3. Supplier capacities for different components are listed in Table 4. The carbon emissions and costs differ by suppliers and components, as shown in Table 5. It is worth mentioning that the mathematical model was formulated using the AIMMS application (CPLEX 12 Solver).

4.1 Results and Analysis

Based on the Pareto frontier method, two objective functions are minimized. The feasible space and the corresponding Pareto frontier are calculated. Two anchor points are obtained by successively minimizing the first and second design metrics. A line joining the two anchor points, called the *Utopia line*, is drawn. The *Utopia line* is divided into $m - 1$ ($m = 20$) segments. Table 6 represents 20 non-dominated solutions

Table 3 The manufacturing process and usage of electricity power (Kuo et al. 2014a)

Process	Workstation	kwh	pcs/kwh
SMT	M _{SMT,1}	0.44	0.0048
	M _{SMT,2}	1.32	0.0145
	M _{SMT,3}	1.1	0.12
	M _{SMT,4}	11	20
	M _{SMT,5}	2.4	0.0264
	M _{SMT,6}	83	0.912
	M _{SMT,7}	3	1.5
	M _{SMT,8}	0.036	0.07
	M _{SMT,9}	0.09	0.36
DIP	M _{DIP,1}	0.363	0.0002
	M _{DIP,2}	33	0.0942
	M _{DIP,3}	0.735	0.002
	M _{DIP,4}	0.09	0.0003
	M _{DIP,5}	0.06	0.0002
F1 (inspection)	M _{F1,1}	0.66	0.033
	M _{F1,2}	0.374	0.0187
Assembly	M _{Assy,1}	0.22	0.0005
	M _{Assy,2}	0.33	0.0007
F2 (inspection)	M _{F2,1}	0.66	0.044

Table 4 Supplier capacities for different components (Kuo et al. 2014a)

	Unit: 1000 pieces												
	C ₁	C ₂	C ₃	C ₄	C ₅	C ₆	C ₇	C ₈	C ₉	C ₁₀	C ₁₁	C ₁₂	C ₁₃
S ₁	1		3						1				2.5
S ₂		1	2.5	4	8			3	1	5			
S ₃		5		3	8	5	4			5	3	5	
S ₄		5			16	4	5	3	2	7	5	6	3
S ₅	6	3	5	3		6		2	5		3	16	3
S ₆	1	3	1.5		8	3	2		2	2	2	5	1
Demand	7.5	7.5	7.5	7.5	7.5	7.5	7.5	7.5	7.5	7.5	7.5	7.5	7.5

on the Pareto frontier, which consists of cost and carbon emissions incurred by 13 components and 6 suppliers. Points A, B, C, and D are also shown in Fig. 3.

Furthermore, we study the relationship between the Pareto frontier of the cost and GHGs. Figure 3 shows the Pareto frontier of the bi-objective model of cost and carbon emissions. The part from D to C does not show much difference in carbon emissions reduction (e.g., the carbon emissions increase only 0.02 kg); however, the cost differs from 531 to 495 NTD. Moreover, there is a significant difference in carbon emissions from C to B. The cost reduces by 7 NTD (from 495 NTD to 488 NTD) while the carbon emissions increase by approximately 1 kg. From B to A, there is a cost reduction by

Table 5 The cost and GHG emissions of different components and suppliers (Kuo et al. 2014a)

	S_1		S_2		S_3		S_4		S_5		S_6	
	GHG	Cost	GHG	Cost	GHG	Cost	GHG	Cost	GHG	Cost	GHG	Cost
C_1	0.265	40							0.184	20	0.143	40
C_2	–	–	0.079	52			0.073	40	0.149	32	0.043	60
C_3	0.001	1.5	0.001	1.3					0.001	0.8	0.001	1.5
C_4	–	–	0.452	26	0.348	22			0.278	16		
C_5	–	–	0.032	2.6	0.027	2.2	0.022	2			0.019	3
C_6	–	–			1.676	8.8	1.547	8	1.289	6.4	0.902	12
C_7	–	–			0.693	44	0.832	4			0.485	6
C_8	–	–	0.078	13			0.127	10	0.069	8		
C_9	0.18	260	0.15	225			0.1	173	0.12	138	0.105	260
C_{10}	–	–	0.458	1.3	0.745	1.1	0.688	1			0.401	1.5
C_{11}	–	–			0.671	49.5	0.619	45	0.516	36	0.361	67.5
C_{12}	–	–			1.68	0.22	1.55	0.2	1.292	0.16	0.904	0.3
C_{13}	3.412	49.5					3.696	33	2.559	26.4	1.99	49.5

Unit: cost (TWD), GHG (kg CO_{2e})

3 NTD, and the carbon emissions increase by 1.30 kg. Therefore, the decision maker selects point C, where the cost and carbon emissions respectively equal 495.443 NTD and 30.665 kgCO₂. Decision makers can determine the appropriate transportation modes (ship, truck, or air) to transport special quantity of raw materials from which supplier to which manufacturer in order to satisfy customer demands.

4.2 Sensitivity Analysis

Two parameters are adjusted for the sensitivity analysis in the mathematical model: order batch size and supplier's GHG emissions reduction.

4.2.1 Order Batch Size

The order batch size assumes the values 50, 100, and 300. Figure 4 shows that, for different order batch sizes, the Pareto frontiers of order quantities 50 and 100 almost overlap. This implies that there is no difference when the order quantity is 50 or 100. However, under the same cost condition, the CO₂ emissions of order quantity 300 (Fig. 4) are higher. Therefore, we suggest that decision makers order quantities less than lot size 100.

4.2.2 Suppliers' GHG Emissions Reduction

The goal of the manufacturer is for its suppliers to reduce their carbon emissions. We assume that a manufacturer desires a 5% reduction in CO₂ emissions and prefers

Table 6 The frontier of the bi-objective model of cost and carbon emissions

Pt	Cost (NTD)	CO ₂ (kg)	Pt	Cost (NTD)	CO ₂ (kg)	Pt	Cost (NTD)	CO ₂ (kg)	Pt	Cost (NTD)	CO ₂ (kg)
D	531.516	30.624	6	518.594	30.626	11	507.287	30.627	C	495.443	30.665
2	528.286	30.625	7	516.979	30.626	12	504.974	30.630	17	493.023	30.764
3	526.670	30.625	8	513.748	30.626	13	502.570	30.634	18	490.618	30.870
4	523.440	30.625	9	512.133	30.627	14	500.166	30.638	B	488.241	31.101
5	521.824	30.625	10	508.902	30.6270	15	497.762	30.641	A	485.869	32.404

Bold notations, such as A, B, C, and D, are displayed in Fig. 3

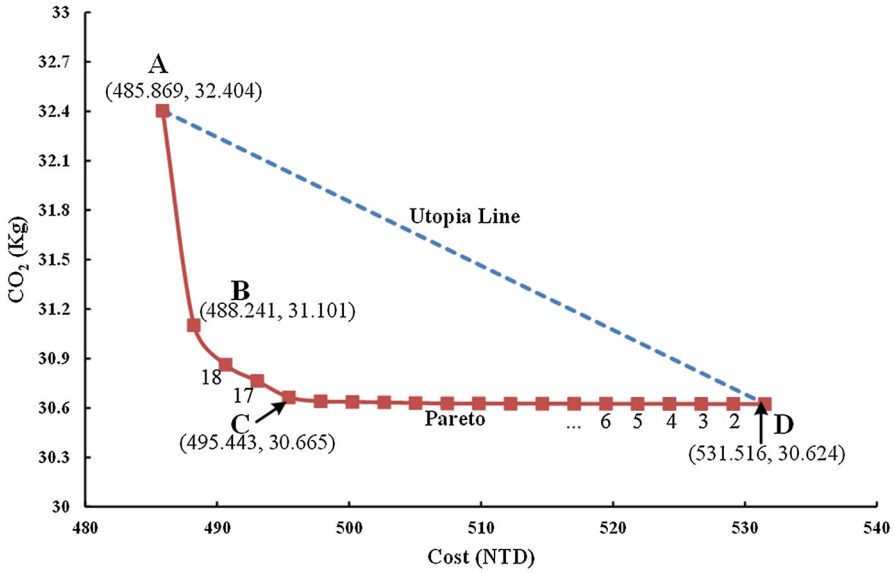


Fig. 3 The Pareto frontier of the bi-objective model of cost and carbon emissions

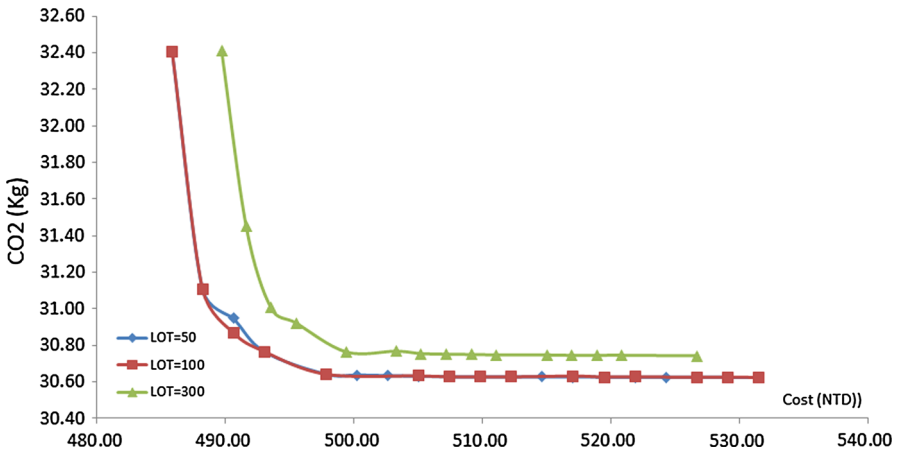


Fig. 4 The Pareto frontiers for adjusting order batch size

suppliers who can achieve this goal at the lowest cost. Here, the reason for a 5% reduction in CO₂ emissions is that the environmental protection agency (EPA) in Taiwan will ask the manufacturer to reduce 5% carbon emission for carbon label application. Therefore, the first Pareto frontier (S_1 Pareto frontier) is acquired by asking the first supplier to reduce carbon emissions by 5%, while the other suppliers'

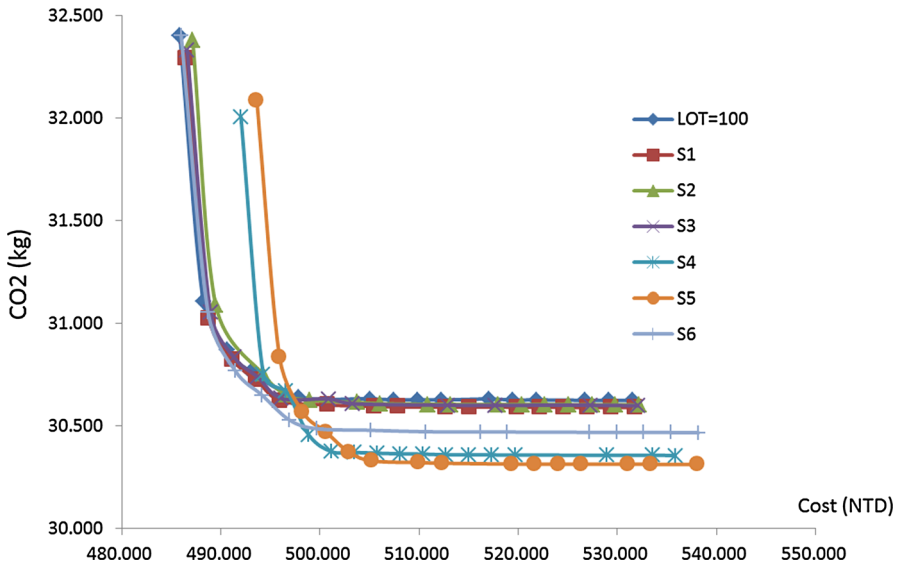


Fig. 5 The Pareto frontiers of suppliers' GHG emissions reduction

emissions remain the same. This process is repeated for six suppliers. Figure 5 indicates that the S_1 and S_2 Pareto frontiers overlap. This suggests that there is no difference between when S_1 reduces a 5% reduction in CO₂ emissions and the other five suppliers have the same CO₂ emissions and when S_2 reduces a 5% reduction in CO₂ emissions and the other five suppliers have the same CO₂ emissions. Similarly, the S_1 (or S_2) and S_3 Pareto frontiers overlap. This suggests that there is no difference between when S_1 (or S_2) reduces a 5% reduction in CO₂ emissions and the other five suppliers have the same CO₂ emissions and when S_3 reduces a 5% reduction in CO₂ emissions and the other five suppliers have the same CO₂ emissions.

However, the carbon reduction efforts of suppliers S_4 , S_5 , and S_6 are greater than those of suppliers S_1 , S_2 , and S_3 . Therefore, the S_1 , S_2 , and S_3 Pareto frontiers are below S_4 , S_5 , and S_6 Pareto frontiers. Furthermore, among suppliers S_4 , S_5 , and S_6 , the CO₂ emissions reduction of S_5 is higher than that of S_4 and S_6 . Therefore, the supply chain manager should adjust the order quantity according to the capacity of supplier S_5 . Table 7 shows the capacities and order quantities for supplier S_5 . Notice that most components ultimately reach a bottleneck. If the goal of the supply chain manager is to reduce carbon emissions, it is advantageous for him or her to only adjust the order quantities of components M_6 and M_{12} .

5 Implications

Nowadays, sustainable development has become a popular topic in the domain of sustainable manufacturing (Jayal et al. 2010). As corporate social responsibility is increasingly emphasized, low carbon design could be a criterion for supplier selection or management. This study aimed to bridge the gap between theoretical and practical

Table 7 The results of quantities of different suppliers

	S_1		S_2		S_3		S_4		S_5		S_6		Demand
	Ship	Truck	Ship	Truck	Ship	Truck	Ship	Truck	Air	Truck	Ship	Truck	
M_1		500							6000		1000		7500
M_2							4200		3000		300		7500
M_3				1000					5000		1500		7500
M_4				1500		3000			3000				7500
M_5											7500		7500
M_6										4500	3000		7500
M_7					4000		1500				2000		7500
M_8				3000					2500	2000			7500
M_9									5000				7500
M_{10}				5000		2000	500						7500
M_{11}							2500		3000		2000		7500
M_{12}									5000			2500	7500
M_{13}							3000		3000			1500	7500
Sub sum	-	500		10,500	4000	5000	11,700	-	4500	35,000	2500	4500	18,800
Sum	500			11,000	9000		16,200		42,000		18,800		18,800

problems. Real data are collected and used based on the ISO standard. The method provided by this research enabled supplier selection based on the cost, capacity, and emission, which are also critical factors. Compared to the results of [Kuo et al. \(2014a\)](#), this research provides additional solutions for decision makers. The sensitivity analyses conducted also considers the risk by analyzing different situations. The decision makers could choose the solutions based on their enterprise's strategies and goals.

The normal constraint method should yield multiple Pareto-optimal solutions rather than a single solution. Most previous research only considered the cost and CO₂ emissions. However, in this study, the suppliers' location and manufacturers' capacity are considered simultaneously. Additionally, the different CO₂ emission of different life cycle stages are also considered and calculated. In this study, it could be found that the distances for $S_4 - S_6$ are greater than for $S_1 - S_3$. If the manufacturer wants to reduce the carbon emissions, $S_1 - S_3$ should provide more components for the manufacturer. However, this inference will be affected and limited by the suppliers' technology and cost. Therefore, the manufacturer should choose suppliers in proximity. The implication of this result is that the supply chain network design could affect the CO₂ emissions reduction significantly. The Pareto frontier provides an effective method for solving multi-objective problems of supply chain network design. It also provides the assurance that all regions of the design space are adequately represented in the generated sample.

It is worth mentioning that some researchers have proved that a low carbon supply chain can improve firms' environmental performance ([Tseng and Hung 2014](#); [Kawasaki et al. 2015](#); [Urata et al. 2015](#)). Although the parameters in this research differ from those in the existing literature, the results are consistent with other studies.

6 Conclusion

Traditionally, supply chain network design focuses on global adjustments of production plants and distribution centers of a firm and its links to suppliers and customers ([Melo et al. 2009](#); [Brandenburg 2015](#)). The main issues include quality, delivery, cost, service, and technology. However, as global warming becomes more threatening, carbon emissions reduction is very important for firms; in particular, the supply chain manager must consider carbon emissions and cost reduction simultaneously. Therefore, the supply chain concept is important to evaluate and select appropriate suppliers.

The selection of appropriate suppliers is only one of many possible ways to reduce the emissions. With sophisticated network design, the firms redesign their network to become more sustainable. According to [Wu and Dunn \(1995\)](#), transportation could be seen as the largest source of emissions in the logistics system. Therefore, proper optimization of the supply chain may decrease the emissions of a supply chain. In this research, we used the Pareto frontier method to investigate the bi-objective supply chain network design in order to obtain uniform non-dominated Pareto solutions. This was the main difference between this research and previous literature on the multi-objective model of the low carbon supply chain network design. In addition, the suppliers' production capacity is added in this research. The sensitivity analysis is also conducted to find the difference between the change of cost and CO₂ reduction.

From the case study, we observed there is a limit to CO₂ reduction even though the cost is increased highly for manufacturers of downstream suppliers.

Although the proposed mathematical model has made a noteworthy contribution to the literature on low carbon network design, it has its limitations. First, it considered carbon emission, cost, and manufacturing capacities separately, while other models integrate these performance indices into a single index. Second, it only considered electricity. Other fuels used in the manufacturing site are excluded. Future research should develop a Pareto frontier with a better fit in order to find a better solution. In addition, the suppliers' priorities and evaluations (such as quality, cost, delivery, service, and technology) could be considered for more practical applicability. Our study could also be extended to include more objective problems, such as toxic materials management, water resources management, and recycling rates.

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